



NIKOLAOS TOUMASIS

SECURING LANDSCAPE RESILIENCE

SCHOOL OF WATER, ENERGY AND ENVIRONMENT

PhD

Academic Year: 2020-2024

Supervisor: Professor Ron Corstanje

Associate Supervisor: Professor Jim Harris, Lecturer Dr Daniel
Simms

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degree of PhD

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Abstract

Climate-induced perturbations are expected to increase in frequency and intensity and affect wetlands by altering its hydrology. An essential first step in comprehending the wetland hydrological and ecological resilience to future amplified climatic disturbances in coastal regions and beyond is this work, which enhances the approach for measuring wetland hydrologic resilience at a regional scale.

Land use change, natural disturbance and climate change directly alter ecosystem productivity and resilience levels. The estimation of ecological resilience dynamics depends on the quality of land cover change data and the effectiveness of the ecosystem models that represent the vegetation growth processes and disturbance effects. We used different mathematical approaches determining resilience, land cover change data to examine landscape resilience of the ecological networks in terms of scale, and how resilience exhibits as an emergent behaviour in different types of ecosystems, with its influencing factors, suggesting application to other estuarine ecosystems. A set of quantitative metrics was developed including the variations of landscapes, utilizing spectral power to determine changes in autocorrelation and variance as measures of critically slowing down, detecting the early warning signals with the development of the Dynamic Linear Model (DLM).

The coastal landscape, which includes coastal-herbaceous wetlands, was then subjected to this method detecting the influence of salinity intrusion on estuarine systems along geographical and temporal salinity gradients. We discovered that an excellent indication of resilience is the multiscale autocorrelation fluctuations of wetlands, affected by the temporal trends in data, under various climatic circumstances.

Climate interannual variability was the key driving force for the large interannual changes of ecosystem state level while extreme weather events and drought were the dominant driving forces for resilience balances in several specific ecoregions. There is a need for techniques that may be utilised to recognise when

a major transition is about to happen because these events might happen without warning and are challenging to handle. A number of "early warning signals" can be used to determine a system's near to a critical transition, according to recent theory, and successful empirical examples point to the possibility of practical use. Our study provides a practical toolbox that can be applied in a variety of sectors to help identify early warning signs of crucial transitions in time series data, in addition to a methodological guide.

Keywords:

Ecological networks, climate change, resilience, early warning signals, critical transition, autocorrelation.

Word count: 58,341

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List of Abbreviations

ACF	Autoregressive Conditional Heteroskedasticity
AEM	Airborne Electromagnetic
ALN	Abnormally Low NDVI
AR (1)	Autoregressive Model of order one
BISE	Best Index Slope Extraction
BGS	British Geological Society
CRMS	Coastwide Reference Monitoring System
CSD	Critical Slowing Down
CWPPRA	Coastal Wetlands Planning, Protection, and Restoration Act
CWT	Continuous Wavelet Transform
DLM	Dynamic Linear Model
ENSO	El Niño Southern Oscillation
EWS	Early Warning Signal
FCS	Favourable Conservation Status
FFT	Fast Fourier Transform
GEMS	Global Environment Monitoring System
GIS	Geographic Information System
LST	Land Surface Temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalised Difference Vegetation Index
NIR	Near Infrared
PH	Potential of Hydrogen
QGIS	Quantum Geographic Information System
ROI	Region Of Interest
SAV	Submerged Aquatic Vegetation
SLR	Sea Level Rise
STA	Stormwater Treatment Area
TP	Total Phosphorus

1 General Introduction

According to the Intergovernmental Panel on Climate Change (IPCC), the world's leading authority on climate science, human activity is changing the Earth's climate in ways unprecedented in hundreds of thousands of years with some of the changes now 'inevitable' and 'irreversible'. In order to improve resilience to climate change, it is necessary to understand and estimate climate risks, producing projections of a wide range of policy-relevant indicators covering heat extremes, agriculture, wildfire and hydrological systems. Tipping points are typically observed in systems where strong positive feedback drive the establishment of alternative stable states. Ecological tipping points are difficult to detect (Dakos et al., 2012).

Critical Transition Theory in ecology, a cornerstone in understanding ecological stability and resilience, suggests that ecosystems can undergo sudden and dramatic changes in response to gradual changes in environmental conditions or internal dynamics. One prominent figure in this field is Scheffer et al., 2009 who have extensively studied critical transitions and tipping points in ecosystems. Their work emphasises how subtle changes in variables like nutrient levels, species populations, or climate conditions can indicate an approaching tipping point, leading to a sudden shift in the ecosystem's state. Small changes in an ecosystem - like variations in species populations, chemical cycles, or physical conditions - can indeed act as early warning signals. These signals help predict potential tipping points, where the ecosystem might shift dramatically to a different state. For example, if a lake is becoming increasingly eutrophic (nutrient-rich), subtle changes such as a decrease in water clarity or shifts in algae species composition can indicate it's nearing a tipping point. Once this tipping point is reached, the lake could transition to a turbid, algae-dominated state that's difficult to reverse. Early detection of these signals is crucial for environmental management and conservation efforts. It allows for timely interventions that can prevent undesirable shifts and promote ecosystem sustainability (Zhang et al., 2010).

This risk is typically quantified by indicators of resilience based on critical slowing down and include an increase in recovery time back to equilibrium after a perturbation, a rise in variance as the state of the ecosystem fluctuates more widely around its equilibrium, and an increase in autocorrelation because the state of the ecosystem more closely resembles its previous state near a tipping point. These indicators have been empirically tested in laboratory experiments and in the field with a focus on the dynamics of the ecosystem state while neglecting any trait changes. My thesis explores and develops various ways of quantifying these indicators in practice (Corstanje et al., 2016; Song et al., 2018).

In addition to assessing the current state of an ecosystem, the influencing factors and conditional structures of landscape resilience also examine diverse landscapes worldwide, ranging from wetlands to agricultural landscapes, grasslands, and saline landscapes of estuarine systems. The factors that are thought to be able to highlight landscapes are as varied as the forms of geography. Even though the case studies are rather diverse in their specifics, their intriguing mosaic simultaneously demonstrates that there are general guidelines that may be applied to specifically boost landscape resilience so that environments come out of crises strengthened rather than weakened.

Our understanding and oversight of the natural world are seriously challenged by the knowledge that complex systems, including ecological communities, can abruptly collapse or switch regimes without swift external pressing. In spite of such obviously unexpected behaviour, the ability to detect early warning signs that would enable researchers and administrators to anticipate these events before they occur has therefore been a priceless discovery that provides a path forward. According to research on early warning signals, in certain scenarios, it is feasible to identify the presence of these early warning signs before the shift occurs. In this piece, we outline the trend that is becoming apparent as additional research is done to determine how broadly these results can be applied. The phenomenon of rapid regime transitions, a pattern of "critical slowing down" that

can be implemented to identify the impending shift, and the process of bifurcation causing the abrupt change are the three characteristics that a core group of cases have. It is now obvious that not all systems exhibiting regime transitions also display critical slowing down, or vice versa, since research has broadened beyond these fundamental scenarios. Statistical detection is challenging, even in cases when systems show serious slowing down. We examine the literature on these edge cases and emphasise the necessity of (a) novel early warning behaviours that can be used when there is no critical slowing down of rapid transitions; (b) the development of methods to identify which behaviour might be an appropriate signal when encountering a novel system, bearing in mind that a positive indication for some systems is a negative indication in others; and (c) statistical methods that can distinguish between signatures of early warning behaviours and noise (Milne et al., 2011; Carpenter et al., 2011).

Global ecosystems are under severe threat from the rising frequency of catastrophic events as well as long-term pressures brought on by anthropogenic activity and climate change. One of the fundamental goals of biological conservation is to promote ecological resilience, or 'ecosystems capacity' to withstand change and continue to operate. The fundamental assumption of many empirical approaches to resilience evaluation is that, in the absence of disruptions, ecosystems would be in a 'static' baseline state. Ecological systems are actually very dynamic and go through stages of growth and restructuring as a result of successional changes that occur naturally and their reaction to various interrelated factors. Therefore, "dynamic regimes" rather than "stationary states" are a preferable way to characterise ecological states (Sánchez-Pinillos et al., 2024).

Implementing robust monitoring systems can help detect early signs of instability. This includes tracking species populations, water quality, and other vital indicators. Using an adaptive management approach allows for flexible strategies that can be adjusted based on monitoring data. This helps in implementing timely interventions. Protecting keystone species, preserving habitats, and restoring degraded ecosystems can enhance their natural feedback mechanisms.

Promoting sustainable agriculture, forestry, and fishing practices helps maintain the natural balance and prevents overexploitation of resources. Homeostatic feedback, also known as negative feedback, is a self-regulating process by which biological systems maintain stability while adjusting to conditions that are optimal for survival. In ecology, it refers to mechanisms that help ecosystems resist drastic changes and maintain equilibrium. It stabilises the system by counteracting changes. For example, if a population of a species increases too much, factors like disease, food scarcity, or predation might increase, bringing the population back down. This feedback ensures balance within ecosystems, allowing them to withstand minor disturbances and return to a stable state. Understanding and managing homeostatic feedback is crucial for maintaining the health and stability of ecosystems, ensuring they continue to provide vital services for humans and the planet.

Managing for resilience means keeping a variety of functions and homeostatic feedback in place, guiding systems away from potentially dangerous thresholds, improving the system's capacity to acquire and modify knowledge in order to adapt to changing circumstances, and enhancing the system's ability to retain its identity under a variety of circumstances. For instance, restocking a top predator, enforcing regulations to limit the amount of phosphorus entering the lake, and demonstrating upstream landowners about proper riparian zone management techniques could all be a component of a management strategy that preserves clear water in a shallow lake (Carpenter et al., 2011; Folke et al., 2004).

Rather than focusing on specialised, in-depth knowledge from isolated system components, resilience management should aim to increase understanding of the entire system of interest. Understanding that systems can be extremely robust even when they are in unstable states is crucial. Thus, the three main components of managing for resilience are: 1) recognising potentially unstable regime shifts within the system and taking preventative measures to avoid them (as in the case of the lake), 2) preserving a diversity of components and feedback interactions that maintain a system within a specific desired state, and 3) taking measures to minimise the chance that a system could fail or switch into a different

state, such as managing invasive species, keeping vigilant on and maintaining hydrological processes, or maintaining a head out of emerging diseases (Desjardins et al., 2015).

To illustrate the three fundamental components of managing for resilience in practice, we provide the following: Managers of wildlife must recognise signs that point to a system's loss of resilience. It is crucial to increase resilience, and this could be accomplished by preserving the patterns of ecological function distribution both within and between scales. The elements of resilience can be identified with the use of adaptive management. Management interventions are thought of as adaptive management experiments. Adaptive governance may lead to a shift in the context of environmental policy since it views policy options as conjectures that need to be tested. The foundation of resilience management is a systems approach. It cannot be successfully implemented without science and monitoring generated from science, nor will it work if the dynamic interactions between ecosystems and society are disregarded. Effective resilience management requires that important system components and interactions be described that important uncertainties be identified and, if feasible, reduced through intentional management experiments, and that possible future perturbations be enumerated, assessed, and addressed beforehand (e.g., through scenario planning), (Browne et al., 2009).

Variability in ecological processes and the scales at which they function should be encouraged by management. In an analogous way, proactive management should take disruption into account at several temporal and spatial scales. Certain types of perturbations are frequently expected to happen, even if it may be difficult to anticipate when or to what extent they will occur. It is preferable to manage the system so that it is robust enough to recover from unanticipated scenarios rather than designing it to try to prevent those events and thus reduce resilience (Holling 1973; Carpenter et al., 2011).

Freshwater, marine, and terrestrial ecosystems are experiencing significant changes as a result of human activity and anthropogenic climate change. These

changes are having an impact on relevant ecological processes and the integrity of ecosystems worldwide. Threats like this highlight the critical need for management initiatives that support ecosystem persistence, stop biodiversity loss, and save endangered species from going extinct. In this context, maintaining ecosystem resilience has emerged as a fundamental goal for ecosystem management on a global scale, as well as specific attributes of climate change likely to impact habitats, which is central to any adaptive ecological management strategy by scientists, professionals, and policymakers. The ability of ecosystems to tolerate changes in state variables and processes while continuing to function in the wake of disturbances is known as resilience, and it was first defined in the ecology literature (Holling 1973; Corstanje et al., 2004; Dakos et al., 2012).

The origin of the English term "Resilience" comes from the Latin verb "resilio", which means "recover". The use of the term is found in several disciplines (i.e. in ecology, psychology, economics, geography, political science, etc.). The definition of mechanical strength was probably the first attempt to introduce the term into the sciences. Then came the sciences of ecology and psychology ('70s & '80s) in order to describe different phenomena. Gradually the use of the term spread to other sciences, such as social and economic.

One researcher who attempted to interpret the term resilience was Holling in 1996, who argued that resilience is the ability of a particular system to maintain its structure and function against disturbances, as well as the ability of the system to reorganize, after the change caused by the disorder. Desjardins et al. (2015) expressed the view that robust systems are those that are flexible in dealing with various changes. Along with resilience, additional complementary concepts have been developed (i.e. adaptability, flexibility, etc.), which result in the mobilization of these bodies / social groups that will promote learning processes and at the same time introduce innovations (Desjardins et al., 2015).

Initially, according to Holling (1996), the concept of ecological resilience "is the ability of systems to absorb change and continue to exist". This type of resilience

was intended to describe ecosystems, in which adverse conditions still exist. A few years later, Holling (2002) added to ecological resilience the idea that a system can absorb a disturbance's size before it impacts its structure. However, adaptation strategies should aim to increase the flexibility in ecological management of vulnerable ecosystems, enhance the inherent adaptability of the ecosystem processes within vulnerable natural systems, and reduce trends in environmental pressures that increase vulnerability to climate variability.

Disturbance regimes that encompass a variety of temporal and spatial scales affect the majority of ecosystems. The natural disturbances having a distinct magnitude and frequency distribution are typically associated with pulse disturbances. Compound perturbations are created when human activities convert pulse disturbances into stress or chronic disturbances. Functional groupings of species must continue to be open to renewal and reorganisation in order to maintain desired ecosystem states in the face of compounding disruptions (Carpenter et al., 2011).

1.1 Theoretical background to resilience concepts

1.1.1 Definition of resilience and properties

The relationship between the theory of dynamical systems and the idea of resilience, highlighting ideas like equilibrium, stability, phase space, and domains of attraction in particular. Since then, a great deal of theoretical work on resilience theory has been created to explain the dynamics of ecological systems after disturbances through the implementation of differential equation-based mathematical models. However, the lack of a model explaining ecological dynamics and the challenge of accounting for the complexity of ecosystems—including randomness, geographically heterogeneity, and many state variables—

may limit the application of these methods in real systems. Resilience metrics and analyses that are not necessarily directly related to the theory are prevalent as a result of the necessity to derive practical knowledge from empirical data to support decision-making and prioritise conservation strategies (O'Neill et al., 1986; Hirota et al., 2011).

The subcategories of ecological resilience (ecological and mechanical) show significant differences between them (Holling and Gunderson, 2002). For example, ecological resilience does not provide much basis for system recovery time but focuses on the number of shocks a system can withstand. The main difference, however, is that ecological resilience assumes that there are many balances, rather than a non-negotiable one, and that systems are therefore moving towards alternative fields of consistency. Setting objectives for the ecosystem, determining regions that need more protection, and creating policies regarding human activity all require a thorough understanding of the ecosystem in which the management is taking place. This entails determining the ecosystem's structurally and functionally significant features, the type and extent of human activity, and the ways in which these elements interact across various temporal and spatial scales.

Table 1-1 Differences between engineering and ecological resilience.

	Engineering Resilience	Ecological Resilience
Theoretic Construct	Resilience=Resistance+Recovery	Resilience=Tolerance+Reorganization
Types of Equilibrium	One Equilibrium (One Regime)	Multiple Equilibria (Multiple Regimes)
Pre-conditions	Stability near Equilibrium	Far from Equilibrium
Focus	<ul style="list-style-type: none"> ▶ Speed to return to the Equilibrium ▶ Protect the existing configurations of the system 	<ul style="list-style-type: none"> ▶ System evolvement through multiple Equilibrium ▶ Explore modifications of the system ▶ Detect regimes

	► Detect the engineering Equilibrium	
Roles of Shocks	Threats	Learning Opportunities
Properties	► Robustness ► Redundancy ► Resourcefulness ► Rapidity	► Self-organization ► Adaptive Capacity ► Redundancy
Measurement Scale	Quantitative	Mainly Qualitative

As discriminated by Holling in his seminal paper (Holling et al., 1973) engineering resilience denotes the system's ability to recover its pre-perturbed equilibrium state as measured by the speed of return. The ecological concept considers a system's tolerance against disturbance without shifting to a replacement regime governed by fundamentally different processes and mechanisms (i.e., a domain of attraction) as quantified by the general area of the domain of attraction or the depth of the basin.

Engineering resilience describes the system's ability to withstand disturbances and quickly regain its equilibrium. It is a concept developed in the context of systems ecology. A measure of mechanical strength is the time t it takes for the system to return to its equilibrium point after a disturbance. The faster the system recovers the more durable it is. In this sense resilience is used in psychology and in the study of natural and man-made disasters to describe the ability of people, a community or a wider area to return to the point of reference after a trauma or external blow (Frey et al., 2013).

Mechanical resilience, as used in both ecology and regional studies, reflects a linear view of the system: the system changes as a result of a cause-and-effect relationship with its environment. In environmental studies, this view shapes the dominant way of managing the environment today. Man can derive the goods

and services he needs from an ecosystem by intervening to maximize his efficiency in these elements. In other words, we can control the system to increase its productivity as long as we periodically control the operation of the ecosystem, so that our interventions do not destroy it (Walker et al., 2012). However, ecosystems are not just linear systems in which human intervention can have controlled and desired effects. Or at least it is not so on a larger scale of space and time than the duration and extent of a human business.

Resilience has been broadly articulated as a system's ability to get over disturbance. Diverse interpretations emerge however, counting on what's considered "recovery" and the way that recovery is quantified. In contrast, resistance has been defined with relatively less confusion, e.g., because the degree to which a system's state or function is insensitive to disturbance (Konopka et al., 2015).

As an easy distinction, resilience is all about how well a system can bounce back after being disturbed, like a rubber band snapping back to its original shape after being stretched. It's the system's ability to absorb shock and return to its normal state. On the other hand, resistance is the system's ability to withstand a disturbance in the first place, like a wall standing firm against strong winds. It's about maintaining function despite facing potential disruptions. Both concepts are crucial in understanding how systems respond to challenges and maintain stability over time.

Studies that have long emphasised the significance of non-equilibrium and transient dynamics in ecological systems are implicitly ignored by such techniques. Ecosystems in nature are always changing for a variety of causes. An ecosystem might be considered out of balance if its internal dynamics oscillate regularly or irregularly, if a situation has changed and the system is moving towards a new equilibrium, or if it has been disturbed and is still recovering from the disturbance. Long transient dynamics can also result from persistently tiny perturbations or from a large number of species interacting within ecosystems at various scales and spatial dynamics. Thus, in order to quantify resilience in non-

equilibrium ecosystems while taking into account their stochasticity and complexity, instruments that bridge the gap between theoretical and empirical ecology are required. Resilience theory benefits greatly from Lewontin's "vector field model" in 1969.

The approach involves use of an n-dimensional space that is defined by a set of variables 'state variables' that describe the current state of the system. This dynamic state space is a vector field that is defined by a collection of transition vectors that specify a system's path based on where it is in the state space (Carpenter et al., 2011; Scheffer et al., 2009).

Lewontin's 'vector field model' suggested using probability density functions to identify the patterns dynamical systems adhere to and, in the end, the geometric properties of the "basin of attraction" for the system, because real ecosystems include random forces that make it difficult to identify ecosystem dynamics in the dynamical space. Moreover, the notion of 'ecological dynamic regimes' is highly beneficial. Scheffer et al. (2009) and Carpenter et al. (2011) noted that although this term has been used in earlier research, it is still relevant when referring to stable but non-static states. They contended that although "stable state" seems to ignore the dynamic character of ecological systems, "dynamic regime" explains the oscillations of ecosystems around a mean or trend (Sánchez-Pinillos et al., 2024; Carpenter et al., 2011).

Human disturbances, including nutrient enrichment, nitrogen deposition, acid rain from NO_x and SO_x , overfishing of fisheries and wildlife stocks, and unsuitable livestock grazing, can all lead to shifts in stable states. A "command and control" approach, for example, that emphasises the maximum output of one or a few variables and ultimately reduces the range of natural fluctuations in the system, may additionally provide rise to them over time. Examples of such actions include stabilising river flows with dams, putting out fires in ecosystems that are prone to them, maximising timber yield, or maintaining steady, high populations of deer. Also, climate change may be further destabilising processes, such as fire regimes, and affecting species distributions. The actual shift in states may be

triggered by stochastic events such as climatic extremes, disturbances like floods or wildfires, increased contagion of forest area, oil spills, and forest density, or insect outbreaks. They may also happen more gradually, as in the case of ecological structure modifications, species replacements, and changes in the composition of functional groups brought about by climate change, nutrient enrichment, or acid rain-induced changes in soil characteristics. The most well-researched instances include the eutrophication of lakes and coastal waters, shifts in grasslands' and woodlands' cover types, the degradation of coral reefs, and regional fluctuations in temperature. These long-term stresses can affect the ability of the system to respond to a shock. A resilience framework focuses attention on shocks (pulse disturbances), long-term stresses (press disturbances), and the response of complex systems to those shocks and stresses (Ives et al., 2003; Scheffer et al., 1998; Allen et al., 2018).

Considerations of resilience are especially important in systems that undergo persistent and fundamental shifts in structure and performance after disturbances ("regime shifts"). Increasing resilience can reduce the danger that the system will cross critical thresholds and undergo a detrimental regime shift. On the opposite hand, decreasing resilience can increase the probability of a beneficial regime shift. Understanding of the way to increase or decrease system resilience places a premium on knowledge of system dynamics, including feedback among system components, as well as uncertainty and variability in dynamic systems (Walker & Salt, 2006).

System resilience can play a crucial role in maintaining conditions that will sustain the supply of ecosystem services that contribute to human well-being. However, a narrow specialisation in stabilising complex systems to provide a continuing flow of ecosystem services may reduce system resilience and increase vulnerability (Gunderson et al., 1995). An event may disrupt service provision, but a resilient ecosystem will allow faster recovery so that services will return sooner rather than later or never (Table 1-1).

When an ecosystem crosses a threshold, it can shift from one stable state to another. For example, a clear water lake might shift to a turbid, algae-dominated lake due to nutrient loading. This transition can be difficult to reverse because of both biotic (living organisms) and abiotic (non-living environmental factors) barriers. Examples of biotic barriers might be the invasion of exotic species or altered species interactions (e.g., the common reed, *Phragmites* spp.) that excludes less competitive species, or a disease (e.g., chestnut blight) that eliminates a dominant member of the biological community. Examples of abiotic barriers include saltwater intrusion into a freshwater wetland as a consequence of rising water level, climate change, soil degradation, or hydrological changes (Figure 1-1).

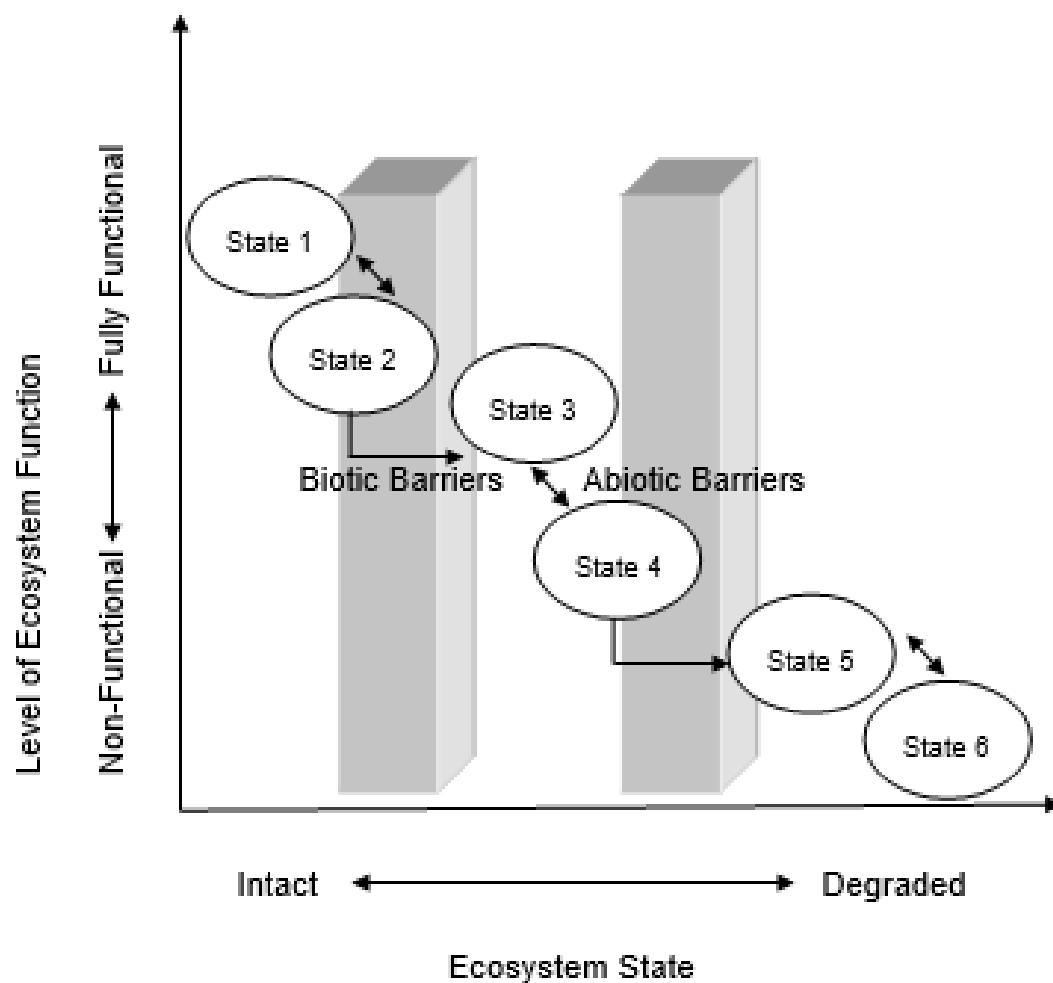


Figure 1-1 Examples of biotic and abiotic barriers (source: redrawn from Hobbs & Cramer 2008).

1.1.2 Ecosystem structure and functions. The two faces of resilience.

The Engineering Resilience is one of the foundations for economic theory that concentrates on stability near an equilibrium steady state, where resistance to disturbance and speed of return to the equilibrium are used to measure the property. In ecological resilience, the measurement of resilience is that the magnitude of disturbance is that the magnitude of disturbance is the amount of

disturbance that will be absorbed before the system changes its structure by changing the variables and processes that control behaviour. Emphasises conditions far away from any equilibrium steady state, where instabilities can flip a system into another regime of behaviour.

The two contrasting aspects of stability - essentially one that focuses on maintaining efficiency of function (engineering resilience) and one that focuses on maintaining existence of function (ecological resilience) - are so fundamental. There is an implicit assumption of worldwide stability that just one equilibrium steady state exists, or if other operating states exist, they ought to be avoided by applying safeguards. Moreover, it becomes obvious that the variability of critical variables forms and maintains the stable landscape.

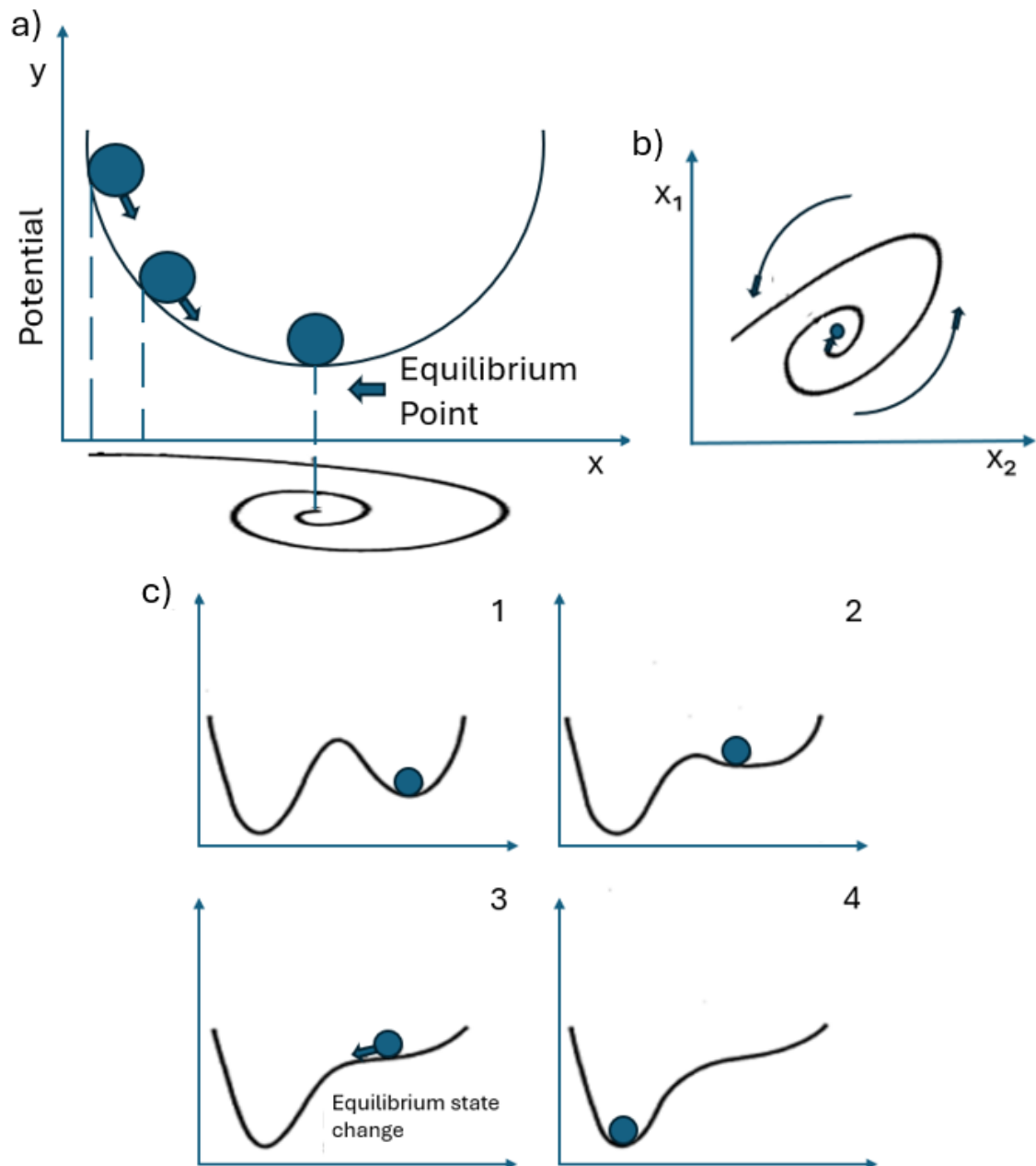


Figure 1-2 A single globally state equilibrium from two perspectives: a) an analogy between topography and a mechanical ball, b) showing how a point moves towards the stable equilibrium in abstract state space, with x_1 and x_2 denoting the population densities of two competitors, c) Analogies between topography and state space perspectives on changing nature. As the system progresses from state 1 to 4 it alters its own potential states. In this scenario the perturbation required to shift the system's equilibrium state from one domain to the other decreases with time until the system switches states on its own. An illustration of

engineering resilience determining how quickly the ball returns to the equilibrium point and how resistant it is to perturbations that deviate from it. (Source: Redrawn from National Academies of Sciences, Engineering, and Medicine, 1996. Engineering within Ecological Constraints. Washington, DC: The National Academies Press, 1996. <https://doi.org/10.17226/4919>).

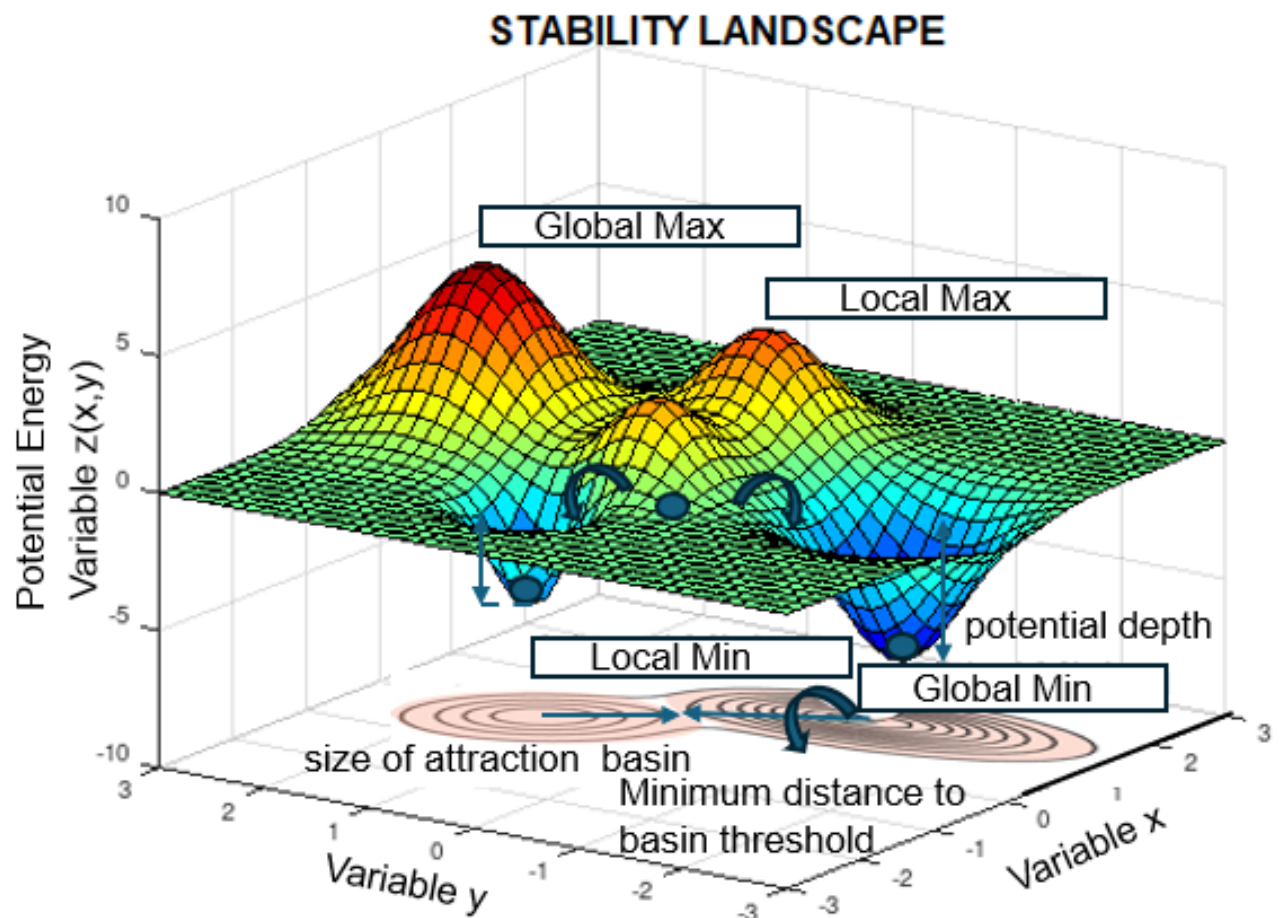


Figure 1-3 The figure is known as balls-and-cups landscape which is a fictitious stability landscape of a two-dimensional system with hilltops and valleys. The stable states symbolised by the blue balls found at the bottom of the valley are such that the ball will 'gravitate' towards the bottom if it is disturbed. The Local-Global Minima are represented in the figure, as well as the size of the attraction basin with the pink cyclical areas. The blue arrows show the potential depth.).

1.1.3 Ecosystem disruptions of resilience and critical points.

In shallow lakes with low phosphorus levels, plants inhibit the growth of algae by absorbing phosphorus. However, algal blooms that restrict light penetration and damage plants can result from increased phosphorus inputs, which release more phosphorus for algae. Management and resource exploitation can cause savannas to become shrub-dominated semideserts, forests to become grasslands, fisheries to collapse, and waterways to become overloaded with nutrients.

The idea of "natural variability" often refers to the natural fluctuations in environmental conditions, such as temperature, precipitation, or nutrient levels, which play a crucial role in maintaining the balance of ecosystems. Reducing this inherent unpredictability may make ecosystems more susceptible to disruptions. Critical points might refer to thresholds or tipping points in an ecosystem where a small change can lead to a significant impact, potentially altering the system's structure and function. One is that ecosystems become less resilient and more vulnerable when the variability of important variables is decreased. The second is that resource development cannot be managed or benefitted from in a different way by organisations or individuals. Even though the effects of climate change may be severe, existing management techniques such as establishing coastal defences, controlling flooding, and excluding fires can make them worse. Methods of adaptation designed to protect financial interests frequently conflict with strategies for preserving biodiversity. There is a greater chance of population collapse and lower sustainable harvest rates when there is more environmental unpredictability. Climate change has the potential to significantly impair the appropriateness of habitats and endanger species with restricted means of dispersal. In these situations, management initiatives to improve landscape connectivity might not be as effective as carefully thought-out species translocations (Ives, 1995; Carpenter, et al., 1997; Scheffer et al., 2009).

Table 1- 2 Indicators and metrics to detect resilience.

Indicators of resilience	Metrics and analytics used to detect resilience
Critical Slowing Down (CSD)	→ Autocorrelation (ACF)
Increased Variance	→ Wavelet Power Spectrum
Recovery time	→ Pinpointing the event, identifying the baseline from adjusted salinity graphs

1.2 Analytics and metrics

1.2.1 Finding the optimal ecosystems to estimate important slowing down indications

The scale (temporal and spatial), controllability, and boundaries of the ecosystem being studied will all have a significant impact on the viability of identifying CSD. Ecosystems with short time periods are just better for data collection and are generally more suited for research and manipulation. For example, it will be more effective to measure CSD in phosphorus perturbation studies in a targeted wetland, such as STAs (Storm Water Areas - large, constructed wetlands with emergent and aquatic plants) in South Florida, than to perform the same experiments in a large-scale estuarine ecosystem, such as the coastline of Louisiana, or in an extensive grassland ecosystem (Table 1-3). Furthermore, estimating CSD indicators is more challenging for large-scale ecosystems because of their uniqueness than for ecosystems for which we have numerous "replicates" (such as lakes or rock intertidal pools). As systems approach nearer to critical transitions, the rate at which they recover to equilibrium following a

(small) disturbance slows down. This slow return rate, which has been termed "critical slowing down," can be identified by alterations in a time series' correlation structure. Specifically, when correlation is at low *lags* of a system prior to a transition, essential slowing down leads to an increase in "short-term memory." The most straightforward method of measuring slowing down is autocorrelation; a rise in autocorrelation at *lag*1 signifies that the system's state has been more similar between successive measurements (Ives et al., 2003; Box et al., 2008).

Autocorrelation is a key statistical tool for analysing time-series data. It measures the relationship between observations at different times. When you are looking for signs of "slowing down," autocorrelation can help identify how strongly current values of a time series are related to past values. In the context of an Autoregressive Conditional Heteroskedasticity (ACF) model, autocorrelation can provide insights into patterns of volatility and whether there's a persistent effect over time. Essentially, if your data shows high autocorrelation, it indicates that past values have a strong influence on future values, suggesting less randomness and more predictable patterns. Autocorrelation is a valuable metric for understanding the internal dynamics of a system. By leveraging insights from autocorrelation, you can better predict future trends, identify patterns, stress-test systems, and allocate resources more effectively. All these factors contribute significantly to the resilience of ecosystems.

Autocorrelation at *lag*1 can be measured in at least three different methods. The most common is to estimate the first value of the autocorrelation function with:

$$\rho_1 = \frac{E[(z_t - \mu)(z_{t+1} - \mu)]}{\sigma_z^2}, \quad (1-1)$$

where μ is the mean and σ is the variance of variable z_t . As an alternative, an autoregressive model of order 1, linear AR(1)-process, of the following form can be fitted using the conditional least-squares method: $z_{t+1} = \alpha_1 z_t + \varepsilon_t$, where ε_t is a Gaussian white noise process, and α_1 is an autoregressive coefficient, while ρ_1 , α_1 , are equivalent in terms of mathematics. Return rate, which is the inverse of the first-order term of a fitted autoregressive AR(1) model [$1/\alpha_1$], is another way

to quantify slowing down. Another approach to describe the return rate is as $[1 - \alpha_1]$, which shows the percentage of the distance from equilibrium that decreases with each time step (Carpenter et al., 2011).

Power spectrum analysis may indicate changes in a time series' complete spectral features before a transition, while autocorrelation at *lag*1 ignores changes in correlation structure at higher lags. Power spectrum analysis divides a time series' degree of variation into distinct frequencies. Spectral reddening, or increased variance at low frequencies, is a characteristic of a system at a transition. Estimating the entire power spectrum and seeing a shift in the power of spectral densities to lower frequencies is one method of expressing changes in a time series' power spectra. Another method is to estimate the spectral exponent of the spectral density using the slope of a linear fitted model on a double-log scale of spectral density versus frequency (Biggs et al., 2009).

Autocorrelations should be near zero for all *lags* for random data and this condition is known by analysts as white noise. When dealing with non-random data, the presence of significant lags indicates that past values have a substantial effect on future values. This is where time series analysis becomes invaluable. Incorporating *lags* into regression analysis, also known as autoregressive models, helps in capturing these dependencies. For example, an Autoregressive Integrated Moving Average (ARIMA) model can be used to analyse and forecast time series data. By accounting for lags and trends, ARIMA models can provide more accurate predictions and insights into the data's underlying structure. So, when you observe non-random patterns with significant *lags*, it's a strong indication to employ time series methods to effectively model and analyse the data.

With the term 'stationarity' in the time series indicated that does not have a trend, but has a constant variance, and a constant autocorrelation pattern (Frost et al., 2019). The autocorrelation function declines to near zero quickly for a stationary time series, while contrarywise the ACF drops slowly for a non-stationary time series. Generally shorter lags have large positive correlations in a time series,

when trends are present, because observations closer in time tend to have similar values. The correlations tend to reduce as the lags increase but when seasonal patterns are present, the autocorrelations are larger for *lags* at multiples of the seasonal frequency than for other lags. If there's a trend, the ACF plot will show slowly decreasing or increasing autocorrelations as the *lag* increases. This is because a trend indicates a persistent, directional change over time. If there's seasonality, the ACF plot will show periodic spikes at lags corresponding to the seasonal period. For example, if the data exhibits a yearly seasonal pattern, you'll see significant autocorrelations at *lags* of 12, 24, etc., if the data is monthly. When you observe both trends and seasonality, the ACF plot will typically show a pattern where autocorrelations do not drop off quickly (due to the trend) and show periodic peaks (due to the seasonality). To handle such data, you might consider using models that account for both trends and seasonality, such as Seasonal ARIMA (SARIMA) or Exponential Smoothing State Space Model (ETS). These models can effectively capture and predict the underlying patterns in your data (Lark & Webster, 2001; Frost, n.d.; Crossland et al., 2005).

Continuous Wavelet Transform (CWT) and wavelet decomposition are powerful techniques for analysing time-series data, especially when dealing with non-stationary signals, offering a way to examine data across different scales and can uncover both time and frequency information simultaneously. These statistical techniques using the continuous wavelet transform (CWT), and wavelet decomposition in R were illustrated using autocorrelation and time series methods (Rashid et al., 2014).

The autocorrelation plot shows the value of the autocorrelation function on the vertical axis, and it could range from value -1 to 1 . The horizontal axis of an autocorrelation plot shows the size of the lag between the elements of the time series where *lag.max* is the maximum lag at which to calculate the (ACF).

Autocorrelation measures how a series is correlated with a lagged version of itself (Figure 1-4). The Pearson correlation between process values at various times, as a function of the two times or of the time lag, is known as the autocorrelation

of a real or complex random process in statistics. For a given time series X with $lag\ k$ the autocorrelation is calculated using the following equation:

$$\rho_k = \frac{\sum_{t=1}^{T-k} (X_t - \bar{X})(X_{t+k} - \bar{X})}{\sum_{t=1}^T (X_t - \bar{X})^2}, \quad (1-2)$$

where ρ_k is the autocorrelation coefficient at $lag\ k$, X_t is the value of the series at time t , $\bar{X}$ is the mean of the series, T is the length of the time series. The *lag max* parameter typically refers to the maximum number of *lags* for which you want to calculate the autocorrelation. In practice, autocorrelation functions ACFs are often used to visualize autocorrelation up to a certain number of lags, helping to identify patterns or periodicity in the data.

When calculating autocorrelation, the maximum lag (*lag.max*) is often automatically limited to one less than the number of observations in the series ($N - 1$). This is because, at each *lag*, you need enough paired observations to compute the correlation. For example, if you have 100 observations in your time series, the maximum *lag* you can use for autocorrelation calculation is $100 - 1 = 99$. This ensures that you have sufficient data to calculate the correlation coefficient at each lag without running out of paired data points. The autocorrelation with *lag2*, for example, is the correlation between the time series elements and the corresponding elements that were observed two time periods earlier. Also, the autocorrelation with *lag0* always equals 1, because this represents the autocorrelation between each term and itself.

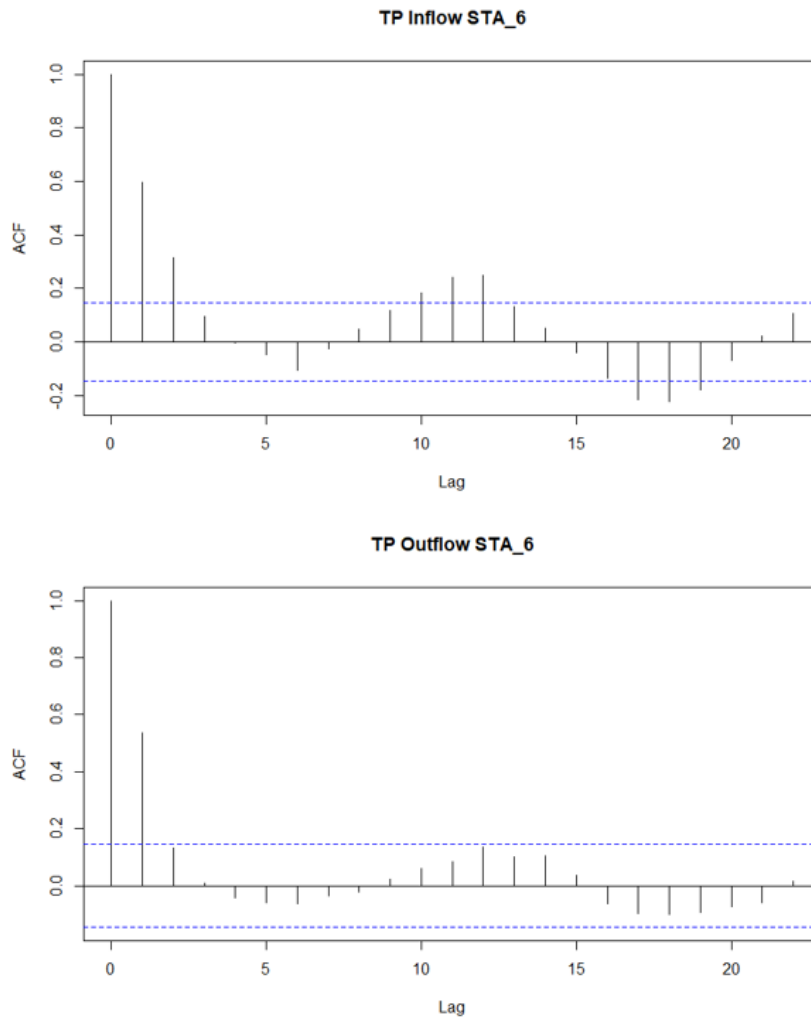


Figure 1-4 The sine function displayed in an autocorrelation-generated correlogram regarding the Total Phosphorus (TP) Inflow-Outflow for Storm Water Treatment Area 6 of Everglades (STA_6).

Climate change impacts temperate humid grasslands. Using NDVI (Normalised Difference Vegetation Index) time series data the NDVI is a useful indicator of vegetation health and productivity and analysing it can identify trends and patterns in vegetation growth over time. A Bayesian dynamic linear model (DLM) is used to estimate autocorrelation in NDVI time series derived from MODIS/Terra datasets, focusing on grassland habitats in the United Kingdom. To mitigate noise in the data, an algorithm is developed to produce high-quality NDVI time series,

accounting for seasonal variations. The algorithm uses an iterative Fourier transform to eliminate high-frequency fluctuations and establish a threshold for invalid observations. The DLM application to grassland sites revealed increased autocorrelation during droughts and a long-term trend of rising autocorrelation (Chapter 3).

1.2.2 Wavelet analysis and its applications using the WaveletComp package in R software.

Wavelet Analysis was used with an R package called "WaveletComp" to examine the data and try to assess the resilience. 'WaveletComp' employs a tiny waveform known as a wavelet to calculate the strength of different periodicity lengths along any type of continuous data, often time-series data. It can be used to calculate the Wavelet Power Spectrum which can be visualized with a power diagram which highlights (in red) the areas of the dataset where the power changes significantly. Additionally, a cross-wavelet power diagram can be produced. The wavelet power spectrum is a powerful tool for analysing localized variations in power within a time series. Unlike traditional Fourier analysis, which provides frequency information but lacks temporal resolution, wavelet analysis decomposes a signal into time-frequency space. This allows to identify dominant modes of variability and observe how these modes evolve over time. Wavelet power spectra are particularly useful in fields like geophysics, climate studies, and signal processing. They can reveal patterns such as periodicities, trends, and abrupt changes in data. For example, they have been applied to study phenomena like the El Niño-Southern Oscillation (ENSO) and atmospheric cold fronts.

The wavelet variance from the other hand, as a statistical tool is used to decompose the variance of a time series across different scales (Figure 1-5). It provides insights into how variability in a dataset changes over time and across

frequencies. This method is particularly useful for analysing processes with time-varying statistical properties, such as environmental or climate data. Applications include studying phenomena like ocean shear, subtidal sea level fluctuations, and other processes with complex temporal dynamics. When two separate variables experience increases or decreases simultaneously, it can be a sign of a correlation between them. Correlation measures the strength and direction of the linear relationship between two variables. While creating a wavelet power diagram, two equations are used:

$$\mathbf{W}(\alpha, x_j) = \frac{1}{a} \sum_{i=1}^N \mathbf{f}(x_i) \mathbf{g}\left(\frac{x_i - x_j}{\alpha}\right), \quad (1-3)$$

This equation is part of the wavelet transform process, where: $\mathbf{W}(\alpha, x_j)$ is the weighted value you're calculating, α is the scale parameter, x_j is the position, α is a normalizing factor, the summation runs over all data points i , $f(x_i)$ represents the data values at each point, $\mathbf{g}\left(\frac{x_i - x_j}{\alpha}\right)$ is the wavelet function applied to the scaled difference between x_i and x_j . This equation uses the dataset to calculate the appropriate size of the wavelet according to the number of points in the dataset.

The second equation is used to calculate the variance or power, and output the power diagram at each scale α :

$$\mathbf{V}(\alpha) = \frac{1}{n} \sum_{j=1}^N \mathbf{W}^2(\alpha, x_j), \quad (1-4)$$

where: $V(\alpha)$ represents the variance or power at scale α , n is the normalizing factor. The summation runs over all positions j , $\mathbf{W}(\alpha, x_j)$ is the wavelet transform calculated from your first equation, which measures the wavelet coefficient at scale α and position x_j . This equation squares the wavelet coefficients and averages them, giving you a measure of the signal's power at each scale. By plotting $V(\alpha)$ against α , you get the wavelet power diagram, which helps to analyze the signal's characteristics at different scales.

The only constraint imposed on a function ψ , real or complex valued, in order to be a wavelet is the admissibility condition which requires:

$$C_\psi = (2\pi)^n \int_{\mathbb{R}^n} |\widehat{\psi}(\mathbf{k})|^2 \frac{d^n \mathbf{k}}{|\mathbf{k}|^n} < \infty, \quad (1-5)$$

The term C_ψ is known as the admissibility constant. For a wavelet function ψ to be admissible, this constant must be finite. Where: $\widehat{\psi}_k$ is the Fourier transform of the wavelet function ψ , k is the frequency variable, n is the number of spatial dimensions. The integral is taken over the entire frequency domain $\mathbb{R}_n$. The inequality $< \infty$ ensures that the integral converges, indicating that the wavelet function is admissible. The admissibility condition ensures that the wavelet transform is invertible, meaning you can reconstruct the original signal from its wavelet transform. It's a crucial property for the wavelet function to be useful in practical applications. With $\widehat{\psi}(\mathbf{k}) = (2\pi)^{-n} \int_{\mathbb{R}^n} \psi(\mathbf{x}) e^{-\sqrt{-1}\mathbf{k}\cdot\mathbf{x}} d^n \mathbf{x}$, if $\psi(\mathbf{x})$ is integrable this actually implies that it has zero mean:

$$\int_{\mathbb{R}^n} \psi(\mathbf{x}) d^n \mathbf{x} = 0 \text{ or } \widehat{\psi}(|\mathbf{k}| = 0) = 0, \quad (1-6)$$

This integral suggests that the function $\psi(\mathbf{x})$ integrates to zero over the entire space $\mathbb{R}^n$. This could imply that the function is centered around zero, indicating a balance of positive and negative values throughout the space. In Fourier analysis, $\widehat{\psi}$ denotes the Fourier transform of ψ . This equation means that the Fourier transform of ψ at zero frequency $|\mathbf{k}| = 0$ is zero.

In practice the wavelet should also be well-localized in both Physical (in the time or spatial domain), and Fourier Spaces (in the frequency domain).

When studying the behaviour of the M th derivative of a function $f(\mathbf{x})$, the wavelet should have cancellations up to order M . This means that the wavelet can capture variations in the function that are of the same order or higher, while ignoring lower-order variations.

Mathematically, this is expressed as:

$$\int_{\mathbb{R}^n} \psi(\mathbf{x}) \mathbf{x}^m d^n(\mathbf{x}) = 0 \text{ for all } \mathbf{m} \leq \mathbf{M}, \quad (1-7)$$

where $\psi(x)$ is the wavelet function, and x^m represents the polynomial terms up to order M .

This ensures that the wavelet transform is sensitive to the desired order of the derivative while filtering out the influence of lower-order terms.

1.2.3 Mathematical description of wavelets

The Continuous Wavelet Transform (CWT) is the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet. Wavelet coefficients that depend on position and scale are the result of this procedure. The CWT is characterised with regard to a particular function, called a 'mother wavelet,' that fulfils some particular properties. The CWT is a particularly useful tool for the study and creation of signal processing algorithms for a set of wideband and nonstationary signals. These signals are of special interest in advanced dispatches and radar systems and indicate a particular advantage to considering the CWT as part of a signal intelligence toolkit. This time series is a good illustration of a flash waveform with certain fresh characteristics. The CWT face has features that can supposedly be attributed to the shock and aftershock features in the event, and these features aren't readily apparent for the time series or a spectral estimation from the time series. The Morlet wavelet, in the frequency domain, is a complex bandpass clear-out. Its effect as a filter might be to restrict a sign to a band focused approximately on the frequency. Due to the fact that all records have been converted to anomalies prior to the CWT, the calculated wavelet strength represents the relative power of periodicities in the frequency spectra of the ambiguity statistics set. As a result, it may be able to produce low frequencies that rely on inner variance in preference to an outdoor force and can produce low frequencies as a feature of internal variance instead of an external forcing. A significant noise (AR1) test has been done on all wavelet transforms to decide where the periodicities located as part of the CWT are likely to be caused

by noise because datasets can easily exhibit pseudo-periodic behaviour due to their lag-1 autocorrelation (AR1). Datasets with greater AR1 generally tend to have spectra biased closer to low frequencies; thus, they're described as containing red noise (Meinke et al., 2009).

The WaveletComp package analyses univariate and bivariate time series' frequency structure using the Morlet wavelet. This complex-valued, continuous wavelet transforms the time series under study into a complex-valued, continuous wavelet transform, keeping all of the original data. Coherency among two-time series may be studied by examining the transform's real and imaginary parts, which provides information on both the local amplitude and the instant phases of any regular process over time. WaveletComp's implementation of Morlet's "mother" wavelet is:

$$y_t = \pi^{-1/4} e^{i\omega t} e^{-t^2/2}, \quad (1-8)$$

where: $\pi^{-1/4}$ is a normalization factor, $e^{i\omega t}$ represents a complex exponential (sinusoidal wave) with angular frequency ω , $e^{-t^2/2}$ is a Gaussian envelope centered at $t = 0$, which decays exponentially as t moves away from 0 (Kobayashi, 1998).

The "angular frequency" ω , or rotation rate in radians per time unit, one revolution is equal to 2π (radians); therefore, the period (or inverse frequency) measured in time units equals $\frac{2\pi}{\omega}$. WaveletComp is built on the Morlet wavelet found in Equation. Convolution of a time series with "wavelet daughters" formed by the mother wavelet by translation in time by τ and scaling by s :

$$\text{Wave}(\tau, s) = \sum_t x_t \frac{1}{\sqrt{s}} y^* \left(\frac{\tau - t}{s} \right), \quad (1-9)$$

is the Morlet wavelet transform of the time series. Where: $\text{Wave}(\tau, s)$ is the wavelet transform coefficient at scale s and position τ , x_t is the original time-series data, $\frac{1}{\sqrt{s}}$, is a normalization factor to ensure the energy is consistent across

scales, $y^* \left(\frac{\tau-t}{s} \right)$ is the complex conjugate of the mother wavelet y , scaled by s and translated by τ (Antonini et al., 1992).

The asterisk indicates that the conjugate is complex (*). The localizing time variable is adjusted by time increments of dt to identify the position of the specific daughter wavelet within time domains. The frequency-domain wavelet coverage of the series is determined by the collection of scales s . This transform essentially decomposes the signal x_t into its wavelet components, providing a time-scale representation of the signal. It's a powerful tool for analysing the frequency content of non-stationary signals.

Fractional power 2 is used to determine how many "voices" there are in an "octave" with $\frac{1}{dj}$:

$$s_{\min} 2^{j \cdot dj}, j = 0, \dots, J, \text{ with } J = \delta_j^{-1} \log_2 \left(\frac{N}{s_{\min}} \right), \text{ (1-10)}$$

The components represent: The minimum scale $s_{\min}$ at which the wavelet transform is evaluated, which is determined by the parameter j and the step size dj . The total number of scales considered J , which depends on the inverse of dj (the step size) and the logarithm base 2 of the ratio between N (likely the total length of the data) and $s_{\min}$ (Florack et al., 2012).

The lowest or maximum scale is determined by the selection of the least or greatest period of interest and the conversion factor $\frac{6}{2\pi}$. When evaluating a formula, WaveletComp makes effective use of Torrence and Compo's Fast Fourier Transform algorithms. The modulus of a wavelet transform may be used to get the local amplitude and temporal evolution of any periodic element in the time sequence under consideration. The modulus of the wavelet transform can indeed lead to biased amplitudes, particularly overestimating high-frequency events. To address this issue, WaveletComp uses a corrected amplitude version as proposed by Liu et al. (2019). The corrected wavelet amplitude is given by:

$$\text{Ampl}(\tau, s) = \frac{1}{s^{1/2}} \cdot |\text{Wave}(\tau, s)|, \text{ (1-11)}$$

This correction ensures that the amplitude is properly scaled, mitigating the bias toward high-frequency events. The factor $\frac{1}{s^{1/2}}$ normalizes the amplitude by accounting for the scaling factor s , leading to a more accurate representation of the wavelet transform. WaveletComp's approach, based on Liu et al.'s work (2019), provides a more balanced and reliable analysis of time series data, allowing for better detection of patterns and anomalies across different frequencies.

The wavelet power spectrum, which is the square of the amplitude, provides a measure of time-frequency wavelet energy density. This means it shows how the energy of the time series is distributed over both time and frequency, making it a powerful tool for identifying significant patterns and features in the data. The wavelet power spectrum is computed as:

$$\mathbf{Power}(\tau, s) = |\mathbf{Ampl}(\tau, s)|^2 = \left(\frac{1}{\sqrt{s}} |\mathbf{Wav}(\tau, s)| \right)^2 = \frac{1}{s} \cdot |\mathbf{Wave}(\tau, s)|^2, \quad (1-12)$$

This representation allows for a detailed analysis of the energy distribution, helping to highlight regions with high energy concentrations and providing insights into the time-frequency characteristics of the signal. The work by Carmona, R., et al., (1998) further emphasizes the importance and utility of the wavelet power spectrum in various applications, such as signal processing, geophysics, and biomedical engineering.

The sequence variation with proportional factor $\frac{1}{s}$ in this corrected form of wavelet strength corresponds to the prediction of white noise at every time or level. Since the wavelet power can only be measured in terms of unit-variance white noise as well as another time sequence, standardizing the time series to be studied after detrending has long been considered standard practice. WaveletComp comes preloaded with local polynomial regression detrending and internal normalization. To view the wavelet power spectrum, an image plot is the most common way to do so; in WaveletComp, the time-period domain by default, but time-scale and time-frequency axes may also be customized. The ridge of power in a band of nearby periods can be extracted and applied to the power spectra using a

process that is conducted by default. It's the same with the influence cone, which doesn't include any locations that may be affected by edge effects.

Simulation methods are used to determine significance when evaluating the null assumption of "no periodicity." A range of substitutes to test against are accessible, and these surrogate time sequences are supplied: white noise, mixing the supplied time series, similar-spectrum data, AR, and ARIMA. Using contour lines in the wavelet output spectra is a great way to highlight significant areas, making it easier to identify patterns and anomalies in your data. The time-averaged wavelet output spectrum, or global wavelet spectrum, helps in summarizing the overall frequency content of the time series, providing a comprehensive view of the dominant frequencies.

As for the wavelet phase, it indeed represents an angle in the interval $[-\pi, \pi]$. The phase is calculated using the argument of the complex wavelet transform:

$$\text{Phase}(\tau, s) = \arg(\text{Wave}(\tau, s)) = \tan^{-1} \left(\frac{\text{Im}(\text{Wave}(\tau, s))}{\text{Re}(\text{Wave}(\tau, s))} \right), \text{ (1-13)}$$

as a displacement of periodic events with respect to the localizing source moved across the time domain. In this formula: $\arg(\text{Wave}(\tau, s))$ denotes the argument or phase of the complex wavelet transform. The $\text{Im}(\text{Wave}(\tau, s))$ is the imaginary part of the wavelet transform. The $\text{Re}(\text{Wave}(\tau, s))$ is the real part of the wavelet transform. The $\tan^{-1}$ is the arctangent function used to compute the phase angle.

By examining the wavelet phase, you can gain insights into phase relationships, synchronization, and phase shifts within the time series, enriching your analysis. To better understand the time of structural breakdowns in periodic events, it may be necessary to investigate specific phase routes (or phase pictures). To get and plot averaged phase routes for specific periods or period bands, as well as to plot the general phase image, WaveletComp provides a set of tools summing across a collection of reconstruction waves can smooth and even recreate the original time series, as the Morlet wavelet transform is a band-pass filter.

$$x_t = \frac{dj \cdot dt^{\frac{1}{2}}}{0.776 \cdot y(0)} \sum_s \frac{\text{Re}(\text{Wave}(\tau, s))}{s^{1/2}}, \quad (1-14)$$

where: dj is the scale step, dt is the time step, $y(0)$ is the value of the mother wavelet at zero, $\text{Re}(\text{Wave}(\tau, s))$ is the real part of the wavelet transform, and s is the scale factor. This formula involves summing the contributions of the real part of the wavelet coefficients across different scales, weighted by the inverse square root of the scale factor.

The normalization factor $\frac{dj \cdot dt^{\frac{1}{2}}}{0.776 \cdot y(0)}$ ensures that the reconstructed time series has the correct amplitude. By using this approach, you can effectively reconstruct the original time series from its wavelet transform, capturing both the time and frequency characteristics of the data (Wu et al., 2023).

1.2.4 Research gap and potential confounders of resilience

Research gaps in ecological resilience often revolve around the need for more practical applications of theoretical frameworks, especially in resource-constrained environments. While there is extensive documentation on the theoretical aspects of ecosystem resilience, there is a need for more customized methodologies to address the unique challenges faced by different regions, particularly developing countries (Beck et al., 2025). Additionally, there is a lack of localized data and infrastructure, which hinders the effective implementation of resilience strategies.

Potential confounders of ecological resilience include factors such as **as inadequate education, insufficient infrastructure, and limited access to localized data**. These confounders can significantly impact the ability to predict, manage, and enhance resilience in ecosystems. Other confounders may include **climate change, habitat fragmentation, pollution, and invasive species**,

which can all affect the capacity of ecosystems to recover from disturbances (Beck et al.; Granata et al., 2025).

Addressing these research gaps and confounders requires a multifaceted approach that integrates ecosystem restoration, capacity building, technological solutions, and community-based strategies. By promoting accessible technological innovations and fostering interdisciplinary collaboration, we can enhance our understanding and management of ecological resilience.

Ecosystem resilience, which measures an ecosystem's ability to withstand and recover in the face of shocks, is an important indicator of ecosystem stability (Dakos et al., 2015; Scheffer et al., 2015). The widespread phenomenon known as critical slowing down, or CSD, has attracted a lot of interest. A system recovers from short-term shocks more slowly as it progressively loses resilience and becomes more unstable (Scheffer et al., 2009; Liu et al., 2019). Due to this slowness, the system state fluctuates very close to its prior state, as indicated by the *lag1* auto-correlation AR(1) in the time series, which shows growing correlation to the previous state at a one-time step, and by the more general variability of natural fluctuations, which are evaluated in terms of variance. Regional studies have quantified ecosystem resilience, but they have several drawbacks: 1) most are based on mean climatic state and cannot show the variation in ecosystem resilience; 2) CSD has only been applied practically to rainforests and other vegetation types, and drought gradients outside of humid tropical areas have not been extensively studied; and 3) there are no corresponding attributes of ecosystem resilience dynamics, nor anthropogenic, climatic, or CO_2 elements that can affect productivity and biomes (Smith et al., 2022; Tasser, 2017).

Consequently, evaluating ecological resilience at the regional level is an essential undertaking. In order to estimate the level of threat that particular ecosystems are exposed to, the idea of ecological resilience may be used in combination with other metrics like integrity or vulnerability. There has been limited knowledge on the influencing factors of ecosystem resilience; operational indicators of

resilience have received little attention in the literature; there is no consensus on the indicator system of ecosystem resilience. There is a very complex relationship between the grassland's ecosystem resilience and its influencing factors. Understanding this relationship can provide very significant information for further research on the change of grassland ecosystem resilience (Walker et al., 2006; Ven, 2017).

Understanding a system's activity requires an understanding of its constituent elements and their interplay. Here, I advocate for a greater focus on our understanding of ecological resilience; that is, the mechanisms that allow elements of various ecological levels to withstand or recover back from shocks. So, to better protect and manage ecosystems, we need to understand their resilience to single and multiple perturbations. The ongoing problem in ecological modelling, however, is that statistical models are correlative and may not identify the relevant underlying mechanisms even if they fit the current data well, while theoretical models are useful for understanding causality but challenging to test critically with data. However, taking into account disturbances at various ecological levels in relation to eco-evolutionary characteristics and functions enables the development of theories regarding the influence of previous disturbances on present-day and projected resilience. While ecologists and analysts possess the necessary tools to examine both structure and function, their attempts to integrate their knowledge over ecological layers and exploit massive ecological datasets remain limited. So, to understand resilience and the factors that underpin it (e.g., complexity/biodiversity), we need to be able to measure it. In addition to outlining some of the difficulties in gaining an understanding of ecological resilience, we suggest that combining eco-evolutionary knowledge with conceptions of resilience at the ecosystem level will offer the mechanical basis required to enhance management of human, natural, and agricultural ecosystems. lakes (Matsumoto et al., 1979; Carpenter et al., 2011).

Numerous types of factors, such as biodiversity and habitat variability, have been identified as influencing factors of ecosystem resilience in the literature. However,

overall, the research on these factors has been far from systematic, and there have been numerous disagreements regarding the identified influencing factors. The following are some potential influencing elements for ecosystem resilience. There have been numerous ongoing discussions over the role that biodiversity plays in ecosystem resilience, despite the fact that it is an emergent ecosystem feature that is enriched by biodiversity on multiple levels. While some studies discovered a positive correlation between ecological resilience and biodiversity, others found that the relationship increased and approached a line; Furthermore, several studies discovered that biodiversity did not boost ecological resilience. The biodiversity index is typically used to represent biodiversity; discrepancies between earlier studies may arise from a lack of understanding of the roles that various species play in the environment. In the ecosystem, different species have distinct functions to play; they are not all equally significant (Moore et al., 1993; Dakos et al., 2012).

The discrepancy between previous studies may have resulted from the different ways in which species composition affects ecosystem resilience. Walker divided the functional classifications into two groups: drivers and passengers. The drivers are the major species that will determine how the ecosystem develops in the future, while the passengers have little to no impact on the resilience of the ecosystem. In contrast, the typical biodiversity measure that has been employed in earlier studies is unable to capture the variations in these species' roles. An important aspect of ecosystem resilience is the ecological memory, which is the network of species, their dynamic interactions with the environment, and the collection of structures that allow for reorganisation following disturbance. Ecological memory refers to both exterior and internal ecological memory. The former is made up of both structural and biological legacies—the remains of the species that survive in the disturbed area—and the biological structures that act as foci for regeneration and permit species to colonise. Species that colonise damaged patches find sources of support and resources in the external ecological memory. In the latter scenario, as the spread of many plant seeds is restricted by a number of parameters, these immigration-influencing elements,

such as the species' life history and distance from the seed source, are essential to the reorganisation of an ecosystem. Research on ecological memory has been done relatively infrequently thus far; further research is still required (Walker et al., 1969; Seekell et al., 2011).

Local factors have a major impact on ecological succession; ecosystems recover fastest in areas with favourable microhabitats, such as the well-watered zone. Ecosystem resilience is influenced by the habitat in a variety of ways. In this case, over time, the range of temperature, radiation, and moisture in the climate primarily affects the rates of photosynthesis, respiration, and other forest functions. The ability of the landscape to sustain infiltration, water storage capacity, and nutrient cycles—all of which are endangered by soil loss and structural change—determines the resilience of the ecosystem at the local level. Soils that are physically resistant to change would be a feature of an ecosystem that is naturally resilient. Although the question of whether humans are a component of the ecosystem is still up for debate, there is no denying that humans have altered ecosystem resilience. The combined effects of human activities have a substantial impact on the dynamics and structure of ecosystems. Human activity has impacted the ecosystem in a number of ways, such as reduced landscapes, fragmented habitats, altered species composition, etc. (Stone et al., 1996; Esquivel-Muelbert et al., 2019).

1.3 Research aims and objectives

The current study's key components include statistical data analysis and quantitative research in ecological systems. Ecosystem resilience represents a multidimensional concept, as it mirrors the different frameworks of various scientific disciplines. My primary aim, therefore, is:

To determine if there are general analytical approaches that can be used to establish the ecosystem resilience of any given ecosystem in terms of scale (local, regional, and national) as a key target of the sustainable development.

By studying the phenomenon of resilience, and more specifically in the context of habitats, it is realised that it contributes substantially to the sustainable development of the areas. Consequently, my aims are:

- 1) To compare different mathematical approaches determining resilience,
- 2) To determine how resilience exhibits as an emergent behaviour in different types and scales of ecosystems, with its influencing factors.

With a focus on three main objectives, this study assesses and uncovers the dynamics of ecosystem resilience from multiple angles, having profound implications for conservation strategies, resource management, and understanding the impacts of climate change. Here is a breakdown of the three objectives:

- 1) **Dynamics and Measures of Ecosystem Resilience:** Exploring how ecosystems adapt and recover from disturbances, considering factors like climate change, phosphorus levels, and human activities. This involves analysing long term-data to identify patterns and thresholds. Investigating whether resilience metrics can be derived from long-term time series data and how resilience evolves across spatial and temporal scales, provides insights into the stability and adaptability of ecosystems.
- 2) **Comparative Responses of Ecosystems:** Examining how different ecosystems vary in their resilience matrix, especially under stressors like drought. This reveals unique traits or vulnerabilities in specific ecosystems.
- 3) **Detecting Resilience Metrics:** Identifying ecosystem characteristics that make resilience metrics more detectable and understanding the interplay between natural and social factors in shaping resilience. In order to better and more accurately anticipate ecological risk areas, we hope to uncover

the underlying mechanisms that promote ecosystem growth rather than relying solely on visual greenness or vegetation cover as an indication. The principal idea of the thesis is to continue the investigations as to the extent of the resilience of ecosystems.

1.3.1 Three case studies showcase various strategies and approaches to enhancing landscape resilience, from wetlands to coastal ecosystems

The first case study is seeking to investigate ecosystem complexity and those dynamic properties that emerge from functioning systems, such as resilience to perturbation, using streamflow data, water quality, and nutrient TP loads across these systems. We are particularly interested in the most and least resilient areas of the Stormwater Treatment Zones. It has been hypothesised that slow internal critical transitions often made STAs less resilient over time, setting them up for collapse. Here we provide quantitative evidence for this concept. Explaining the considerable collapses and transformations observed in concentrations of total phosphorus (TP-Mg/L) and in loading (TP-Kg) is an obvious approach to investigating external perturbations that would be responsible. Here we examine whether a loss of resilience is making the STAs increasingly fragile. The aim of this case study is to investigate the capacity of an ecosystem to absorb disturbances and still maintain its essential functions, structure, identity, and feedbacks, the system modified by hurricanes, droughts, and tropical storms based on the Stormwater Treatment Areas (STAs) in the Everglades, South Florida (Corstanje et al., 2016). The Everglades is a very large subtropical-tropical wetland area that occupies the southern part of the US state of Florida. It is in the neotropic ecozone and covers the southern portion of a sizable drainage basin. The Everglades begin north near Orlando, with the Kissimmee River flowing into the great shallow Lake Okeechobee. The water that overflows from this lake during the rainy season forms a body of water with a very slow motion,

a very wide (almost 100 kilometres) river, which flows 160 kilometres to the southern tip of the Florida peninsula on limestone rocks (Corstanje et al., 2016).

A complex system's declining rate of equilibrium following a disturbance is known as temporal loss of resilience, and it frequently occurs before an ecosystem degrades. An increase in temporal autocorrelation in remotely sensed imagery can be used to identify this. In this study, autocorrelation in an NDVI time series produced from daily MODIS/Terra datasets is estimated using a Bayesian dynamic linear model (DLM). This is based on a recently published methodology for monitoring resilience in Californian forests and is used to monitor resilience in different types of grassland ecosystems across regions in the United Kingdom. The high frequency of cloudy days in the UK, which causes a lot of noise in the time series, is one of the primary distinctions between conditions here and California. As a result, an algorithm was created and put into practice to provide an NDVI time series of high quality for the DLM. By repeatedly using a Fourier transform to eliminate high-frequency fluctuation from the dataset and establish a threshold for erroneous observations, the method is made to identify legitimate values based on seasonal variation present in the time series data. By using the Bayesian DLM on grassland locations across the United Kingdom, periods of higher autocorrelation that coincided with periods of drought were found, along with a long-term trend of rising autocorrelation (Desjardins et al., 2015; Liu et al., 2019; Pimm 1984; Verbesselt et al., 2016).

As a third study, a coastal area in Louisiana was chosen so that the influence of salinity intrusion on ecosystems could be examined along geographical and temporal salinity gradients. Louisiana's Mississippi Delta's coastal regions are due primarily to sea level rise brought on by climate change; freshwater systems in Florida are becoming more and more prone to saline intrusion, which is threatening the productivity of agriculture. This allowed researchers to identify which development paths could lead to resilient landscape ecosystems. The district is split into four transects, of which fifteen stations are divided into three transects along the coastline structure and another six stations are located close to the Mississippi River diversion, which is located further inland but nearest to

the Mississippi River and which is shielded from saline intrusion by a system of dikes and is primarily used for farming. While complementary or alternative methods exist to strengthen the resilience of social-ecological systems with respect to saline intrusion, the construction of constructed infrastructures is currently advocated. These include changes in ecosystems, agronomic practices, upstream river control, and regeneration of coastal ecosystems. The transitional areas between fresh and salt water are known as estuarine systems. Estuaries are extremely productive and essential to coastal fisheries because freshwater inflow brings in influxes of terrestrial nutrients, but they are also frequently subjected to hydrological change (Hyndes et al., 2014). According to climate projections, precipitation patterns will be more variable during the next century, with many regions seeing less frequent but more intense precipitation episodes. There is little question that this trend will have an impact on estuarine systems' input and water quality. Via physical, biochemical, and physiological pressures, changes in the environment can disrupt the organisation of ecological communities (Van Diggelen et al., 2016). Significant variations in salinity and input are caused by tropical systems and climatic cycles like the El Niño Southern Oscillation (ENSO) in the coastal United States (Tolan, 2007).

This is expected to: 1) improve the overall understanding of the impact of ecological resilience on the agricultural landscape, and 2) identify optimised strategies for landscape resilience. Together with the results of the prior literature review, the statistical analysis contributed to the development of conclusions and recommendations for the necessary steps to improve the benefits of green infrastructure for the benefit of society. (Folke et al., 2010).

1.3.2 Thesis structure

This thesis is structured into six chapters, as outlined in Table 1-3 Thesis structure and status of paper submissions with links to specific journals. To

visually represent the methodology of three different case studies at local, regional, and national scales, we used a layered diagram that emphasises the distinct yet interconnected nature of the scales (Figure 1-5).

The first chapter serves as a general introduction, providing an overview of the research topic and the thesis's aim and objectives. Chapters two through four comprise the core of the research, each focusing on a specific aspect of the study and written papers. Insights gained at each stage of the research process comprised the basis for the development of subsequent work, creating a cohesive and progressive narrative. Although the chapters build upon one another, each one is a standalone chapter designed to be read independently.

To address this heterogeneity, Chapter Two presents an alternative approach to investigate the factors influencing resilience, using wavelet analysis methods to detect significant changes in the wavelet correlation between modelled and observed channel flows and the wavelet variance of the model residuals at one-of-a-kind scales. Continuous Wavelet Transform (CWT) and wavelet decomposition were used to determine the periodicity of any cyclical activity in the data and utilise spectral power to determine changes in autocorrelation and variance as measures of Critical Slowing Down. Ecosystems nearing a tipping point lose their ability to withstand disturbances and shift towards an alternate state. Recently, it has been suggested that an ecosystem's loss of resilience might be identified by an increase in autocorrelation as well as variability in the fluctuations of the ecosystem's state. Autocorrelation and variance can be used to predict upcoming crucial transitions. Autocorrelation is essential in hypothesis testing and making statistical inferences about ecological data. For example, it can help determine if observed patterns are due to random processes or underlying ecological mechanisms. Autocorrelation is used to analyse temporal dependencies in data, such as climate variables, and identify patterns and trends in data. Analysis and simulations reveal that variance may reduce near a changeover. Stochastic changes in the environment can limit the ecosystem's ability to track high-frequency fluctuations, and this can occur when the ecosystem is less sensitive to these changes as it approaches the threshold. The

presence of low-frequency components near a transition can skew the estimation of variance, particularly when the sample size is limited. This phenomenon is often observed in ecological and environmental studies, as well as in various fields dealing with time series data.

Data was gathered according to South Florida Water Management District (SFWMD) and flow data from the five Everglades Stormwater Treatment Zones (STA's)-STA-1E, STA-1W, STA-2, STA-3/4, STA-5/6 (Figure 2-1) was received for each STA confirming that the most significant concentration levels of total phosphorus (TP) occurred for inflow-way and water P increased with P input.

In Chapter Three, we developed a set of quantitative methodological approaches to analyse the data collected. Throughout the entire study area, the sites for detecting resilience features were selected among the largest of the grassland study sites available and according to previous monitoring campaigns, which defined these areas as reliable for collection and encompassed the most significant data. To compare the performance of the eight grassland sites across the UK satellite-based data was analysed in detecting the increasing autocorrelation and the early warning signals as well as the development of the Dynamic Linear Model (DLM). Climate data for each observation in the time series and long-term climate averages for each day of the year composed the NDVI time series. The framework for generating the structure of the model was temperature and precipitation and from Liu et al, (2019) perspective temperature was analysed but for the purpose of remaining the computational load low only precipitation as climate variable was investigated. In this study model manipulations were executed in Python and QGIS.

The factors controlling the resilience of a terrestrial ecosystem have been shown to be associated with vegetation collapse or even desertification characteristics and may increase the likelihood of a shift in grassland ecosystems (West & Harrison, 1997). A combination of several indicators into a composite indicator could be more reliable inferring regime shifts than a single leading indicator of critical transitions (Su et al., 2020).

Chapter Four presents an application of the conceptual framework that integrates resilience and shifts in ecosystems facing salinity intrusion. A study coastal area in Louisiana was chosen so that the influence of salinity intrusion on agro-ecosystems could be examined along geographical and temporal salinity gradients (Figure 4-1). This allowed researchers to identify which development paths could lead to resilient agro ecosystems. The district is split into four transects, of which fifteen stations divided into three Transects along the coastline structure and another six stations located close to the Mississippi river diversion which is located further inland but nearest to the Mississippi river, and which is shielded from saline intrusion by a system of dykes and is primarily used for farming.

This flexible modelling approach can assist policymakers in designing interventions to promote landscape resilience examining the current state of these models and how they are used to study sediment transport and hydrodynamics in the lower Mississippi River channel. Additionally, because the Lower Mississippi River's sediment budget has a significant influence over any future management plans that call for significant diversions, it is recommended to quantitatively analyse the sediment budget in this area as a potential site for construction of a diversion in South Louisiana (Mead et al., 2010).

Chapter Five discusses the main findings of this thesis. Chapter Six provides a summary of the entire body of work presented in this thesis and also discusses avenues for future work and research. Supplementary material of this research is provided in the annexes of this thesis.

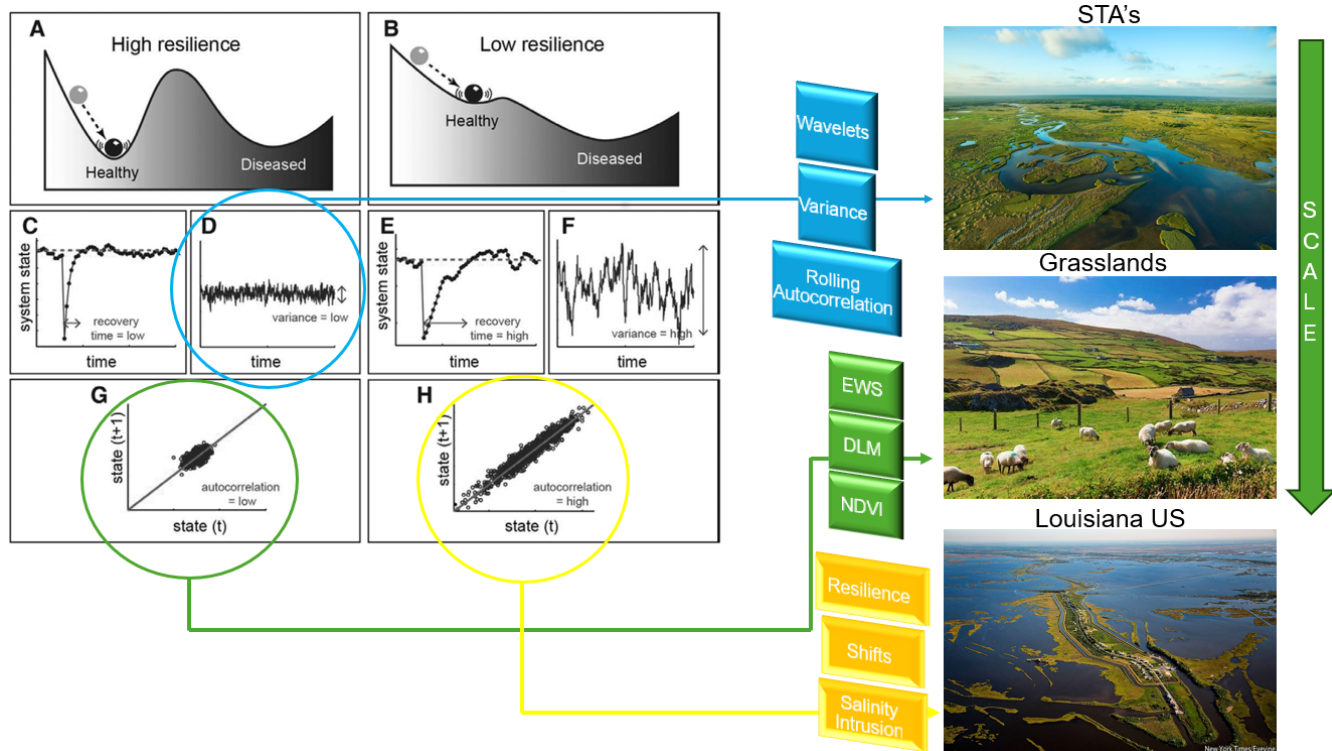


Figure 1-5 A structured visual representation to illustrate the methodology of three different case studies.

1.3.3 Contribution to jointly authored papers

The thesis includes published papers, papers accepted for publication and papers prepared for submission for publication. These papers are jointly authored and are therefore written using plural first-person pronouns. I can confirm that I am the lead author of the research papers included in Chapters 2, 3, and 4 and that I have made a substantial contribution to each of the papers included. A description of my contribution to each paper is given below, and an estimate of each author's contribution to the research and preparation of the manuscript is given in Table 1-4.

Chapter 2 is formed by the following published review paper: ‘Emerging Resilience metrics in an intensely managed ecological system’ (ECOLENG-D-23-00678), Accepted Nov 25, 2023.

Chapter 3 consists of the following manuscript for publication in Ecological Engineering Journal subject to minor revisions.

I carried out the research described in collaboration with my co-authors and prepared the original draft and revisions of the manuscript.

Chapter 4 consists of the following manuscript for publication in Ecological Engineering Journal subject to minor revisions.

Table 1-3 Thesis structure and status of paper submissions with links to specific journals.

Chapter Link	Title	Journal	Status
1	Thesis Introduction		
2	Emerging Resilience metrics in an intensely managed ecological system.	Ecological Engineering	Ecological Engineering (ECOLENG-D-23-00678) Initial Date Submitted Jun 19, 2023, Revised Form Sep 29, 2023, Accepted Nov 25, 2023, Published
3	Monitoring resilience in UK grassland sites by reconstructing cloud free NDVI composites and	Ecological Engineering	Under submission

	investigating for early warning signals.		
4	Resilience and shifts in ecosystems facing salinity intrusion in Mississippi Delta, Louisiana, Florida	Ecological Engineering	Under submission
4	Assessing ecological resilience and impacts as a key concept for Louisiana region during and after drought events	Ecological Engineering	In preparation
1	Off-Stage Ecosystem Service Burdens: A Blind Spot for Global Sustainability	International Journal of Novel Research in Civil Structural and Earth Sciences	Novelty Journals Vol. 9, Issue 2, May 2022 - August 2022 Submitted, Published
2	Biodiversity and Ecosystem Service Sustainability	International Journal of Novel Research in Civil Structural and Earth Sciences	Novelty Journals Vol. 10, Issue 1, January 2023 - April 2023 Submitted, Published
3	Operationalising ecological resilience	EGU General Assembly 2024	EGU General Assembly 2024, Vienna, Austria, 14–19 Apr 2024,

			EGU24-16180 Abstract Submitted, Published
5	Discussion		
6	Conclusions and future work		

Chapter 2

2 Emerging Resilience metrics in an intensely managed ecological system.

Authors: Nikolaos Toumasis¹, Daniel Simms¹, Will Rust¹, Jim Harris¹, John R. White², Joanna Zawadzka¹, Ron Corstanje¹.

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A cornerstone principle of landscape resilience management is to focus on early warning indicators like recovery time, variance, and autocorrelation providing valuable insights into the stability and resilience of ecosystems. These metrics can help predict tipping points and potential regime shifts. In this chapter utilizing Constant Wavelet Transform (CWT) and wavelet decomposition is an effective way to analyze periodicity and detect changes in the dynamics of the ecosystem. This method allows for a detailed examination of how variance and autocorrelation evolve over time. The long-term temporal analysis of the STAs is crucial for identifying trends and patterns that might not be apparent in shorter time frames. This comprehensive dataset strengthens the reliability of my findings. Identifying STAs that are vulnerable to perturbations has practical implications for management and conservation efforts. I describe the development of a novel model by highlighting areas at risk, and my study can inform targeted interventions to enhance resilience.

The following manuscript was published in Ecological Engineering Journal in January 2024.

2.1 Abstract

There is growing interest in understanding resilience of ecosystems because of the potential of abrupt and possibly irreversible shifts between alternative ecosystem states. Tipping points are typically observed in systems where strong positive feedbacks drive the establishment of alternative stable states. Ecological tipping points are difficult to detect. However, theory suggests that subtle changes in the dynamics of an ecosystem state can provide early-warning information on the underlying stability and risk of a tipping into an alternate state. The likelihood of this occurring can be observed through metrics associated with critical slowing down (CSD) such as an increase in recovery time back to equilibrium after a perturbation, a rise in variance as the state of the ecosystem fluctuates more widely around its equilibrium, and an increase in autocorrelation because the effect of a perturbation lasts longer. These indicators have been empirically tested in laboratory experiments and in the field with a focus on the dynamics of the ecosystem state while neglecting any trait changes. Here we present a long-term temporal analysis of several large, intensely monitored constructed wetlands, the Everglades Stormwater Treatment Areas (STAs), in which sudden changes in plant community composition have been observed. Using wavelet analysis, significant increases and decreases of variance properties can indicate when and which STAs are less resilient to perturbations. In this study, Constant Wavelet Transform (CWT), and wavelet decomposition were used to determine the periodicity of any cyclical activity in the data and use spectral power to determine changes in autocorrelation and variance as measures of CSD. These were applied on long-term flow data, water quality and nutrient TP loads across these systems. The change detection methods were used to find significant changes in variations and correlations across the time series. By employing these techniques, we were able to spot substantial shifts in model-observed wavelet correlation and model residual wavelet variance and thereby identify where these systems exhibit CSD. Although our analysis is limited to historical data, the proposed approach has practical value in that it identifies STAs that may be

vulnerable to perturbation. The study also presents one of the few studies in which CSD is observed in practice rather than modelled in theory.

Keywords: wavelet analysis; continuous wavelet transform; Stormwater Treatment Area; total phosphorus; inflow; outflow; soluble reactive phosphorus; autocorrelation; resilience.

2.2 Introduction

Since its inception in 1973, resilience has been given heuristic, symbolic, and normative dimensions (e.g., Holling 1996, Parrot, 2010, Pickett et al. 2004, Murmu et al. 2019) in addition to its initial significance as a description of ecological processes (Holling 1973). Ecological and social systems may be studied using this method in a broad variety of scientific domains (Moore et al. 1993; Folke 2010). However, the idea of resilience is often difficult to put into practice in ecological research. Because of this, the development and maturation of resilience theory is hindered (Armstrong et al., 2023).

The ecological literature defines system resilience in two ways, each reflecting a distinct feature of stability. Holling (1973) began by emphasizing these many dimensions of stability so to illustrate the distinctions between efficiency and persistence, constancy and change, and predictability and unpredictability. Holling defined stability as the endurance of a system near or towards equilibrium. Resilience in dynamic systems is about how much disruption a system can handle before it fundamentally changes its state. When a system faces disturbances—like environmental changes, economic shifts, or social upheavals—it must reorganize itself, adapting its variables and processes to continue functioning. It's like a tree in a storm bending with the wind to avoid breaking. Ecological resilience is predicated on the existence of many stability domains and the system's tolerance for shocks that enable transitions between stable states. As a result, ecological resilience refers to the breadth or limit of a

stability domain, which is determined by the amount of disturbance that a system can tolerate before changing stable states.

Stability landscapes, in terms of ecosystem resilience, contain multiple possible regimes each with a particular parameterisation around equilibrium, resilience, tipping points and can contain multiple possible pathways (good or bad) based on the efficacy of adaptation. Regime shifts are abrupt changes that arise when an ecosystem exhibits a nonlinear or discontinuous response to a driver variable causing it to undergo radical change due to incremental increase in external forcing. Instead of trying to predict regime shifts by estimating critical values critical slowing down results in generic changes in dynamical behaviour that can be used to signal the approach of a critical transition. When an ecosystem approaches a critical transition its dynamics "slowdown" resulting in increases in summary statistics like variance and autocorrelation. This slowing down occurs because an ecosystem near a critical transition has low resilience, resulting in a slower approach to equilibrium following perturbation.

Using wavelet analysis to investigate ecosystem complexity and resilience is a powerful approach. Wavelet analysis allows researchers to examine non-stationary data, capturing both frequency and time information, which is particularly useful for understanding dynamic properties in ecosystems (Cazelles et al., 2008).

The Everglades Stormwater Treatment Areas (STAs) in South Florida are an excellent case study for this kind of research. These managed wetlands are designed to remove excess nutrients, like phosphorus, from stormwater runoff before it enters the Everglades. By analysing flow data, water quality, and nutrient loads, we can gain insights into how these ecosystems respond to disturbances and maintain their resilience (www.sfwmd.gov).

The large-scale constructed wetlands of the Everglades Stormwater Treatment Areas (STAs) are vital for protecting the Everglades ecosystem. They were indeed constructed in the 1990s and 2000s to treat stormwater runoff, removing excess nutrients like phosphorus before the water is discharged into the

Everglades. This helps mitigate the harmful effects of nutrient pollution, which can lead to issues like algal blooms and habitat degradation. The STAs are subjected to various perturbations, including hurricanes that can cause significant physical damage to the wetland vegetation and infrastructure, as well as introduce large volumes of water and debris. During periods of heavy rainfall, the wetlands receive large influxes of water, which can challenge their capacity to effectively treat stormwater. Extended dry periods can reduce water levels, affecting the health of aquatic vegetation and the overall functioning of the wetland system.

We are particularly interested in the most and least resilient zones of the Stormwater Treatment Areas. It has been hypothesized that slow internal critical transitions often made STAs less resilient over time, setting them up for transition change. Sudden changes in the dominant plant communities have been observed within these systems, changes such as a fully vegetated emergent marsh shifting to open water communities, with associated effects on biogeochemical cycling and water quality. We investigate whether the variation observed in concentrations of total phosphorus concentrations and loads (TP-mg/L) into and out of the STA, can indicate STA to disturbances such as hurricanes, high flow conditions and droughts.

2.3 Materials and methods

2.3.1 Study area – location of the STAs

Five STAs were constructed from the 1990s to 2000s and encompass 62,000 acres just north of the Everglades Protection Area (EPA), in the State of Florida. They were built to remove excessive phosphorus (P) primarily from agricultural

and urban runoff, to enhance the quality of water that enters the EPA (Armstrong et al., 2023).

2.3.2 Background

The Everglades STAs are the largest treatment wetland system in the world that retain nutrients through complex biogeochemical processes including vegetation growth and the accumulation of dead plant waste. Armstrong et al. (2024) provide a comprehensive overview of the design and construction of these wetland systems, as well as the establishment of sampling stations for Emergent Aquatic Vegetation (EAV) and Submerged Aquatic Vegetation (SAV). Their work is crucial for understanding how these wetlands function and contribute to the overall health of the ecosystem. Zhao and Piccone (2020) evaluated STA performance by comparing annual and long-term average annual flow-way and treatment cell TP flow-weighted mean outflow (FWMC) concentrations, TP load retention percentage, and TP FWMC reduction percentage. The results of an evaluation of the effects of annual hydraulic loading rate, annual phosphorus loading rate, annual average hydraulic residence time, inflow TP FWMC, and annual average water depth on annual flow-way TP FWMC showed that TP settling rate alone is insufficient to assess STA treatment performance, particularly when hydraulic loading rates vary. Under controlled steady-state settings, the P retention mechanisms acting in this sizable SAV wetland may be sustained. However, it is still a top research priority to determine how vulnerable the SAV is to extreme environmental perturbations in these and other wetlands.

The South Florida Water Management District (SFWMD) operates a system for regional flood protection, water supply, and quality improvement in the South Florida ecosystem, including the Everglades. Effectiveness depends on vegetation, inflow water quality, hydraulic loads, and flow events.

Since the inception of STA's operations, their nutrient removal effectiveness has been closely monitored. The improvements in water quality are verified by monitoring the concentration of total and inorganic P levels in the inflow and comparing them to concentrations in the outflow (Gao, 2006; Delgado-Moreno & Gao, 2022). Factors like hydraulic and phosphorus loading rates can affect efficiency. The Everglades STAs aim to maintain a daily target depth of 0.4 to 0.5 m for plant health and TP retention. These wetlands are efficient biological engineering solutions to reduce nonpoint source pollution but require specialised design, operation, and maintenance. Agriculture and soil oxidation have also altered the Everglades' water quality by increasing dissolved nutrients, particle matter, and pesticides in stormwater runoff (Zhao and Piccone, 2020).

2.3.3 Disrupting events and challenges to their operation

In 2005 Hurricanes Francis and Jeanne wreaked havoc on STA-3/4, but little damage was seen in the wetlands (Pietro et al, 2006). Submerged Aquatic Vegetation (SAV) in Cell 2B was somewhat damaged by Hurricane Wilma in 2006, whereas the emergent vegetation was moderately damaged (Pietro et al., 2006). In 2018, South Florida was hit by two major hurricanes, Michael and Irma. In 2011, a regional drought resulted in dry out and damage to the SAV in treatment Cells 1B, 2B, and 3B. The Cells 3, 4N, and 4S in STA-1E Central Flow-Way (1E-CFW) had to be put into operation earlier than expected in response to storm flows from Hurricanes Frances and Jeanne in 2004 (Pietro et al., 2006). Among all the Flow Ways (FWs) under study, this Flow-Way generated some of the most fluctuating yearly outflow TP concentrations, going through periods of good and bad performance around every two to four years. Poor vegetation coverage resulting from windstorm damage can be blamed for the 1E-CFW's poor performance in these early years.

Monthly summed flow and load data from the five Everglades Stormwater Treatment Zones (STAs)-STA-1E, STA-1W, STA-2, STA-3/4, STA-5/6 (Figure 2-1) was received (according to SFWMD) for each STA in a single spreadsheet of data with daily measurements aggregated by month for further analysis. Station records were merged and summarised for each flow-way depicted in Figure 2-1. In order to prepare the data for time series and other statistical analyses several steps were taken using the R statistical software package. First, all records containing only flow data were deleted to leave only those providing water quality data. Secondly, different chemical measurements focused on phosphorus (Inflow-Outflow total and dissolved phosphorus concentration (mg/L)-loading(kg)), and auto and grab samples were kept separate due to exhibiting statistical differences. Water quality measures included Calcium (*Ca*), Ammonia (*NH₃*), Nitrate and Nitrite (*NO_x*), Sulphate (*SO₄*), Soluble Reactive Phosphorus (*SRP*), Total Alkalinity (*T. Alk*), total dissolved phosphorus (*TDP*), Total Kjeldahl Nitrogen (*TKN*), and Total Phosphorus (*TP*).

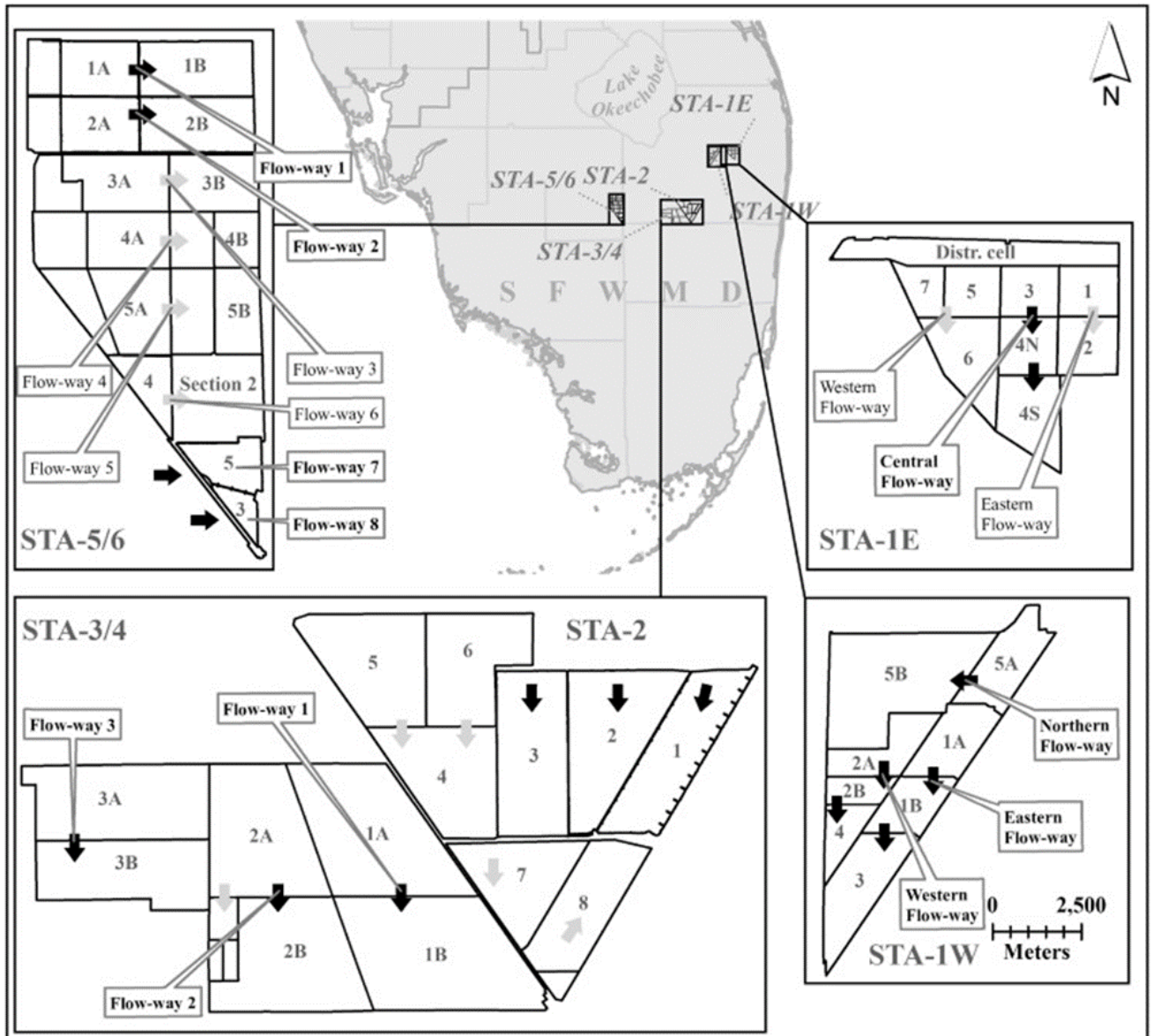


Figure 2-1 Locations of the Stormwater Treatment Areas in South Florida, USA, indicating individual treatment cells and direction of flow with bolded flow-way names and darkened arrows denoting flow-ways in STA-1E, STA-1W, STA-2, STA-3/4, and STA-5/6 (Source: R. Corstanje, J. Zawadzka, 2016).

In this case study, we follow a similar pre-processing methodology described by Rust et al. (2019), which, in summary, consisted of centring the time series on the long-term mean and normalized to the standard deviation to produce a time series of anomalies. This procedure allows spectra between dates and

phosphorus concentration and between STAs across South Florida to be more easily compared.

The wavelet transformations carried out on streamflow data, TP loads. Flow stations in STAs recorded automated sampling data of total phosphorus (*TP*) at regular intervals. These time series are analysed to test for the occurrence of temporal trends versus random noise, determine the periodicity of any cyclical behaviour present in the data, but more the spectral power, which was used as a proxy for autocorrelation, and consider a smoothing model to forecast the data and test for fit. Typically, wavelet analysis methods require that the time series compare a series of measurements that have been made at regular intervals in time. Gaps in the data make it difficult to estimate wavelet variance and correlation, and interpretation may also be compromised (Milne et al., 2011). Lark and Webster (2001) discussed various alternative detection methods for identifying significant changes in variation and correlation within time series data. These methods are particularly useful in environmental science for detecting shifts in ecosystem dynamics over time. These methods were used to detect significant changes in the wavelet variation between STA inflow and outflow characteristics. Any wavelet transforms for which the wavelets are discretely sampled are known as a DWT. It captures both frequency and time, which is a fundamental benefit over Fourier transforms. These were applied to the water quality data from the STAs.

Wavelet Analysis was used with an R package called “WaveletComp” to examine the data from the STA's and try to assess their resilience. ‘WaveletComp’ employs a tiny waveform known as a wavelet to calculate the strength of different periodicity length along any type of continuous data, often time-series data in this case. The output is a power diagram, or power spectrum, which is a graphical representation that helps in understanding how different periodic components contribute to the overall variance in a time series. By using wavelet analysis or similar methods, I can identify and visualize the dominant frequencies and how their importance changes over time.

This approach is particularly useful in ecological studies, where complex interactions and periodic phenomena (like seasonal changes or hydrological cycles) play a significant role. The power diagram can reveal patterns and shifts that might not be immediately apparent through simpler statistical methods. Shifts from low power to high power, over time, are indicative of changes in variance within the data.

2.4 Results

2.4.1 Comparison of STA-1E and STA-3/4 wavelet power spectra in terms of variance

Comparing the wavelet power spectra of STA-1E and STA-3/4 we can analyse fundamental shifts in these systems. Bifurcations represent critical points where a system undergoes a significant change in behaviour, and understanding these shifts can provide valuable insights into the resilience and adaptability of the STAs. We can also identify how the periodic components in each system's time series data behave differently. This comparison can help highlight the specific conditions or perturbations that lead to these fundamental shifts (see Appendix B).

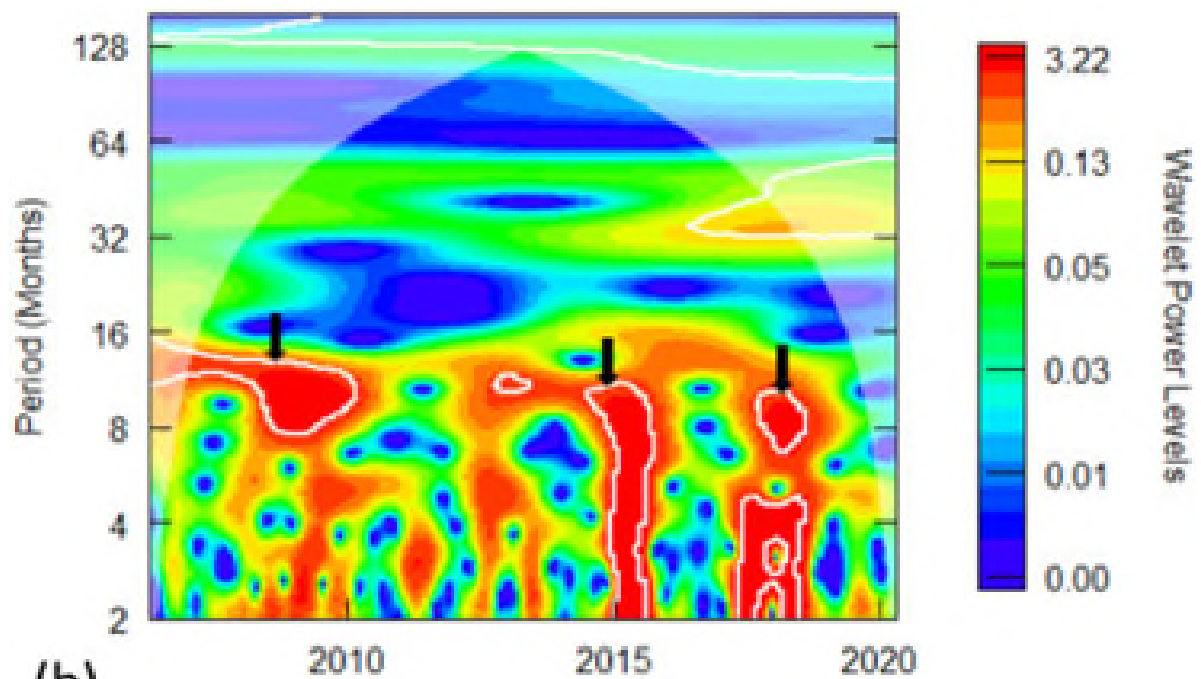
The type of environmental monitoring analysis can be crucial for monitoring changes and identifying periods of significant shifts. Understanding periods of high variability can help in assessing the resilience of ecosystems or processes to various stressors. The use of wavelet power spectra to analyse the variance in time series data, specifically in the context of TP (Total Phosphorus) concentration inflow-outflow in month's period (Figure 2-2, Figure 2-3), is a method used to identify periods of increased variability or resilience in the data. The Wavelet Power Spectrum (Scalogram) is a visual representation that shows

the intensity of different frequency components of a time series over time. It uses a colour gradient to indicate the power (variance) at each scale.

Higher variability in the time series is depicted by "hotter" colours (e.g., red) in the wavelet power spectrum. Here, significant periods of increased variance (resilience) were observed around 2008–2010, 2015, and 2018 in Figure 2-2a; Figure 2-2b; for the period 2008–2010.

The black arrows pointing to the white envelopes in the scalogram highlight periods where the variance becomes significant. This signifies moments of high variability in the inflow, which can indicate intense instability and potential disturbance events on the STA (Stormwater Treatment Area). The consequential response in the outflow would denote a possible indication of CSD, i.e., the STA system is unable to mitigate the disturbance. The associated period gives an indication of the extent over which the disturbance occurred and the length of the possible STA response in the outflow. Although entirely diagnostic in nature, this gives an indication of the period of instability and the ecosystem response to this, the time at which and over which this occurs, which, in aggregate, starts forming indicators of CSD.

(a) STA_1e Inflow Wavelet Power Spectrum



(b) STA_1e Outflow Wavelet Power Spectrum

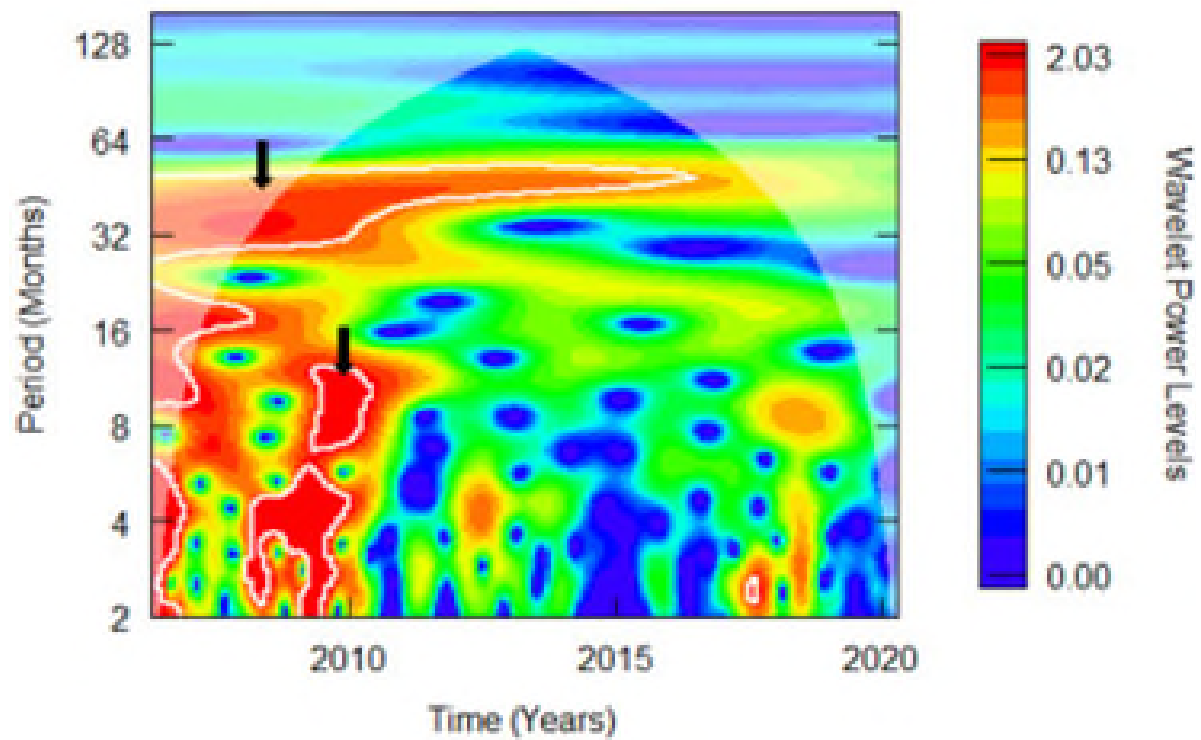
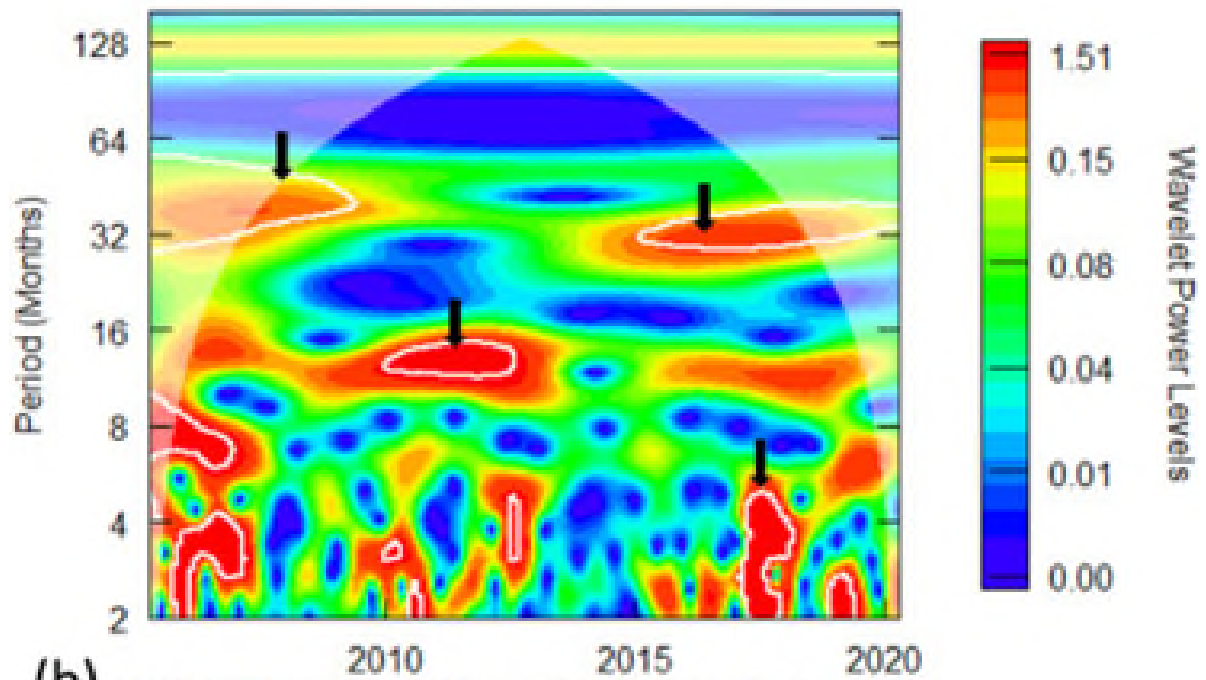


Figure 2-2 The Wavelet Power Spectrum of (a) STA_1E inflow, (b) STA_1E outflow as a function of frequency. The figure shows the realizations of variance of the time series, and the variance increases in red areas and decreases in blue areas. The black arrows indicate the perturbation events occurred in STA_1E for which the segments trend statistic is higher than the trend statistic prior to the event, the white envelopes in the scalogram highlight periods where the variance becomes significant (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

(a) **STA_3/4 Inflow Wavelet Power Spectrum**



(b) **STA_3/4 Outflow Wavelet Power Spectrum**

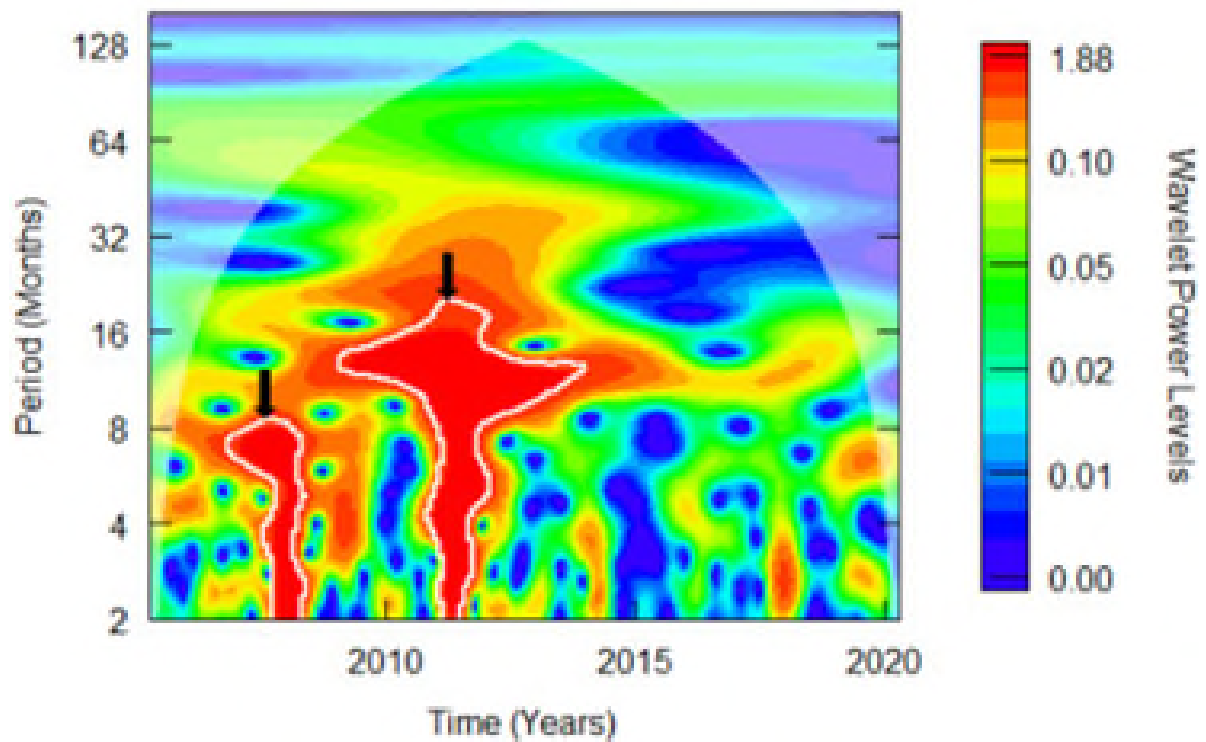


Figure 2-3 The Wavelet Power Spectrum of (a) STA_3/4 inflow, (b) STA_3/4 outflow as a function of frequency. The figure shows the realizations of variance of the time series, the variance increases in red areas and decreases in blue areas. The black arrows indicate the perturbation events occurred in STA_34 for which the segments trend statistic is higher than the trend statistic prior to the event, the white envelopes in the scalogram highlight periods where the variance becomes significant (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

2.4.2 Evaluation of STA-1E and STA-3/4 accumulated rolling autocorrelation

An ACF plot is used to determine where in our time series data there is autocorrelation presence, allowing for a better interpretation of the observed temporal patterns.

In Figure 2-4, Figure 2-6, accumulated rolling autocorrelation analysis is plotted with lagged months-TP (mg/L) (Figure 2-4a, b and Figure 2-6a, b) and autocorrelation analysis of TP inflow-outflow at different lags with maximum lag of ± 24 , one plot for each inflow or outflow (Figure 2-5a, b and Figure 2-7a, b). In these figures, black arrows indicate the regions where the critical transitions were observed through time in the rolling autocorrelation plots. The colour bar graded from blue to red shows the correlation of the values. The CSD relationship and the points where disturbance events took place are represented by the direction of the black arrows (Figure 2-4, Figure 2-6). Whilst the ACF plots show some noise in the data, there are signs of autocorrelations in time indicated by horizontal stretches of pixels of the same hue. The highest positive autocorrelations in the inflow occur for lag of 1 month which may indicate seasonality in TP input to the STA 1E. Autocorrelation measures the correlation of a time series with its past and future values. To properly assess it, you need a sufficient number of measurements to ensure the lagged comparisons

are meaningful, which is symbolized by the grey part of the graph (Figure 2-4, Figure 2-6). For example, if your dataset is too small, the autocorrelation function may not capture reliable patterns, leading to misleading results. More data typically provides better insight into periodic trends, seasonality, or patterns in the time series.

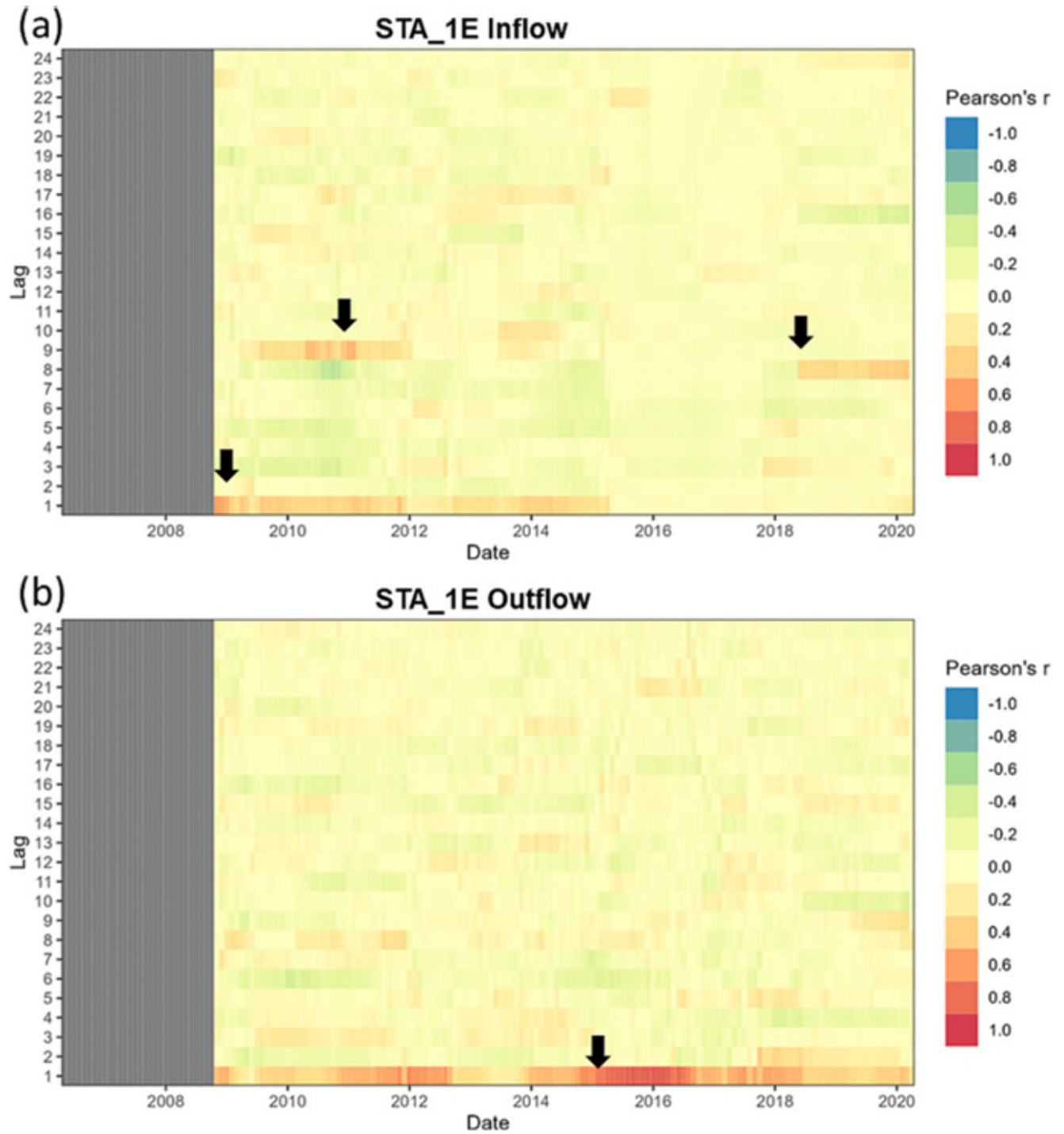


Figure 2-4 Rolling Autocorrelation plot of (a) STA_1E inflow, (b) STA_1E outflow as a function of Dates. We indicated with black arrows the regions where the critical transitions observed through time in rolling autocorrelation plots and according to Pearson's method.

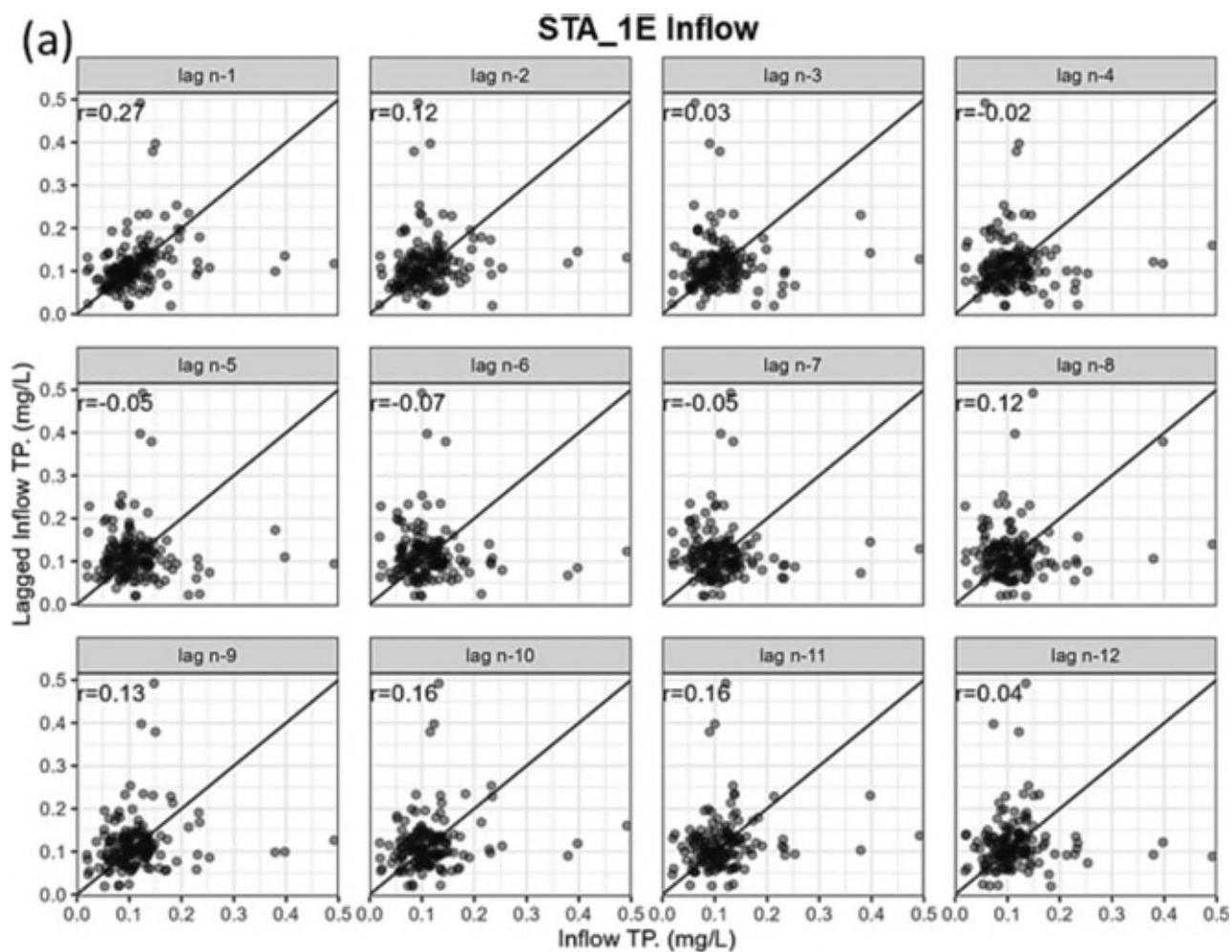
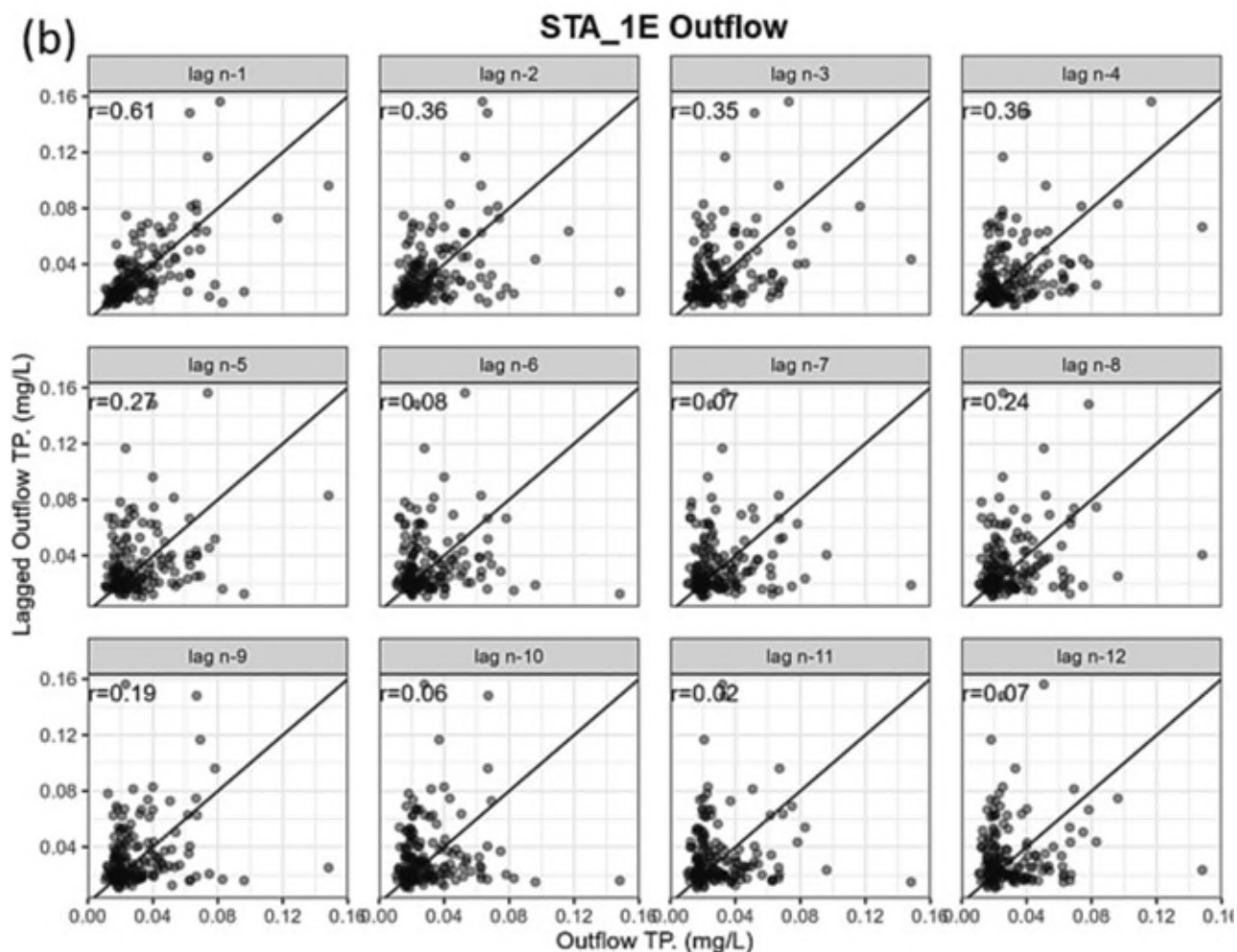


Figure 2-5 ACF plots at different lags of (a) STA_1E inflow, (b) STA_1E outflow. Statistical properties of our indicators of loss of resilience illustrated in the results. The more distributed points in autocorrelation figures indicate at lag1 lower autocorrelation with rising resilience and focused points indicate loss of resilience based on each segment of lags in the system.

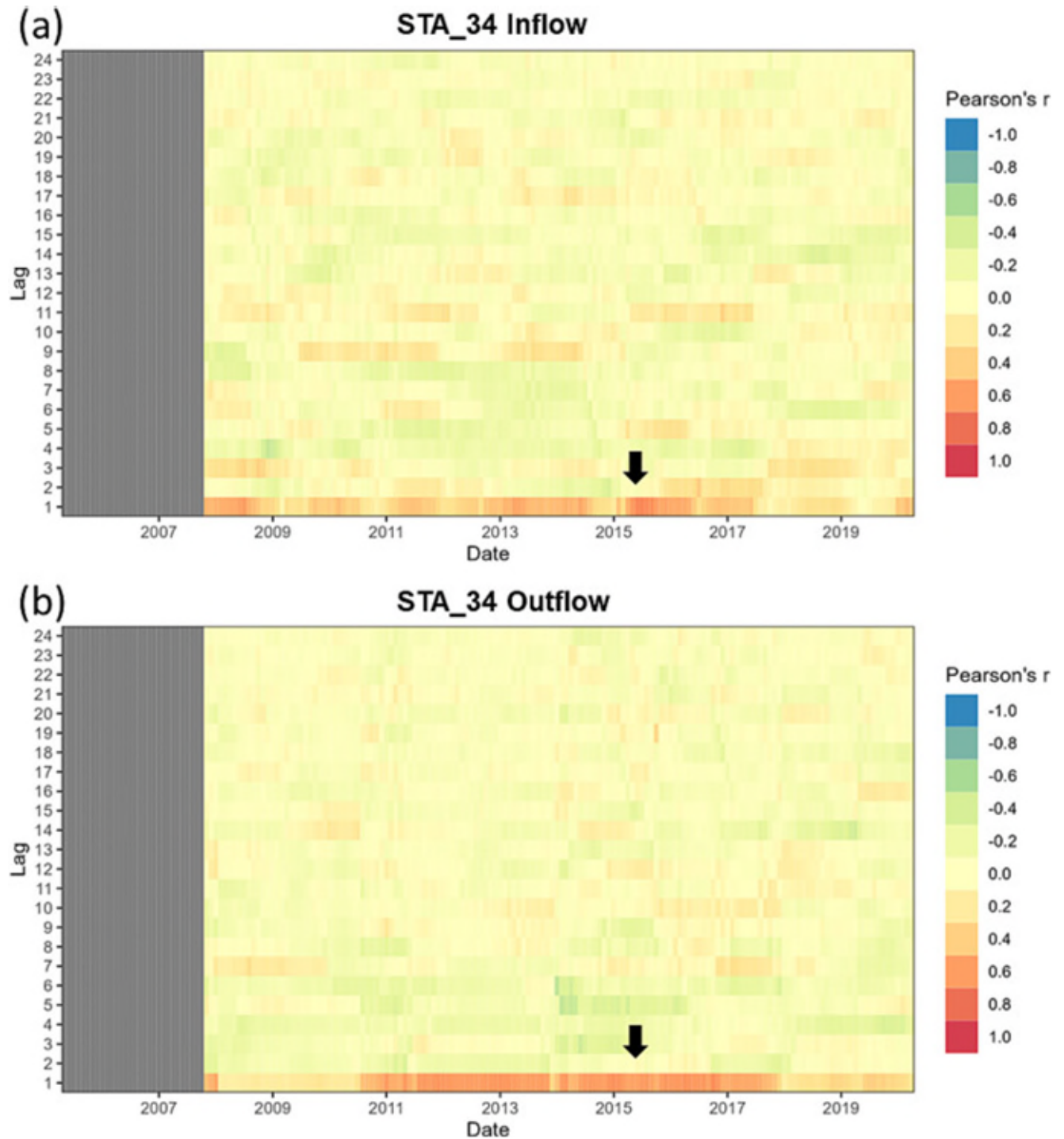


Figure 2-6 Rolling Autocorrelation plot of (a) STA_3/4 inflow, (b) STA_3/4 outflow as a function of Dates. We indicated with black arrows the regions where the critical transitions observed through time in rolling autocorrelation plots and according to Pearson's method.

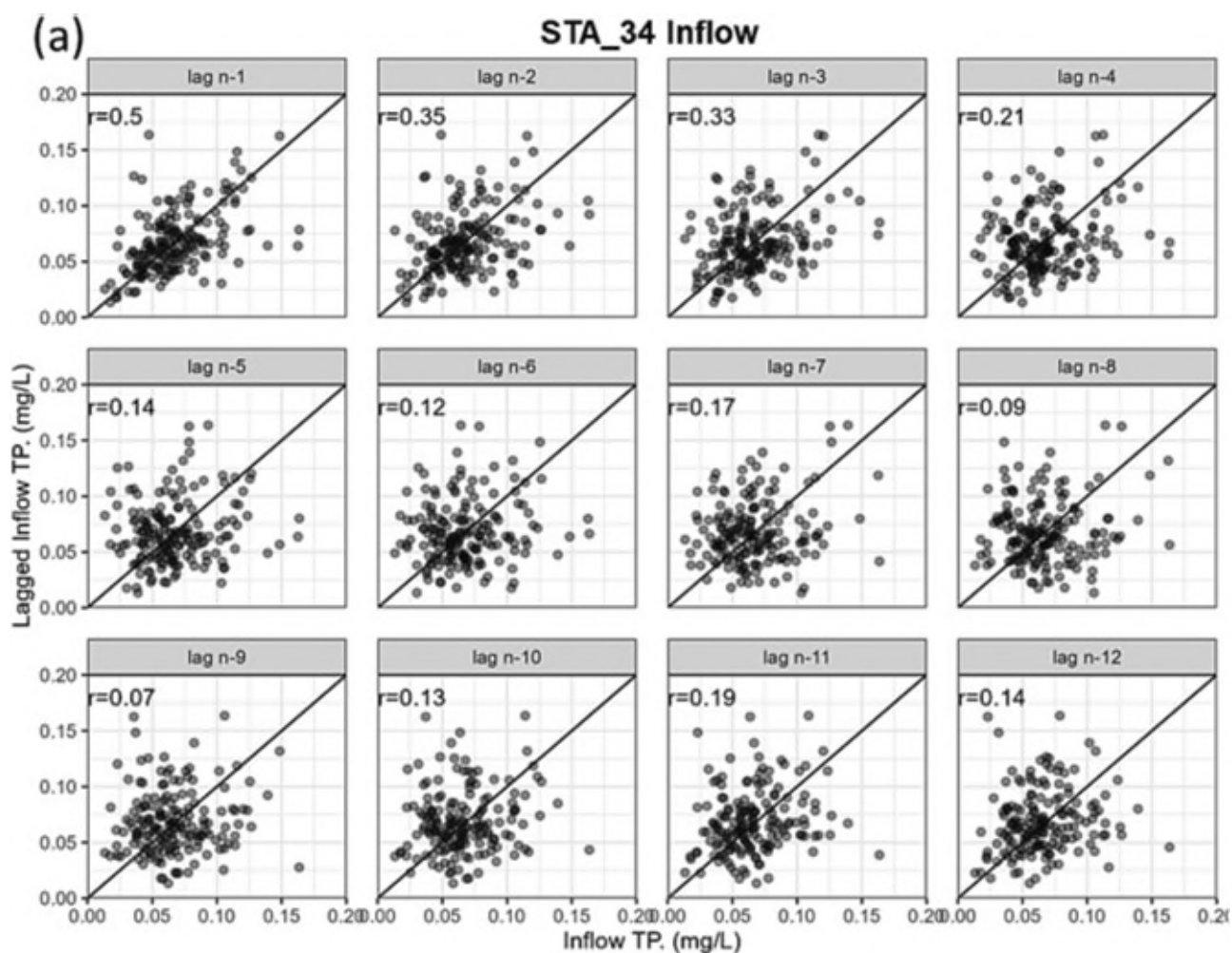
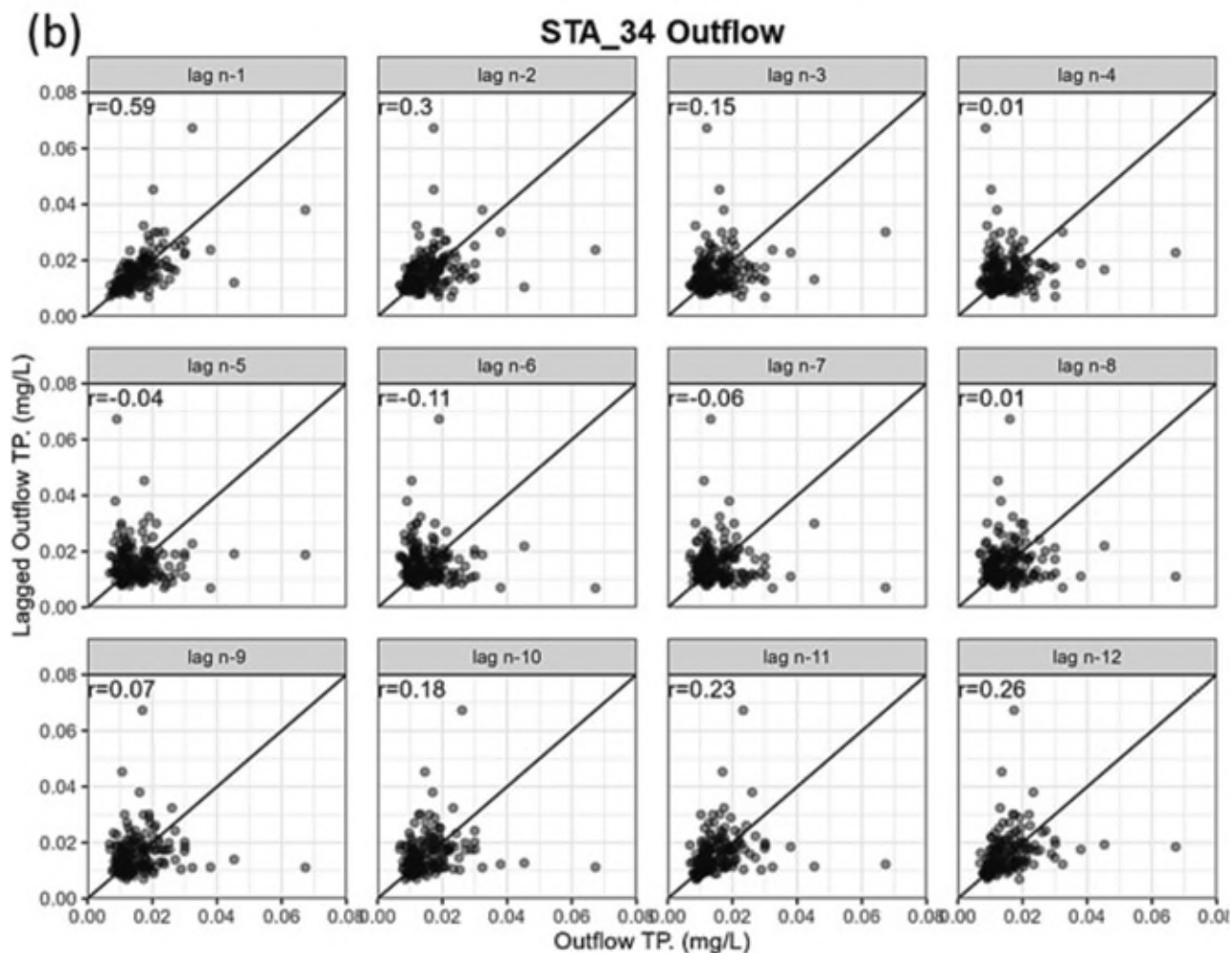


Figure 2-7 ACF plots at different lags of (a) STA_3/4 inflow, (b) STA_3/4 outflow. Statistical properties of our indicators of loss of resilience illustrated in the results. The more distributed points in autocorrelation figures indicate at lag1 lower autocorrelation with rising resilience and focused points indicate loss of resistance based on each segment of lags in the system. The lag1 in outflow is more correlated than others (b).

The significance test, often measured using a p-value, tells you whether the correlation you've observed is likely to be due to random chance or if it's statistically meaningful. If a correlation is significant (p-value below your chosen threshold, such as 0.05), you can confidently interpret the relationship between the variables. On the other hand, the correlation value (negative or positive) tells you the direction and strength of the relationship. A negative correlation means as one variable increases, the other decreases, while a positive one means both increase together. However, even a strong correlation value (positive or negative) is meaningless without statistical significance—it could just be noise (Table 2-1).

So, in a sense, the significance test often takes precedence. Without statistical significance, the correlation value, whether negative or positive, can't reliably be interpreted as a real relationship. But once significance is established, the correlation value becomes critical for understanding the nature of the relationship.

Table 2-1 Correlation analysis between inflow-outflow TP dynamics of STA_1E (mg/L) → concentration and loading→(kg) and environmental-hydrodynamic variables.

STA_1E	TP_interpolated.inflow (Mg/L)	TP_interpolated.loading.inflow (Kg)
TP_interpolated.outflow (Mg/L)	sample estimates cor 0.1886608 $\approx$ 0.19 p-value = 0.01432	
TP_interpolated.loading.outflow (Kg)		sample estimates cor 0.718811 $\approx$ 0.72 p-value < 2.2e-16

STA_3/4	TP_interpolated.inflow (Mg/L)	TP_interpolated.loading.inflow (Kg)
TP_interpolated.outflow (Mg/L)	sample estimates cor -0.1211858 $\approx$ 0.12 p-value = 0.1051	
TP_interpolated.loading.outflow (Kg)		sample estimates cor 0.7628981 $\approx$ 0.76 p-value < 2.2e-16
Computed correlation used Pearson's-method with listwise-deletion		

2.4.3 CSD indicators in STA-1E and STA-3/4 through estimated correlation metrics

The influence of resilience in STAs was detected by generating plots of total phosphorus concentration (mg/L) versus Lag Outflow (Figure 2-8 Inflow-Outflow of STA_1E (a) Total phosphorus concentration (mg/L), (b) Total phosphorus loading (kg) by response of resilience. The blue arrows indicate the most resilient points on the graphs and these points are features that were observed to align

along the direction of high resilience areas (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article), Figure 2-8a, b and Figure 2-9a, b). We highlight with blue arrows the most resilient points on the graphs, and these points are features that were observed to align along the direction of high resilience areas. Estimation of resilience involves investigating the specific indicators through these lagged patterns where points are focused near zero and the y-axis, then we have the least resilient areas, and vice versa, with less resilient areas for more distributed points.

The correlations were determined and calculated as $r = 0.088$, $R^2 = 0.0078$, $p = 0.25$ for STA_1E and $r = -0.0095$, $R^2 = 0.0091$, $p = 0.2$ for STA_3/4 regarding [TP]-mg/L and comparing with TP(kg) loading (for STA_1E, $r = 0.15$, $R^2 = 0.022$, $p = 0.053$ and for STA_3/4, $r = 0.27$, $R^2 = 0.074$, $p = 0.00022$), where the figures show that the most resilient areas are close to zero. As the TP FWMC correlations are not significant the system show resistance.

Illustrating generic indicators of proximity to a tipping point from a normal to an alternative stable state, generally STA systems are mitigating disturbances effectively when comparing the autocorrelation terms across input parameter space to that of the outflow parameter space, disturbances occur over short periods of time (Lag 1) and mitigated effectively as there was no autocorrelation signal in the longer *lags* ($> lag1$).

Statistical treatment of the obtained results was performed by the correlations calculated between the inflow-outflow of the observed flows of the critical STA's using "Pearson's method" and were examined. Overall, the most vulnerable to transition treatment area was STA-3/4 indicating a negative correlation (Table 2-1).

The analysis indicates that STA-1E performed better and exhibited greater resistance and resilience compared to STA-3/4. This suggests that STA-1E is better equipped to handle disturbances and maintain its functionality.

2.5 Discussions

According to our knowledge, this is the first study to investigate indicators of CSD in intensely managed ecological system such as the STAs of South Florida. We observe that one of the most resilient areas is STA-1E with the least evidence of Critical Slowing Down (www.sfwmd.gov).

The resilience of different STAs (Stormwater Treatment Areas) to Total Phosphorus (*TP*) loading (*kg*) is a crucial aspect of their performance. It's interesting to note the sequence of reduced resilience, beginning from the most resilient area we have: STA-1E→STA-1W→STA-2→STA-5/6→STA-3/4. However, this sequence could change due to the dynamic nature of ecosystems, which means they can undergo significant shifts. A weak positive correlation between inflow and outflow *TP* (*Total phosphorus*) concentrations indicates that the STAs (Stormwater Treatment Areas) are functioning relatively well (Table 2-1). The inflow and outflow (*TP*) concentrations aren't closely linked, suggesting that the STAs effectively reduce phosphorus levels.

In contrast, a strong positive correlation between inflow and outflow (*TP*) concentrations would mean that the STAs' performance is impaired (Figure 2-8b, Figure 2-9b). This scenario implies that the phosphorus entering the system is largely passing through without significant reduction, which can compromise the system's efficiency and overall ecological health.

Maintaining a weak positive correlation is thus a key indicator of the resilience and effectiveness of STAs in managing phosphorus loads and supporting water quality improvements. This finding highlights the importance of resilience in managing STAs. Critical transitions can lead to a change in the stability landscape, causing the equilibrium position to shift. This is a reminder of the importance of monitoring and understanding the resilience of these systems. Such transitions might be triggered by various factors like changes in environmental conditions, management practices, or external pressures. The

adaptability of the system to these changes determines its long-term sustainability and effectiveness.

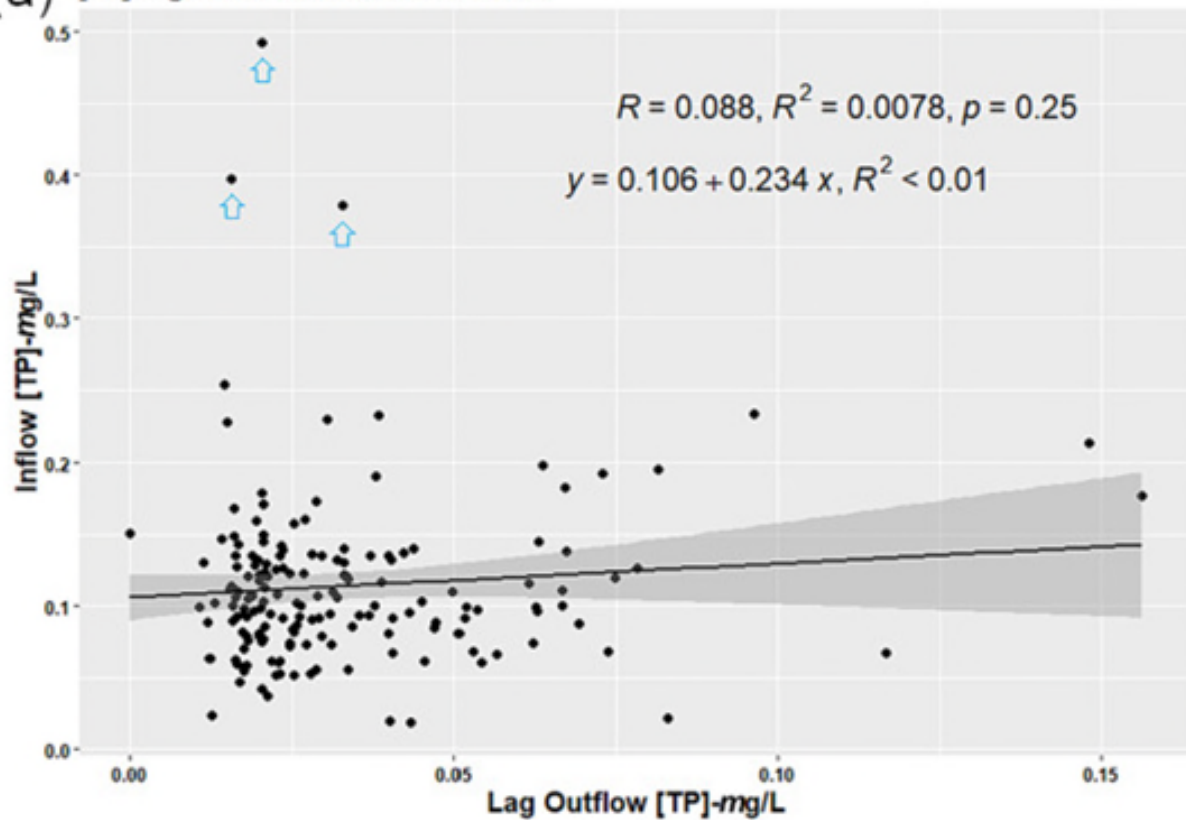
When the points lie in the straight line, which has a negative gradient, this shows that as the inflow *TP* increases, the outflow *TP* decreases, and this can be observed in STA-3/4, which seems to be more resilient area in terms of total phosphorus concentration (mg/L) (Figure 2-9a).

Examining of autocorrelation within a time series (e.g., outflow) the high autocorrelation is one of the indicators of CSD, however we observed that after a period of high autocorrelation, there seems to be system response leading to a period of stability, i.e. less autocorrelation. According to Piccone et al. (2017), *P* removal and *TP* outflow concentrations in STA flow-ways are influenced by internal factors. Concentrations at the outflow structures are an accumulation of upstream flow-way performance, with the marsh parcels closest to the outflow structures having the highest relative influence. More or less resilient areas are differentiated by distinct processes than low *TP* concentrations (13–25 g/L) and ultra-low outflow *TP* concentrations (13 g/L).

It is observed in Figure 2-4, Figure 2-6 that the rise in autocorrelation is likely a more direct of CSD indicator than the rise in variance. This is because change in variance can be confounded by several mechanisms, for instance, a trend in variance may be related to a trend in the mean, so a coupling of variance to mean may partly explain the trends we observe in the indicators of CSD. The analysis of trends in the power spectrum illustrates that rising variability in all STAs (red areas in Figure 2-2, Figure 2-3) may be an observable indicator of CSD associated with an elevated risk of an impending transition within the system, however, it is not clear whether the observed effect in variance might be an effect of increased external perturbations (noise) and not a result of CSD. As temporal autocorrelation and cross-correlations are independent of the means as well as the amplitude of noise, the trends in correlations may be our most robust indicator of CSD (Figure 2-5, Figure 2-7). We can better evaluate the effects of isolated flow events as well as the impacts of multiple, sequential high flow disturbances

as time series of TP concentrations lengthen and modelling tools advance. Even though it is difficult to isolate and quantify functional resistance and resilience due to the short intervals between high flow events, including dynamic flow in our assessment of alternative regimes is an essential next step towards a more comprehensive understanding of frequently disturbed ecosystems (O'Donnell & Hotchkiss, 2020).

(a) [TP]-mg/L Inflow-Outflow of STA1E



(b) TP(kg) Inflow-Outflow of STA1E

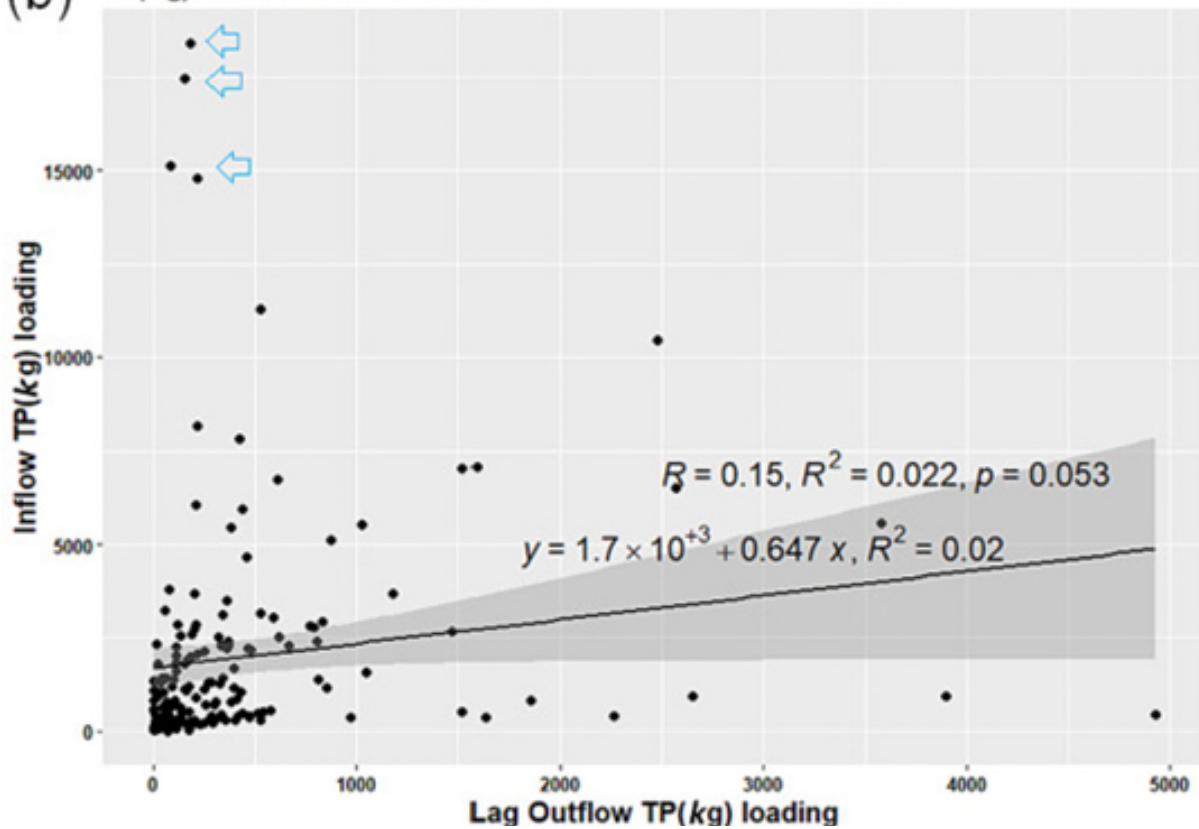
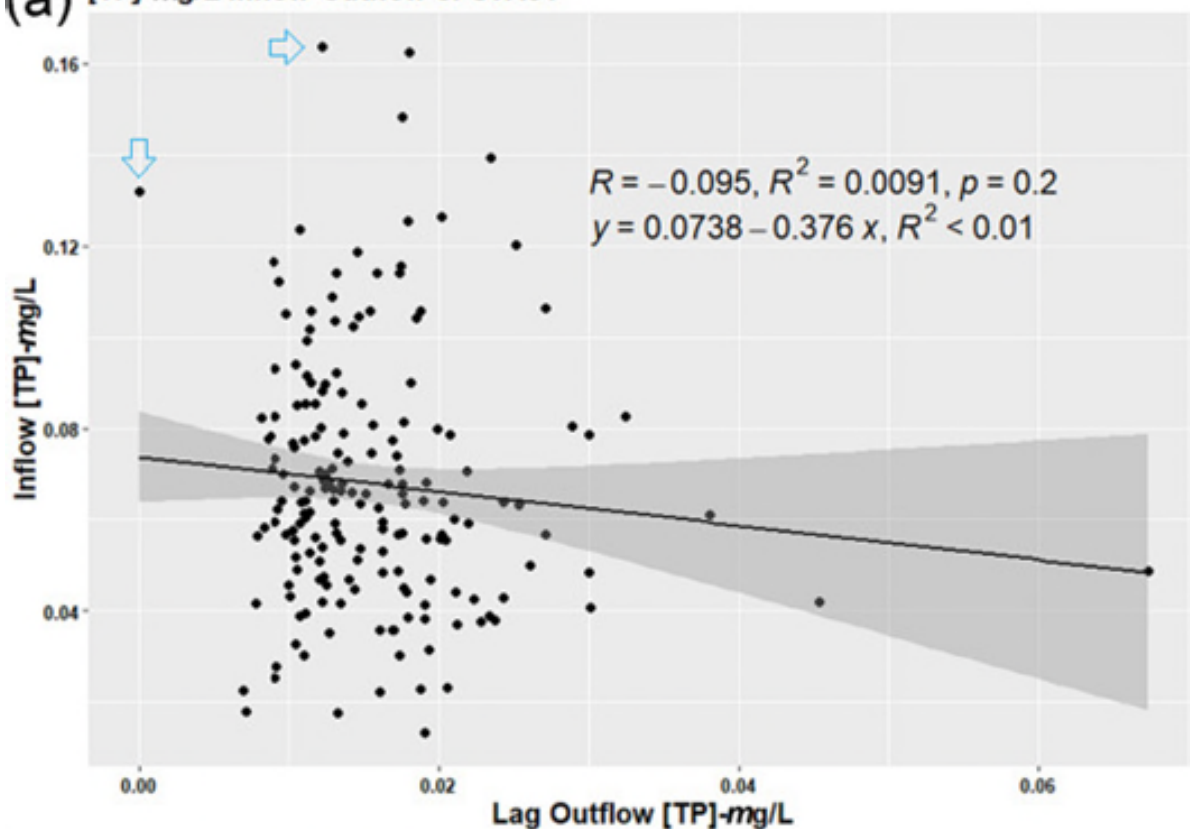


Figure 2-8 Inflow-Outflow of STA_1E (a) Total phosphorus concentration (mg/L), (b) Total phosphorus loading (kg) by response of resilience. The blue arrows indicate the most resilient points on the graphs and these points are features that were observed to align along the direction of high resilience areas (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

(a) [TP]-mg/L Inflow-Outflow of STA34



(b) TP(kg) Inflow-Outflow of STA34

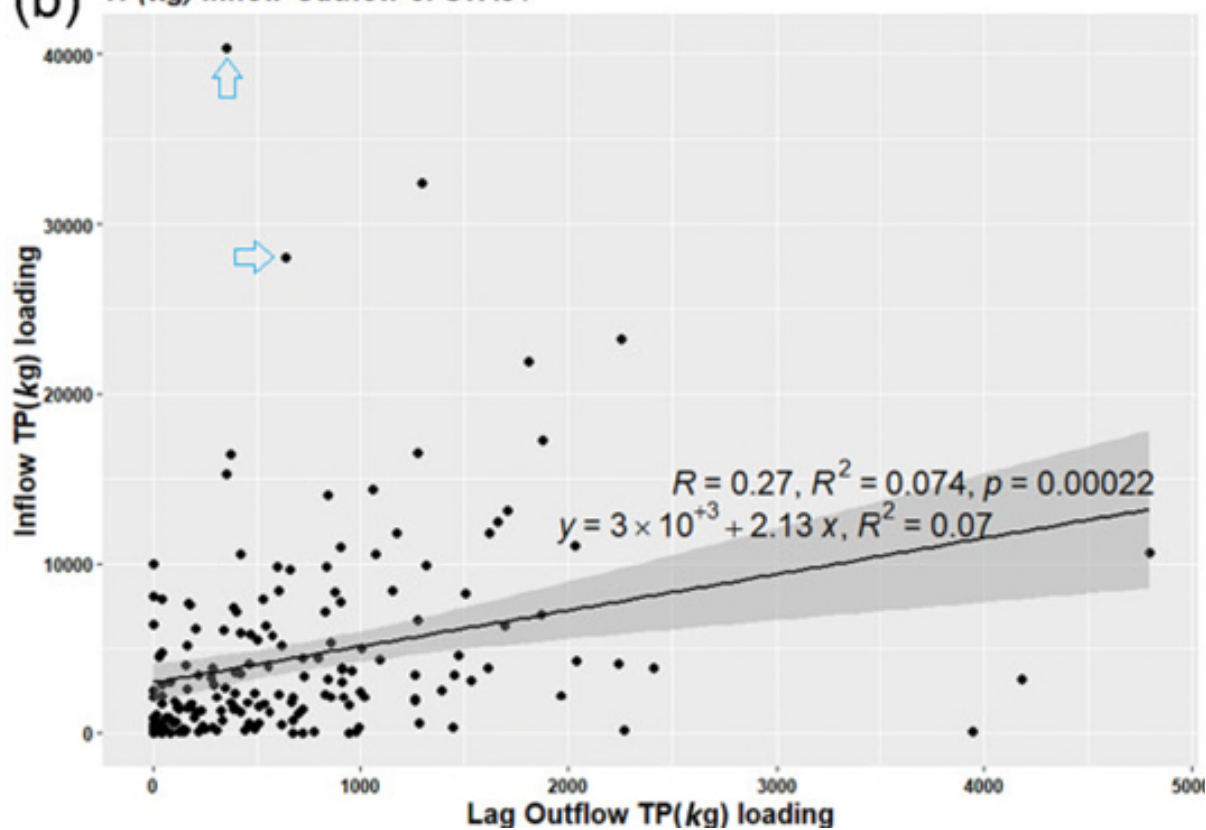


Figure 2-9 Inflow-Outflow of STA_3/4(a) Total phosphorus concentration (mg/L), (b) Total phosphorus loading (kg) by response of resilience. The blue arrows indicate the most resilient points on the graphs and these points are features that were observed to align along the direction of high resilience areas, and the shadow band shows the confidence interval (For interpretation of the references to colour in this figure legend, the reader is referred to the web version).

We have concentrated on linear dynamics near equilibrium, as is the case with most ecological stability theories. In contrast, nonlinearity is well-known for generating transients that are both longer and greater in size. In basic discrete-time predator-prey models (Haderler & Gerstmann, 1990; Neubert & Kot, 1992) and spatial models of single populations, it can cause extended, chaotic transients (Hastings & Higgins, 1994). May and Leonard (1975) found that a nonlinear model of nontransitive rivalry can generate solutions that are asymptotically close to cycle- graphs, but not completely transitory.

Ecosystems nearing a tipping point lose their ability to withstand disturbances and shift towards an alternate state. Recently, it has been suggested that an ecosystem's loss of resilience might be identified by an increase in autocorrelation as well as variability in the fluctuations of the ecosystem's state Lenton et al. (2012) (Figure 2-4, Figure 2-6, indicated by the black arrows). As shown in Figure 2-4, Figure 2-6, in the study period, autocorrelation and variance (Figure 2-2, Figure 2-3) are useful measures of CSD and/or system stability. However, analysis and simulations do indicate that some measures of CSD (e.g. variance) be less sensitive (e.g. in 2012, Figure 2-2b). When comparing the power spectra of the inflow vs outflow in STA 1/2 and 3/4, the presence of a number of disturbances are noted in the inflows (Figure 2-2a, Figure 2-3a as shown with black arrows indicating the extreme events with periodic characteristics of 8–20 months), which correspond to a degree in observed variance in the outflows. These figures indicate that generally the STA's are able to effectively mitigate disturbances and have become more adept at doing this as time has progressed with STA 1 earlier than STA 3/4. Stochastic

changes in the environment can limit the ecosystem's ability to track high-frequency fluctuations, and this can occur when the ecosystem is less sensitive to these changes as it approaches a threshold. However, the preponderance of areas with high at low time frequencies might consequentially lead to an underestimation of variance when data is scarce (Figure 2-2b (period 2012–2020), Figure 2-3b (period 2015–2020) as shown the blue regions during the study period).

To the contrary, autocorrelation is consistently increasing when it comes to important points in our study, as shown when we plotted accumulated rolling autocorrelation analysis with lagged months-TP (mg/L) (Figure 2-4a, b) and autocorrelation analysis of TP inflow-outflow at different lags with maximum lag of 24 months, one plot for each month (Figure 2-5a, b).

There are a variety of indicators that can be beneficial in different types of systems, but there are also number of limits. When it comes to extremely complicated systems such as ecological systems, the largest insights may come from using a variety of techniques as we have demonstrated in this study by using a combination of, moving window correlation and continuous wavelet transform (CWT), to determine changes in autocorrelation and variance as measures of CSD. We do show that resilience may be measured using a set of generic indicators that can be applied to a wide range of data sets (see Appendix B).

2.6 Conclusions

This study used a new integrated approach, based on a combination of wavelet and correlation analysis, which might offer possibilities to monitor measures of CSD in such systems globally. According to these alternate interpretations, disturbance, heterogeneity, and the presence of several stable states all have a significant impact on ecosystem dynamics. Similar to nonequilibrium ecology, state-and-transition models were initially organised around resilience theory to

describe both equilibrial dynamics within states and the occurrence of numerous states. The concept of resilience was developed to explain how dynamic ecosystems may continue to function as self-organised systems. It assumes that ecological processes acting as feedback mechanisms and regulatory factors to restrain community fluctuation in response to disturbances and sustain community structure. Our findings underscore the importance of securing landscape resilience to maintain functional ecosystem characteristics. Reduced resilience can lead to significant changes, potentially disrupting the ecological services these systems provide.

Proactive management, continuous monitoring, and timely interventions are crucial to preserving the stability and health of these ecosystems. Understanding and addressing the factors that contribute to resilience will help ensure that these areas continue to function effectively and sustainably. Finally, the results indicate an anthropogenic environmental influence, which shows that is responsible for detectable environmental changes. Our analysis suggests that the primary distribution of TP in the STAs after perturbations through flow-ways are associated with autocorrelation, accumulated or not, and may begin to follow the variance, as indicators of resilience, measuring such traits not just for preventing collapse, but also for improving the success of ecological restoration.

Chapter 3

3 Identifying early warning indicators within time-series satellite data for effectively monitoring the resilience of grassland ecosystems.

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This case study utilizes a Bayesian dynamic linear model (DLM) to estimate autocorrelation in a time series of the Normalized Difference Vegetation Index (NDVI) derived from daily MODIS/Terra datasets, focusing on grassland habitats in the United Kingdom. The prevalence of cloudy days in the UK leads to significant noise in the data. To mitigate this, we have developed an algorithm that produces a high-quality NDVI time series for use with the DLM, identifying valid values by accounting for seasonal variations. Employing an iterative Fourier transform, the algorithm eliminates high-frequency fluctuations and establishes a threshold for invalid observations. This thresholding algorithm was benchmarked against various existing cloud filtering methods. Our application of the DLM to grassland sites revealed increased autocorrelation during droughts and a long-term trend of rising autocorrelation. This Chapter seems to play a critical role in illustrating the methodology and application of the Bayesian dynamic linear model (DLM) within the thesis narrative, bridging methodological innovation with ecological insights.

3.1 Abstract

Understanding the variation in climate forcing is essential for the detection of Early Warning Signals (EWS), particularly as ecosystems approach tipping points that may induce a transition into a degraded dynamical regime. This complexity has contributed significantly to the limited examples of critical slowing down observed in real natural ecosystems. The application of increased lag-1 temporal autocorrelation within a moving window has demonstrated effectiveness as an EWS for detecting abrupt changes, as evidenced by remotely sensed imagery. This study focuses on the development of Normalized Difference Vegetation Index (NDVI) time series data generated from daily MODIS-TERRA datasets. We propose a Bayesian Dynamic Linear Model (DLM) that utilizes Kalman filtering in conjunction with pertinent climate data to estimate autocorrelation. Grounded in a recent investigation conducted in forested regions of California, we extend our analysis to resilience estimations in grassland sites across the United Kingdom. The reliability of the identified resilience signals based on NDVI values may be compromised by the absence of data resulting from cloudy days, alongside the pronounced levels of precipitation common in the UK. Numerous remote sensing applications that examine land surface properties, in conjunction with cloud cover or suboptimal atmospheric conditions, frequently yield unsatisfactory results. Additionally, uncertainties inherent in NDVI time-series data—such as measurement errors, fluctuations in atmospheric composition over time, and mixed signals from understory species—tend to depress NDVI values. In response to these challenges, we developed an algorithm designed to produce high-quality NDVI time series for use in the DLM. Based on the seasonal variations evident in the data, the Best Index Slope Extraction (BISE) algorithm was established, employing Fourier transformation to eliminate high-frequency fluctuations from the dataset. The derived magnitude of this constant threshold serves as a reference point for defining abnormal ranges in the EWS, correlating with the seasonal variations evident within the time series and aligning with other cloud filtering methodologies. The findings from this newly developed approach

indicate that elevated autocorrelation is a common indicator of critical slowing down, although it does not guarantee such an occurrence. A comprehensive statistical analysis revealed that when the DLM was applied to eight distinct grassland sites across the UK—namely, Aberdeen, Dumfries, Yorkshire, Leicester, Woburn, Somerset, Berkshire, and Dorset—periods of increased autocorrelation were found to be associated with drought conditions. Furthermore, a long-term trend of increasing autocorrelation was identified, representing a significant advantage for processing large-scale datasets. This innovative method holds considerable potential for the early detection of warning signals related to the monitoring of resilience in connection with the degradation of ecosystem services.

Keywords: resilience, NDVI, MODIS, autocorrelation, iterations, Dynamic Linear Model, cloud filtering, EWS, drought, perturbations.

3.2 Introduction

Resilience can be characterized as the rate at which a system returns to equilibrium following a perturbation (Scheffer et al., 1998). A reduction in resilience has been observed as ecosystems approach a "tipping point," which precedes a transition to an alternate state. One illustrative example of such a state shift in grassland ecosystems is the collapse of vegetation subsequent to drought conditions, resulting in a transition to shrubland or grassland in forested areas, and, in extreme instances, desertification in grassland ecosystems. These critical transitions may lead to diminished biodiversity and a loss of ecosystem services, adversely affecting individuals who rely on these habitats for employment or recreational activities. However, it is also important to recognize that non-catastrophic transitions can occur (Desjardins et al., 2015; Liu et al., 2019).

As resilience decreases, the current state of the system increasingly mirrors its historical state, which means that increased temporal autocorrelation may serve as a valuable indicator of diminished resilience (Dakos et al., 2008). A recently published methodology introduces a Bayesian dynamic linear model (DLM) that utilizes a Kalman filter to estimate *lag*1 temporal autocorrelation within a time series of the normalized difference vegetation index (NDVI). This approach aims to monitor resilience in forest habitats in California and employs a loss of resilience as an early warning signal for potential forest mortality. NDVI, being a widely used indicator of plant growth, cover, and activity, provides valuable insights into ecosystem health. The DLM accounts for various factors such as climatic conditions, seasonality, long-term trends, and stochastic noise, making it a robust tool for resilience monitoring. Assessing the data requirements and suitability of this DLM for UK conditions is a crucial step. It will help determine if the model can be effectively applied to monitor resilience in different ecosystems and provide early warning signals for potential critical transitions (Kumar & Garkoti, 2021).

Hypertemporal satellite data is advantageous in generating time series and addressing issues related to cloud cover; however, its low spatial resolution currently limits field-scale applications in various countries. The increasing availability of satellite constellations, including Sentinel-2, RapidEye, and microsatellites from Skybox Imaging, presents a prospective solution to these constraints. Applications of satellite imagery in grassland research have not been fully realized. A comprehensive understanding of backscatter behaviour across different phenological stages is essential for obtaining high-quality measurements, particularly in regions with frequent cloud cover. The advancement of analytical statistical techniques, alongside the development of hyperspectral satellite instrumentation, is expected to enhance our capabilities in creating tools that promote ecological resilience and facilitate more detailed classification of grasslands. This evolution not only emphasizes the importance of technological innovations but also highlights the necessity for ongoing

research and development to ensure the effective application of these methods across diverse environmental conditions.

The distinctions between improved grass and semi-natural grass are significant and can have profound implications for ecosystems. Improved grasslands are typically characterized by a limited variety of species, as they are often cultivated with a focus on high yields and uniformity. This intensive management can involve the use of fertilizers, pesticides, and regular mowing, which not only reduces biodiversity but also diminishes the overall ecological value of these landscapes. Consequently, improved grasslands are less capable of supporting a diverse array of wildlife; the lack of habitat variety and the presence of chemical treatments can deter many species from thriving. Additionally, the soil health in these areas may suffer due to compaction and nutrient depletion, undermining its ability to support plant life and maintain water retention (Waine, 1999).

In contrast, semi-natural grasslands emerge as a more ecologically favourable option. They typically support a rich tapestry of flora and fauna, promoting higher species diversity that includes native plants, insects, and larger animals. This biodiversity is crucial not only for maintaining balanced ecosystems but also for enhancing soil health; the varied root systems help to aerate the soil, improve nutrient cycling, and increase organic matter. Furthermore, semi-natural grasslands play an essential role in carbon sequestration, capturing atmospheric carbon and storing it in the soil and vegetation, which contributes positively to climate regulation. Overall, the shift from improved grasslands to semi-natural grasslands can lead to more sustainable ecosystems, promoting ecological resilience and supporting biodiversity (Verhoeven et al., 2022).

3.3 Materials and Methods

This case study presents an adaptive noise reduction method for clouds based on a Bayesian Dynamic Linear Model (DLM) that implements a Kalman filter, as

proposed by Liu et al. (2019). The effectiveness of this noise reduction technique is quantitatively analysed and evaluated to generate a higher frequency dataset for utilization within the DLM framework. The normalized difference vegetation index (NDVI) serves as a precise indicator of seasonal variations in vegetation monitoring; thus, alterations in daily NDVI time-series data signify changes in vegetation conditions. Focusing on the development of Normalized Difference Vegetation Index (NDVI) time series data generated from daily MODIS-TERRA datasets. The hourly precipitation and daily temperature were also obtained from MIDAS Open dataset. From this, total daily precipitation and mean daily temperature were derived. A Bayesian Dynamic Linear Model (DLM) was applied that utilizes Kalman filtering in combination with pertinent climate data to estimate autocorrelation. The approach tested was to filter cloud affected values in the daily time series, in order to create a higher frequency dataset for implementation with the DLM, because the daily time series is more sensitive to localised changes. This filtering method succeeded in eliminating a significant amount of invalid data points, and long-term means were calculated for each day of the year. This investigation considers two critical factors: 1) the assessment of resilience in grasslands through autocorrelation analysis, and 2) the impact of cloud cover on measurement accuracy (Figure 3-1).

The data-driven Dynamic Linear Model (DLM) necessitates specific data inputs, including an NDVI time series, climate data corresponding to each observation within the time series, and long-term climate averages for each day of the year. The climate variables incorporated into the model for this initiative comprise precipitation and temperature. To maintain a manageable computational load, Liu et al. (2019) ultimately utilized only one climate variable, specifically precipitation, in their final study, despite having tested temperature as well. In this project, both precipitation and temperature have been employed. The processes of pre-processing and model implementation were executed using Python and QGIS. Different indicators have varying predictive abilities. Combining these indicators can therefore enhance the reliability and accuracy of inferring regime shifts. The algorithm detects valid values based on seasonal variation inherent in the time

series by iteratively applying a Fourier transform to remove high-frequency variation in the dataset and establish a threshold for invalid observations. Observations showed periods of increased autocorrelation corresponding with drought periods, alongside a long-term trend of increasing autocorrelation. While the DLM was enhanced through component discounting and successfully applied to UK datasets, it is important to assess the effects of land management practices, daily versus composite time series, and filtering to draw meaningful conclusions about resilience in UK grasslands. The Abnormally Low NDVI (Normalized Difference Vegetation Index) reflects poor vegetation health or sparse vegetation cover (Figure 3-1).

Low NDVI values, typically close to zero, indicate areas with little to no vegetation, such as barren land or urbanized regions. Negative values often correspond to water bodies or snow. On the other hand, high NDVI values suggest dense and healthy vegetation based on the cyclical nature of NDVI in temperate grasslands and forests. The detection of early warning signals depends on the spatial and temporal scale at which data are analysed. Ecosystems often exhibit variability at multiple scales, and short-term trends in autocorrelation may not necessarily reflect long-term resilience shifts (Drake et al., 2010).

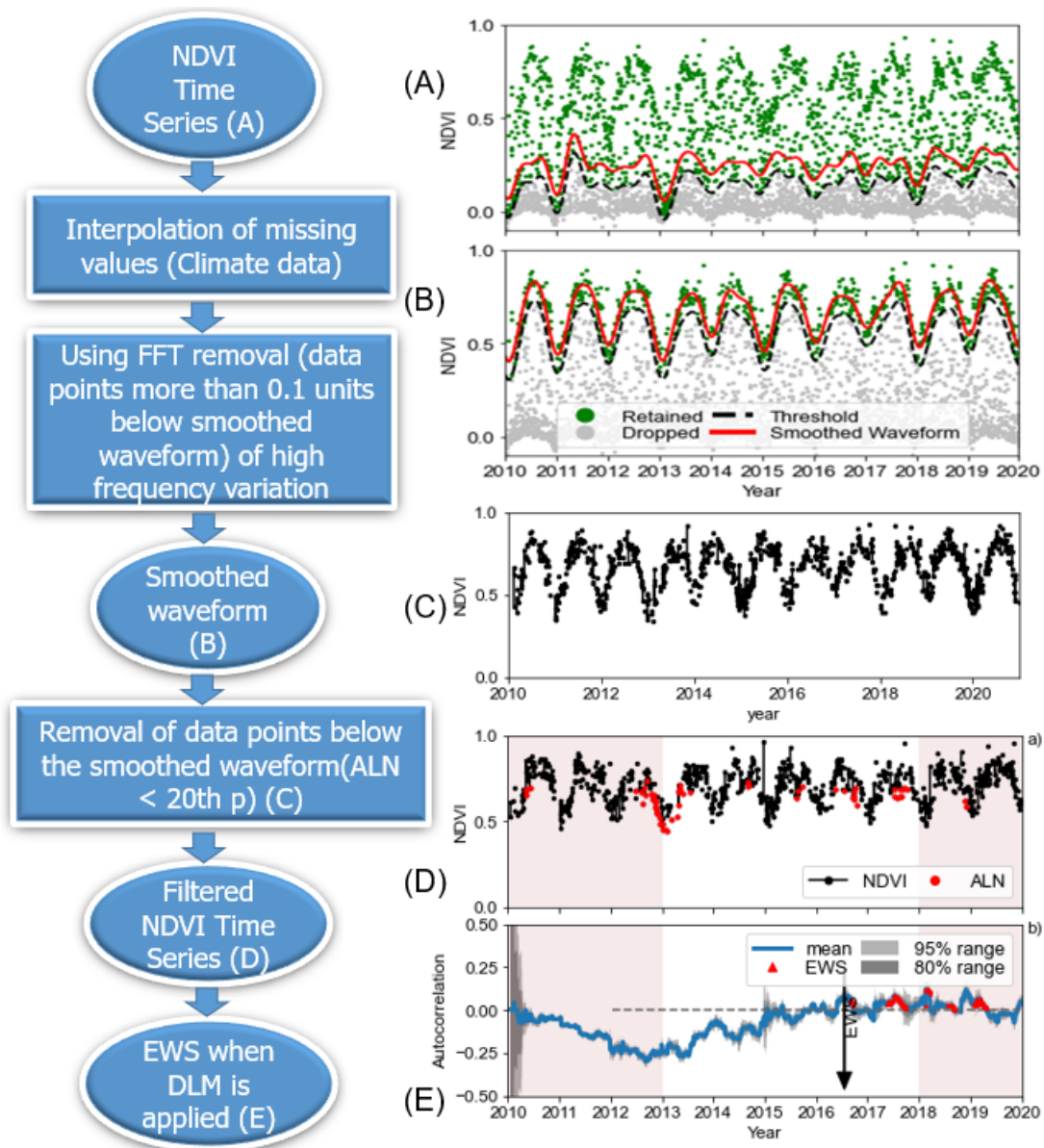


Figure 3-1 A flow diagram that explains the method steps of the algorithm developed to filter cloud-affected data points. (A) First iterations with the raw data, and (B) Final iterations accordingly, of the cloud filtering algorithm. The red line indicates the smoothed waveform and is the result of removing high frequency variation. The threshold is defined 0.1 units below it, (C) Filtered NDVI time series, through the years of the estimation, (D) Daily filtered NDVI time series for each pixel, (E) The lag-1 autocorrelation estimated using the DLM, the dashed lines represent the threshold for an EWS, the shaded areas represent the periods of drought. Mean and uncertainty of temporal autocorrelation estimated using the DLM.

3.3.1 Study sites setting

The present case study was conducted on eight grassland sites across the UK (Figure 3-2). The sites selected for detecting resilience features were carefully chosen to ensure that satellite imagery captures each pixel entirely within the designated fields. Furthermore, due to the proximity of these sites, this arrangement enables a comparative analysis of the results obtained from the Digital Land Management (DLM) system across various locations. By concentrating on these areas, we can gather more comprehensive and reliable data. Previous monitoring campaigns have established these sites as trustworthy for data collection, which enhances the credibility of this study. This is vital for accurately assessing resilience features and understanding the dynamics of these grassland ecosystems. The selected sites have not been strongly influenced by urbanization, guaranteeing that satellite imagery could be acquired where a pixel is enclosed entirely within one of the grids of fields. One pixel is used (a pure pixel of 1 land cover). Starting with satellite or aerial imagery with a resolution fine enough, we distinguish small-scale land cover variations. The higher the resolution, the smaller the pixel size, which reduces the likelihood of mixed land cover within a single pixel. Sophisticated land cover classification algorithms were used to identify and categorise land cover types for each pixel. The classification was validated by comparing the pixel's assigned land cover type with actual on-the-ground data. This step confirms that the entire area within the pixel corresponds to the identified land cover. Also, analysing the spectral signature of the pixel ensures uniformity in the reflected light wavelengths, which correspond to specific land cover types. A consistent spectral profile suggests homogeneity. Sometimes, land cover changes with time (e.g., agricultural cycles). Using multi-temporal imagery ensures the classification reflects stable land cover types and not transient features. Advanced techniques like image segmentation can be applied to ensure that pixels with mixed spectral information are flagged and corrected, ensuring only pure pixels are classified. This

meticulous approach ensures the integrity of land cover classification within a single pixel.

Using a resolution of 250x250 meters per pixel to represent unique spectral signatures, is a powerful technique for large-scale mapping and modelling. By assigning each pixel a pure spectral signature corresponding to one land cover type, we are effectively leveraging remote sensing data to classify and monitor diverse landscapes. This method can enhance precision in applications like land cover classification, vegetation analysis, and even tracking environmental changes over time.

3.3.2 Visualizing land use changes through remote sensing

Exploring the impact of various land use practices on improved and semi-natural grasslands across different elevations in the UK can offer valuable insights. By assessing how these management strategies influence landscape resilience and ecosystem functionality, we can deepen our understanding of the relationship between land use and the conservation of these unique grassland habitats. This research has the potential to inform sustainable practices that enhance the ecological value of these landscapes while also supporting agricultural productivity. Our study included those sites that provided data for the period 2010-2020. All sites have a temperate climate with elevation as a confounding factor, particularly the northeast site grassland in Aberdeen and the northwest grassland in Dumfries. Management varied across sites and included 4–6 grass cuts per year with subsequent manure or synthetic fertilizer applications in the intensively managed grasslands.

In the context of moderately managed grasslands, the implementation of an annual grass cutting schedule represents a methodical approach to land management. This practice serves to uphold the structural integrity of the grassland while minimizing the intensity of disturbances. Periodically substituting

grass cutting with cattle grazing can yield additional advantages, including nutrient recycling, increased habitat diversity, seed dispersal, and a reduction in mowing requirements. The eight grassland sites, including improved pasture and semi-natural grasslands, exhibit distinct characteristics influenced by vegetation health and environmental factors. These areas are typically cultivated and maintained for agricultural purposes, often showing higher NDVI values due to dense vegetation cover and active management practices. The filtered daily NDVI time series for these sites, plotted in black, likely demonstrates consistent vegetation health with occasional dips during drought periods (shaded areas). Temporal autocorrelation evaluated using the Dynamic Linear Model (DLM) might reveal stability in vegetation patterns, with dashed lines marking thresholds for Early Warning Signals (EWS) of potential stress. These grasslands are less intensively managed and may have more variability in NDVI values, reflecting natural fluctuations in vegetation cover and health.

Lag-1 temporal autocorrelation analysis might indicate higher uncertainty, with shaded areas highlighting periods of stress or reduced vegetation health.

Ecosystems are driven by numerous interacting variables, making it challenging to attribute trends in autocorrelation to a single factor, such as declining resilience. Other external influences—like climate variability, human disturbances, or random fluctuations—may obscure or override these patterns. The detection of early warning signals depends on the spatial and temporal scale at which data are analysed. Ecosystems often exhibit variability at multiple scales, and short-term trends in autocorrelation may not necessarily reflect long-term resilience shifts.

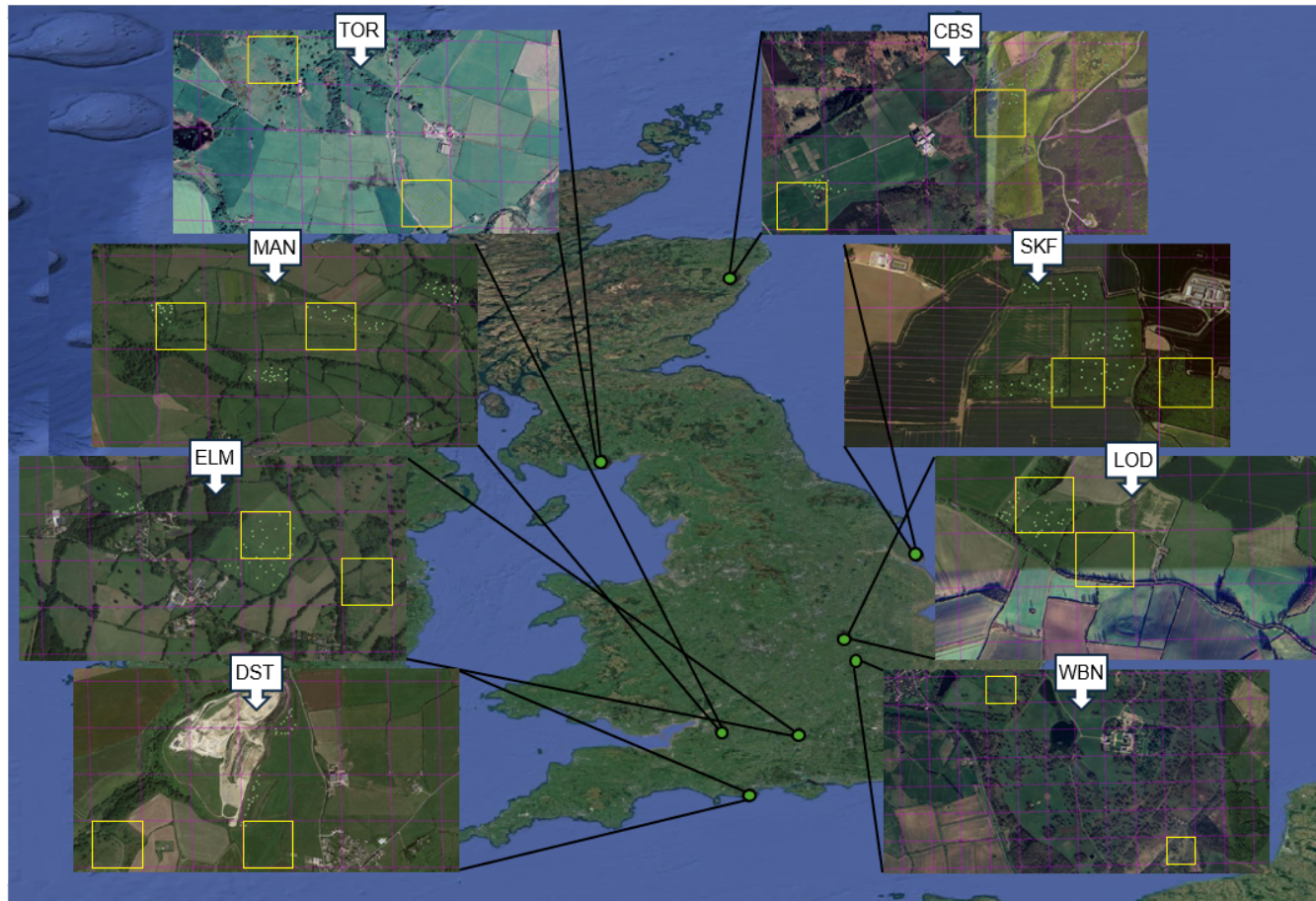


Figure 3-2 The UK grassland sites are located at the green circle, ensuring that satellite imagery could be acquired where a pixel match entirely within one of the fields. As described by the initials: Aberdeen (CBS), Dumfries (TOR), Yorkshire (SKF), Leicester (LOD), Woburn (WBN), Somerset (MAN), Berkshire (ELM), and Dorset (DST).

3.3.3 Data processing and methodology of cloud quality

Clouds and poor atmospheric conditions can depress NDVI values, resulting in sudden drops in NDVI that make it challenging to detect and are not compatible with the gradual process of vegetation change. The United Kingdom's weather is heavily influenced by its geographical position and the movement of different air masses.

The Polar Maritime Air Mass originates over the cold North Atlantic and Arctic regions. It brings cool, moist air, resulting in frequent showers and extensive cloud cover. This air mass is prevalent during autumn and winter, although it can occur throughout the year.

Conversely, the Tropical Maritime Air Mass originates over the warm Atlantic Ocean, particularly in areas such as the Azores and Canary Islands. It is characterized by warm, moist air, which often leads to mild temperatures and significant rainfall. This air mass is dominant in the summer months and can also introduce humid conditions. The interaction between these two air masses plays a crucial role in shaping the United Kingdom's generally wet climate. The Polar Maritime air mass is associated with frequent showers, whereas the Tropical Maritime air mass can result in prolonged periods of rainfall, particularly in the western regions. Both air masses are moisture-laden, which contributes to the prevalence of extensive cloud cover, explaining the relative scarcity of clear, sunny days in comparison to other regions. From the Gulf of Mexico, the North Atlantic Current and the Atlantic Ocean Current transport warm water around the UK, as a result this thermohaline circulation helps retain heat and offers warmth during the winter months, thereby preventing temperatures from declining by an additional 10°C compared to existing conditions. The average annual sunshine hours in the UK are 1,402 according to Met Office Data (1991-2020). However, it may seem less, there are UK regions with plentiful sunshine. In 2020 a dry and unusually sunny spring was recorded, specifically across the southern half of the UK with over 150% of normal sunshine across England and Wales. Last year

(2024), the United Kingdom recorded a total of 626 hours of sunshine, representing 144% of the long-term average for the period from 1981 to 2010. This achievement marks the sunniest spring on record by a considerable margin. Additionally, it was noted that this spring was sunnier than all but three summer seasons in the historical sunshine series of the UK, which dates back to 1919. The Average Sunshine a Year for each of the eight grassland sites is presented at Table 3-1.

In the context of remote sensing applications that concentrate on land surface properties, the prevalence of cloud cover—where over 70% of days are characterized by overcast conditions in the UK—exerts a detrimental effect on remote sensing analyses, typically resulting in decreased Normalized Difference Vegetation Index (NDVI) values. Consequently, I implemented the algorithm as developed by Stojanovic (2021) to reproduce cloud-free imagery for any point within this time series, as referenced by Stowe et al. (1991).

Table 3-1 Average Sunshine a Year for each field in the UK study areas of grassland.

Grassland Sites	Average Sunshine a Year in the UK (Hours)
Aberdeen (CBS)	1447
Dumfries (TOR)	1309
Yorkshire (SKF)	1559
Leicester (LOD)	1501
Woburn (WBN)	1693
Somerset (MAN)	1732
Berkshire (ELM)	1573
Dorset (DST)	1904
Total Annual Sunshine in the UK :	1403

By establishing a defined Region Of Interest (ROI) and filtering out images with over 20% cloud cover, we utilized the resulting collection to refine the dataset over both time and space through the application of median and maximum statistics. The output designated as S2_minMax indicates that for each location in the image and in each band, the pixel value corresponds to the maximum (and minimum) of all unmasked pixels from the input imagery. The term Abnormally Low NDVI (ALN), which may suggest a loss of resilience, denotes instances where NDVI values fall below a specific threshold and persist for at least half of the time during the following three months. This threshold is defined at each pixel location as the lower 20th percentile of all observed NDVI values for that month. However, scale mismatch—differences between the spatial and temporal resolution of satellite data and the ecological processes being studied—can pose challenges. Addressing this requires integrating data from multiple sensors, improving pre-processing techniques, and developing models that account for these disparities.

Estimating the mean and uncertainty range of autocorrelation at each time point, the EWS was identified as the presence of a mean autocorrelation exceeding a threshold and lasting for at least three months. Whilst the threshold was calculated as the long-term average of the 80th percentile of the predicted distribution of autocorrelation. Definitions for early warning signals (EWS) and abnormally low NDVI (ALN) were also used in this study: The ALN is the occurrence of NDVI values lower than a threshold, lasting for at least half of the time in the following 3 months. This threshold is set equal to the lower 20th percentile of all of the observed NDVI values in that month at a given pixel location. The EWS is a presence of a mean autocorrelation exceeding a threshold and lasting for at least 3 months. The threshold was computed as the long-term average of the 80th percentile of the estimated autocorrelation uncertainty range. (Kumar & Garkoti, 2021; Katul, 2019; Porporato et al., 2004; Liu et al., 2019).

3.3.4 The study of using NDVI (Normalized Difference Vegetation Index) time series to map and assess UK grasslands

Time-series data for the Normalized Difference Vegetation Index (NDVI) derived from MODIS/Terra daily surface reflectance product, with a revisit time of 1-2 days and spatial resolution of 250m (Didan & Justice, 2021). The datasets were sourced from Google Earth engine. The MODIS datasets were used with sufficient imagery to calculate the NDVI on the Earth Engine platform and exported as a table for each of the grassland sites. The Sentinel-2 and Landsat 8 satellites were only available in 2015 and 2013, and so we were unable to use the 30m x 30m Landsat 7 images that were used by Liu et al. (2019). According to Liu et al. (2019), the Normalized Difference Vegetation Index (NDVI) was calculated for each 30m x 30m pixel utilizing Landsat 7 imagery across all forested regions in the state of California, USA. However, the dataset required for the period from 2010 to 2020 was incomplete and, consequently, could not be utilized. Additionally, instances of mortality attributed to fire or human activities were excluded from the analyses. The establishment dates for the grassland sites were recorded, and the estimated values following those dates were incorporated into the Dynamic Linear Model (Stojanovic, 2021).

3.4 Climate Data Collection Method

Evaluating past and present climate data types and how weather conditions have been modified by climate change is a crucial point for this study as the pressure systems move across the UK and bring varying weather conditions, depending on the time of year. The Meteorological Office, abbreviated as the Met Office, is the United Kingdom's national weather service (Met Office annual report and accounts, 2022) and provided us with hourly precipitation and temperature data

from the MIDAS Open dataset for the different weather stations across the UK (Figure 3-3).

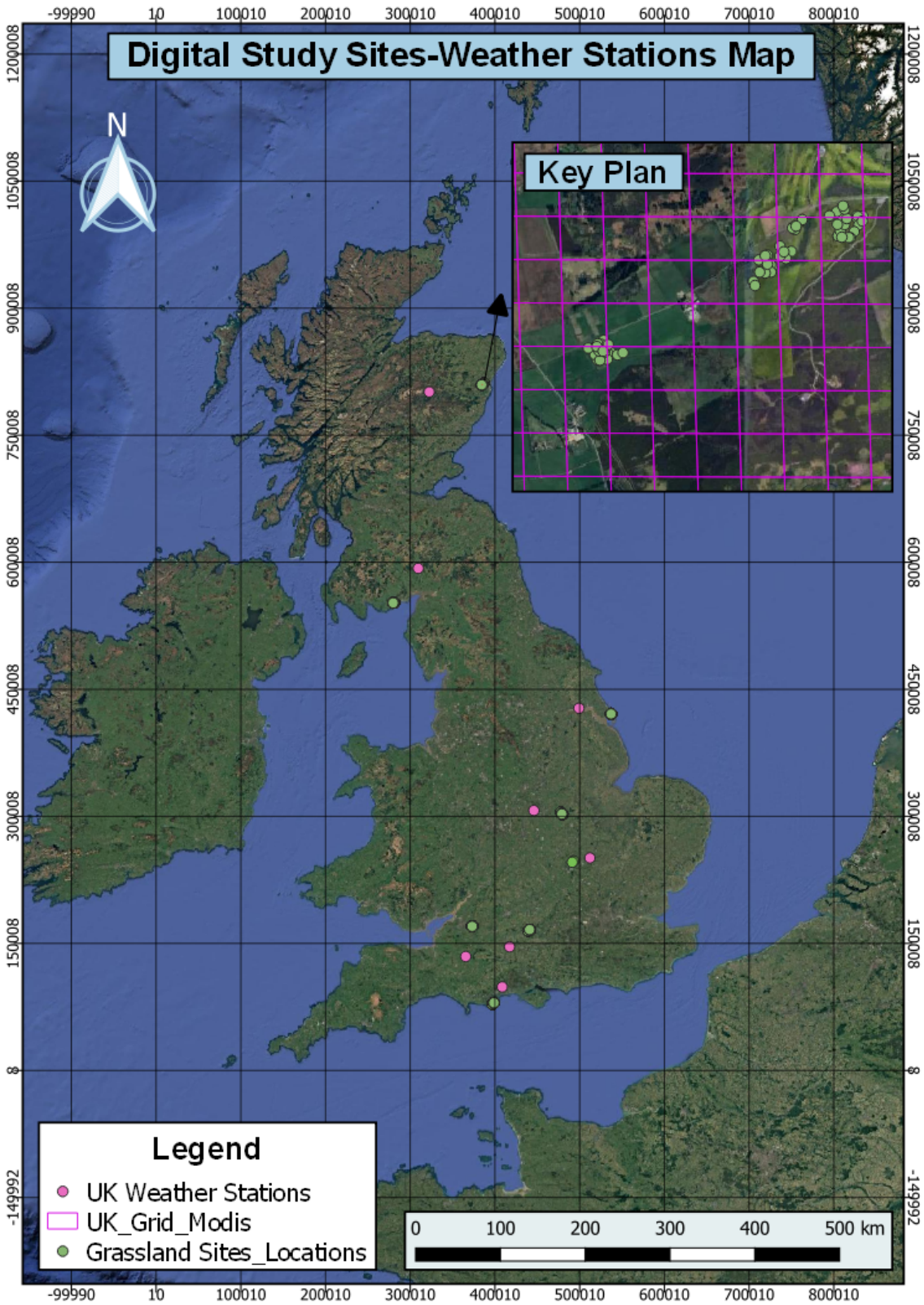


Figure 3-3 The grassland study sites (green circle) and distribution of the UK weather stations (weather station is located at the pink circle).

In order to calculate long-term means (2010-2020) for each day of the year, total daily precipitation and mean daily temperature were generated (Met Office, 2020a). Anomalies of temperature and precipitation were estimated for each day in the NDVI time series by subtracting the long-term average from the daily values, and using the approach described by Liu et al. (2019) we computed the mean anomaly between observations in the datasets was computed (Liu et al., 2019; Hollis et al., 2021).

The application of the Fast Fourier Transform (FFT) facilitates the conversion of NDVI data from the time domain to the frequency domain, thereby uncovering the diverse frequency components present within the dataset. Analyzing these frequency components allows for the identification and classification of data segments impacted by cloud cover. Clouds are known to introduce high-frequency noise within NDVI time series, which can be detected and isolated through FFT methodologies. Upon identifying the high-frequency components related to cloud cover, it is possible to implement a filtering process. This involves establishing a threshold frequency, above which all components are eliminated. Such an approach effectively minimizes noise and preserves the core underlying signal of interest. Following the removal of high-frequency noise, the inverse FFT can be utilized to revert the data to the time domain. This results in a refined NDVI time series characterized by reduced cloud contamination. By applying this methodology across multiple cycles—specifically throughout more than two annual cycles—cloud-free NDVI images can be generated for any particular moment within the time series.

Missing data is a critical issue when implementing methods in the NumPy package, as it can significantly impact the validity of estimates. Missing values (e.g., NaNs) can propagate through calculations, leading to unreliable results. Assuming that vegetation changed little in these strata with no valid satellite

observations, we used linear interpolation, a gap-filling method, which allows for statistically valid estimates but provides a conservative estimate of change caused by the gap filling and those dropped in previous iterations. Considering that variation in valid NDVI values would not be lost during the final iterations, the buffer of 0.1 units is depicted in (i.e. Figure 3-4) by the dotted lines.

3.5 The definition of multiple regression Dynamic Linear Model

The Dynamic Linear Model, provided by Liu et al., 2019, was modified and improved including description, control, and robustness as the model properties. Dynamic Linear Models (DLMs) are a versatile framework for analysing time series data, allowing for time-varying coefficients and state-space representation and they are particularly useful for handling, missing values, and varying observation accuracies. I focused more on improving computational efficiency, adaptability to dynamic environments, and robustness against uncertainties, modifying the statistical analysis method with new climate variables evaluating past and present climate data types with varying weather conditions, depending on the time of year. The approach of Bayesian forecasting, and dynamic modelling contains forecasts derived as probability distributions and probabilistic representation of information about parameters (West & Harrison, 1997). The univariate Dynamic Linear Model is determined by two basic equations, the observation equation **(3-1)**, which describes the relationship between observed NDVI data and unknown state parameters, and the state equation **(3-2)**, which describes the change in state parameters over time. Modelling the series Y_t by regressing of n independent variables $X_1, X_2, \dots, X_n$ the regression vector F_t is given by $F_t' = (X_{t1}, X_{t2}, \dots, X_{tn})$ the multiple regression DLM is given then by the quadruple $\{F_t, I, V_t, W_t\}$ for observational variances V_t and evolution variance matrices W_t . The model equations for each t , is given by:

$$Y_t = F_t' \theta_t + v_t, \quad v_t \sim N[0, V], \quad \textbf{(3-1)}$$

$$\theta_t = G\theta_{t-1} + \omega_t, \quad \omega_t \sim N[0, W_t], \quad (3-2)$$

where Y_t is the NDVI observation at time t , F_t is the regression vector, an n -dimensional vector of known regressors, including climate anomalies and NDVI at time $t - 1$. The state parameter is θ_t , an n -dimensional vector of unknown parameters, it contains coefficients representing to *lag1* autocorrelation, sensitivity to climate anomalies, seasonality, and interannual mean trend. Here θ plays the role of a fixed regression vector. The observation noise is ω_t a zero mean normally distributed stochastic error term with variance V . A known $(n \times n)$ matrix is G , the evolution matrix that is time-invariant defining the relationship among state parameters at time t and $t - 1$. The evolution noise at time t is ω_t , a zero mean normally distributed stochastic error with variance W_t , and is independent of v . The error sequences v_t and ω_t are independent and mutually independent. In some cases, F and G are supposed to be independent of t . Then the model is a time series DLM and if v and W are also time independent then the DLM is constant.

The above components provide one representation of a joint distribution for the observations and parameters, namely that defined via the form:

$$p(Y_t, \theta_t | D_{t-1}) = p(Y_t | \theta_t, D_{t-1})p(\theta_t | D_{t-1}), \quad (3-3)$$

where: $p(Y_t, \theta_t | D_{t-1})$ is the joint probability of observing the new data Y_t and the parameter θ_t given the past data D_{t-1} . It combines the likelihood of both events occurring together. Indexing θ_t by t indicates that the parametrization may be dynamic.

$p(Y_t | \theta_t, D_{t-1})$ is the conditional probability of observing the new data Y_t given the parameter θ_t at the past data D_{t-1} . It shows how likely the new data Y_t is if we already know the parameter θ_t and the past data.

$p(\theta_t | D_{t-1})$ is the conditional probability of the parameter θ_t given the past data D_{t-1} . It represents our updated belief about θ_t after considering all the past data.

D_{t-1} represents all the past data up to time $t - 1$. It's the historical information or prior evidence that we have before the new data Y_t arrives.

Essentially, the equation expresses how we can combine our prior knowledge (D_{t-1}) with new observations data (Y_t) to update our belief about the parameter (θ_t). This process is at the heart of Bayesian inference, allowing us to make more informed decisions as new data becomes available. The relevant one-step forecast may be deduced as the marginal $p(Y_t | D_{t-1})$. Inference for the future Y_t is a standard statistical problem of summarizing the information encoded in the forecast distribution. The Kalman filtering equations (3-3) , (3-5) were manipulated to estimate the posterior distribution of θ_t (3-5) at each time t , by combining the prior distribution at t (3-3), (3-4) given all preceding information and the one step forecast distribution of Y_t (3-4). It should be clear that there are important conceptual and practical differences between our view of time series modelling. Bayesian analyses are well documented and illustrated in (Broemeling, 1985; Zellner, 1971). Indexing θ_t by t indicates that the parametrization may be dynamic. In addition, if hypothesize that the posterior distribution at time $t - 1$ is:

$$(\theta_{t-1} | D_{t-1}) \sim N(m_{t-1} | C_{t-1}), \text{ (3-4)}$$

for some mean m_{t-1} and variance C_{t-1} is known, then the prior at t , the one step forecast and posterior at t are typically defined for consideration as follows.

Here denoted the prior distribution for θ_t is:

$$(\theta_t | D_{t-1}) \sim N(a_t | R_t), \text{ (3-5)}$$

where $D_{t-1} = \{Y_0, Y_1, \dots, Y_{t-1}\}$, $a_t = G_t m_{t-1}$, $R_t = G_t C_{t-1} G_t' + W_t$

The one-step ahead predicted distribution for Y_t denoted:

$$(y_t | D_{t-1}) \sim N(f_t | Q_t), \text{ (3-6)}$$

where $f_t = F_t' a_t$, $Q_t = R_t + V_t = F_t' R_t F_t + V$

The joint distribution of θ_t and Y_t is given by:

$$\begin{matrix} \theta_t \\ Y_t \end{matrix} | D_{t-1} \sim N \left(\begin{matrix} m_{t-1} \\ m_{t-1}' \end{matrix}, \begin{pmatrix} R_t & R_t \\ r_t & Q_t \end{pmatrix} \right)$$

The posterior distribution for θ_t is given $D_t = \{D_{t-1}, Y_t\}$ and is denoted:

$$(\theta_t | D_t) \sim N(m_t | C_t), \text{ (3-7)}$$

where: $m_t = m_{t-1} + A_t e_t$, $C_t = R_t - A_t^2 Q_t$ with $A_t = \frac{R_t}{Q_t}$, $e_t = Y_t - m_{t-1}$, The error term is defined as the difference between the observed value for Y_t and the mean of the predicted value from the previous time step m_{t-1} . This error term e_t represents the deviation of the observed data Y_t from the expected value based on the past data. It's used to update the model's parameters and improve future predictions.

Overall, we formalize the notion of m_t and C_t corresponding to the mean and variance of lag-1 autocorrelation. It should be clear that if the variance of noise is known and the given (m_0, C_0) this can be estimated for all times t . The Kalman filtering equations are amended to report for unknown observational variance, V :

V is assumed to follow an inverse-gamma (IG) distribution (3-6) it can be shown that, unconditional on V , the normal distributions in equations (3-2), (3-5) become multivariate student-T distributions with n_t degrees of freedom at time t by setting the changes as follows:

$Q_t = F_t^T R_t F_t + S_{t-1}$ and $C_t = \frac{S_t}{S_{t-1}} (R_t - A_t Q_t A_t^T)$ where n_t and S_{t-1} are as defined in (3-6).

$$(V | D_{t-1}) \sim IG \left(\frac{n_{t-1}}{2}, \frac{S_{t-1} n_{t-1}}{2} \right), \text{ (3-8)}$$

$$(V | D_t) \sim IG \left(\frac{n_t}{2}, \frac{S_t n_t}{2} \right), \text{ (3-9)}$$

where: $n_t = n_{t-1} + 1$, $S_t = S_{t-1} + \frac{S_{t-1} n_t}{n_t} \left(\frac{e_t^2}{Q_t} - 1 \right)$

This leads to a combined form with mean and variance of *lag1* autocorrelation can be estimated, given initial information $\{m_0, C_0, n_0, S_0\}$, conditional on W_t being known, this is acquired using discounting from **(3-3)**:

$$Var[\theta_t | D_{t-1}] = R_t = G_t C_{t-1} G_t^T + W_t, \text{ (3-10)}$$

Thus far, the treatment of the system variances is more complex. In this case, discount factors can be used and with a discount factor $\delta \in (0,1]$, we have:

$$R_t = \frac{1}{\delta} G_t C_{t-1} G_t^T \text{ and so, given } \delta \text{ and } C_0, W_t = \frac{1-\delta}{\delta} G_t C_{t-1} G_t^T \text{ is interpreted for all } t.$$

Then δ can be thought of as quantifying the percentage information loss $(1 - \delta)$ in the state vector from time $t - 1$ to t (Pole et al., 1994; West & Harrison, 1997).

However, defining $\{m_0, C_0, n_0, S_0\}$, we could estimate the mean and variance of *lag1* autocorrelation. The non-informative priors for m_0, C_0, n_0 and S_0 were provided according to (Liu et al., 2019) paper, and the first two years of the time series were treated as a warmup period using a single discount factor, as a result they were not included for further analysis. The DLM developed by (Liu et al., 2019) is a superposition of three component blocks: one accounts for simple trends in the data, the second composed of an annual and semi-annual harmonic account for seasonality in the time series, and the third models the influence of the NDVI and climate anomalies at the previous time step.

In this analysis, we imported component discounting into the model. Pole A., West M. and Harrison J., (1994) examined separate discount factors for each component block to allow different levels of information loss over the three blocks. Seasonal variation, for paradigm, is typically more robust than a simple trend. Building on the findings, the Python implementation of the Dynamic Linear Model (DLM) was modified to enhance its functionality and incorporate a sampling interval parameter for daily time series data. This adaptation enables the model to handle data at various intervals more effectively. Furthermore, Prado and West (2010) have previously shown that they have an appropriate discounting factor by maximizing the joint log-likelihood function on the observed predictive density **(3-7)**. This method accounts for variances in the forecast

distribution that are unknown by alternative methodologies like minimizing the root mean square or mean absolute error and balances both precision and accuracy in determining an appropriate discount factor (Pole et al., 1994; West & Harrison, 1997; Kalman & Bucy, 1961). Consequently, a new algorithm was introduced that allows one to define the set of discount factors $\{\delta_1, \delta_2, \delta_3\}$ that maximize (3-7) for each time series as follows:

$$\text{LogLike}(\{\delta_1, \delta_2, \delta_3\}) \equiv \sum_{t=1}^T \ln[p(\mathbf{y}_t | \mathbf{D}_{t-1})], \quad (3-11)$$

where T is the length of the time series and $\ln$ is the natural logarithm. On cloudy days where some of the values are missing in the time series, $D_t = D_{t-1}$, then the posterior distribution at time t is equal to the prior (3-5), and the updating equations is given by: $m_t = a_t$, $C_t = R_t$, $S_t = S_{t-1}$, and $n_t = n_{t-1}$

Generally, $(a|b) \sim N(m, V)$: The conditional probability distribution of a given b follows a (multivariate) Normal distribution with mean m and variance (variance-covariance matrix) V . $X \sim \text{IG}(\alpha, \beta)$: X follows an inverse gamma distribution with shape parameter α and scale parameter β .

The target of the methodology was to identify valid observations in a daily NDVI time series exported from MODIS surface reflectance data based on the cyclical nature of NDVI in UK grasslands and forests. We further provided empirical evidence suggesting this algorithm which returns significantly more valid data points than other algorithms (Liu et al., 2019).

3.5.1 Highlighting and defining essential differences of improved pasture and semi-natural grasslands in the United Kingdom for the period 2010-2020.

The management of natural grasslands and pastures presents considerable challenges due to the intricate spatiotemporal interactions among grazed plant species, livestock behaviour, and environmental conditions. The quality of grasslands and pastures is influenced by various environmental factors, including soil type, climatic regimes, and botanical composition. Traditional pasture monitoring tools and techniques are often time-consuming and may complicate the extrapolation of data from field surveys. In recent years, remote sensing technologies, satellite imagery, and airborne imaging have been increasingly utilized for the assessment of botanical diversity, structural characteristics, quality, and quantity of grasslands. Over the past decade, the increasing application of GIS (Geographic Information System) and remotely sensed data has significantly enhanced our ability to assess and monitor landscapes at various scales, from local to regional to global. This technological advancement has enabled scientists to precisely map, analyse, and estimate a wide variety of potential spatial covariates across vast geographic areas. We hypothesized that grasslands would cover a larger portion of the UK (Vavlas et al., 2020; Pricope et al., 2019)

The differences between improved pastured grass and semi-natural grass can be quite pronounced in terms of biodiversity, management practices, and ecological value. Improved pasture refers to grassland that is intensively managed for grazing and/or fodder production, characterized by significantly modified swards produced through the use of fertilizers, herbicides, drainage, and/or occasional reseeded. Typically, species such as rushes, thistles, and bracken are eradicated but may be present in small quantities. Daisies and buttercups can also be found. This type of grassland does not include grass leys and usually occurs within the limits of mechanical operations. The sward may appear lumpy due to uneven fertilization from cow pats and may have artificial

boundaries from strip grazing. Cutting for hay or silage may take place from spring to late summer.

On the other hand, semi-natural grassland consists of enclosed areas that experience little or no management. It is characterized by a high density of native grasses and often contains invasive species such as bracken, bramble, thistles, rushes, and scattered trees, with tussocks sometimes present. This type of grassland generally occurs on steep slopes, poorly drained sites, and soils of low fertility. It frequently includes areas that can be accessed by farm machinery, indicating that it may have been managed at some point in the past (Law & Dickman, 1998).

Throughout this decade, both types of grasslands have encountered significant challenges stemming from climate change, land conversion, and agricultural intensification. However, semi-natural grasslands have received greater attention for conservation purposes due to their ecological significance. The recognition of their role in carbon sequestration and the provision of ecosystem services has fostered policy efforts directed toward their preservation. Concurrently, there has been a gradual shift within the agricultural landscape towards more environmentally sustainable practices in improved pastures (Waine, 1999).

Examining the impact of climate change through climate data (total daily precipitation-mean daily temperature) on temperate humid grasslands using NDVI time series can significantly affect grassland productivity. For instance, increased precipitation can enhance plant growth, while higher temperatures may lead to increased evapotranspiration and potential drought stress (Craine et al., 2025). NDVI is a useful indicator of vegetation health and productivity. By analysing NDVI time series data, we can identify trends and patterns in vegetation growth over time. This can help in understanding the impact of climate variability on grassland productivity (Delgado-Moreno et al., 2022). Soil properties, such as organic matter content, nutrient levels, and soil structure, can change significantly over a decade. These changes can be influenced by factors like land management practices, climate variability, and vegetation cover. Fertilized

grasslands (intensively managed grasslands) typically show higher productivity compared to unfertilized natural fields (non-intensively managed). However, intensive management and fertilization can lead to soil quality degradation, affecting long-term sustainability. By combining climate data, NDVI time series analysis, and soil property changes, we can gain a holistic understanding of how climate variability and land management practices impact grassland ecosystems (Abdennbi et al., 2024; Iepema et al., 2022).

It was found that rainfall in May-June tended to decrease and there was a generalized increase in autocorrelation which means a decrease in resilience for intensively managed grasslands. The most resistant to rainfall variation were grass and plants recovered in natural land. The average yield of intensively managed fields was lower compared to that in the natural land. The yields of intensively managed fields were also influenced by the long-term change of soil properties. These studies will be important in detecting EWS and indicators of resilience for selecting the method for transforming low-productivity arable land into high-productivity areas. Unfertilized managed grasses were more productive compared to fertilized vegetation and this was indicated by a prolonged increase in Abnormally Low NDVI (ALN) which indicates an intensification of EWS.

Other researchers, having studied the correlations between grass productivity and air temperature and precipitation, argue that productivity is affected both by meteorological conditions of a current year and those of previous years. The study results revealed that climate change in the temperate climate zone had a smaller impact on grass biomass compared to changes in soil properties due to long-term land use. Moreover, spring moisture reserves in soil can mitigate the effects of rainfall absence on grass biomass configuration during the intensive growth stage in the period of specific months (e.g. May-June). In long-term natural and unfertilized managed grasslands, the EWS decrease, leading to better conditions for grass development and a consistent increase in grass biomass productivity (Tripolskaja et al., 2022).

3.5.2 Evaluating the variations of Early Warning Signals (EWS) and the Normalized Difference Vegetation Index (NDVI) trends.

Early Warning Signal (EWS) is determined as unusually low resilience measured by high *lag1* autocorrelation in vegetation dynamics. The system slowed down during the period of identified EWS, and the basin of attraction diminished so these shifts represent reduced recovery rate and a higher probability of a change to an alternative state under stochastic disturbances, although a high autocorrelation is a signature of critical slowing down. Also, it does not guarantee the occurrence of critical slowing down, and an impending critical transition, that is necessary but not sufficient, so the increasing-decreasing variations in early warning signals don't fully explain the indicators because the EWS precedes the Abnormally Low NDVI (ALN). Furthermore, we noticed lost points of NDVI in some of the sites and are due to cloud's cover influence. This study counted the EWS in eight grassland sites, across the UK-sample areas (see supplementary Appendix C) and analysed co-located improved pasture and semi-natural managed grassland plots of all grasslands (from Figure 3-4 until Figure 3-11).

Early warning signals in autocorrelation plots for ecosystems like improved pastures and semi-natural grasslands often emerge when these systems are under stress, such as overgrazing, soil degradation, or climate change. These signals, like increased autocorrelation at lag-1, indicate that the system is approaching a tipping point or critical transition.

For example, studies on grassland ecosystems have shown that as grazing pressure increases, the recovery time of vegetation slows down, leading to higher autocorrelation values. This can signal an impending shift from a healthy grassland state to a degraded one, such as desertification or loss of biodiversity.

Early warning signals during droughts, as observed in autocorrelation plots, often emerge when the system shows signs of "critical slowing down." This is characterized by an increase in autocorrelation at lag-1, indicating that the system is taking longer to recover from disturbances. Such signals can precede

significant transitions, like shifts between drought and flood states. For example, a study on the Dongting Lake Basin in China identified early warning signals of drought-to-flood transitions by analysing the standardized precipitation index (SPI). They observed increases in both variance and autocorrelation coefficients, which were detected 5–10 years before the actual state transitions. These findings highlight the importance of monitoring autocorrelation and variance as part of drought early warning systems (Wu et al., 2021).

Early warning signals in an autocorrelation plot typically appear as an increase in autocorrelation at lag-1. This phenomenon, known as "critical slowing down," occurs when a system approaches a critical transition or tipping point. The rate of return to equilibrium slows down, causing consecutive observations in the time series to become more similar. Autocorrelation at lag-1 can be measured using the first value of the autocorrelation function or by fitting an autoregressive model of order 1 (AR(1)). Additionally, changes in the spectral properties of the time series, such as spectral reddening (higher variation at low frequencies), can also indicate early warning signals.

This sharp increase in mortality area (during the second drought in 2018-2020) was in contrast to the temporal variation, which gradually increased during 2012–2014 and remained high afterward. The temporal pattern of mortality follows a typical signature of critical transitions of ecosystems under slowly varying environmental drivers. The fraction of the area showing an EWS exhibited similar temporal autocorrelation, with the areal fraction remaining high during the second drought (2018-2020) but then rising to higher values in all the semi-natural grassland cases by 2018-2019. The computed EWS area (red outlined) was generally larger for improved pasture managed grasslands than the semi-natural managed grassland areas, indicating that some grasslands operated under low resilience. The extent of the area exhibiting EWS and ALN depends on the thresholds used to identify these metrics. All thresholds considered, however, generate temporal patterns of the EWS exhibiting area that resemble mortality and ALN trends. Such prominent temporal correspondence highlights the

potential of using low resilience (high autocorrelation) as an EWS to track interannual variations in grasslands and woodlands mortality.

3.6 Results

During the period 2010-2020 the UK underwent two major droughts spanning 2010–2012 and 2018–2019 which were highlighted by Vicente-Serrano et al., (2022). We plotted from the daily datasets the mean and uncertainty ranges derived from the variance, indicating during the drought of the period 2010-2012 an increase in autocorrelation and shortly after this period. The daily time series shows more sensitivity to changes in autocorrelation, and extra periods of ALN were associated in the dataset as a statistical technique for inferring time-varying autocorrelation and high spatial resolution remote sensing images of NDVI. The tipping point here is the low resilience due to drought. We aimed at maximizing the log-likelihood function for each component (Table 3-2) to define the discount factors, which were similar for each of the fields in the UK grassland sites.

Table 3-2 Discount factors in terms of trend, seasonality and regression determined for each field in the UK study areas of grassland.

Daily Data-Discount Factors				
	UK Site	Trend	Seasonality	Regression
0	Aberdeen	0.991	0.998	0.998
1	Dumfries	0.993	0.997	0.996
2	Yorkshire	0.991	0.997	0.998
3	Leicester	0.991	0.998	0.999
4	Woburn	0.990	0.999	0.997
5	Somerset	0.993	0.997	0.999
6	Berkshire	0.992	0.998	0.997
7	Dorset	0.991	0.998	0.997

The aim of this study is to provide a higher frequency, and cloud-free reconstructed NDVI dataset in the daily time series for implementation in the DLM. Constructing a cloud mask based on hourly cloud cover data from nearby weather stations can help in identifying periods of clear sky or cloud cover over our sites of interest. A cloud mask was used to differentiate between cloudy and clear conditions in the data. It involves setting thresholds based on the cloud cover data to create a binary mask, where one value represents clear sky and the other represents cloud cover.

Aberdeen Study Sites

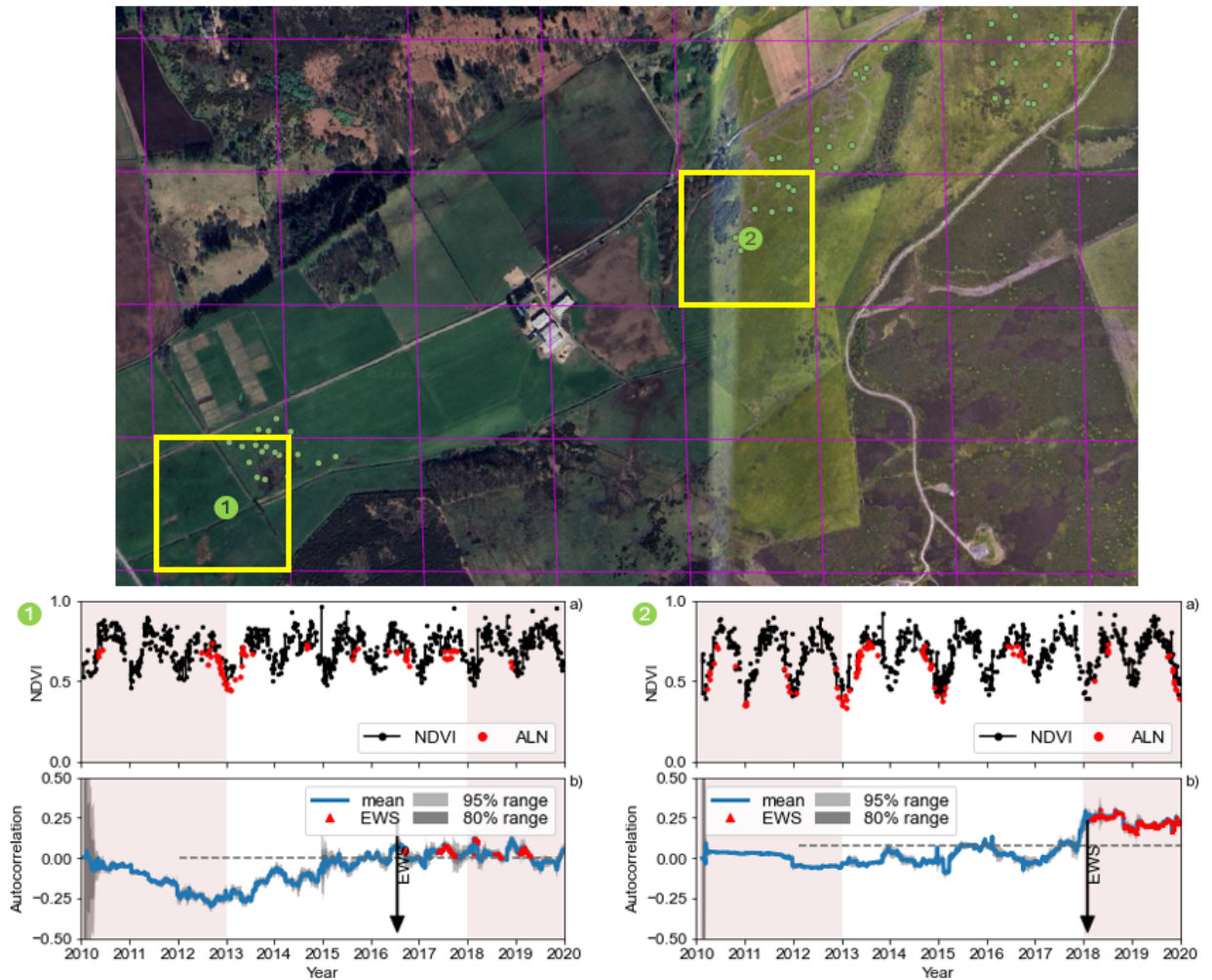


Figure 3-4 Aberdeen grassland sites of: 1) improved pasture managed and 2) semi-natural grasslands. The yellow-lined area represents the spatial resolution 250x250 meters grid with site coordinates (lat: 57.17851, lon: -2.24388). Filtered daily NDVI time series, observations identified as valid using the algorithm are plotted in black series for different types of grassland sites (1,2), b) Mean and uncertainty of lag-1 temporal autocorrelation evaluated using the DLM, using component discounting, the dashed lines symbolize the threshold for an EWS, the shaded areas periods of drought. The Abnormally Low NDVI (Normalized Difference Vegetation Index)-ALN typically indicating poor vegetation health or sparse vegetation cover.

Dumfries Study Sites

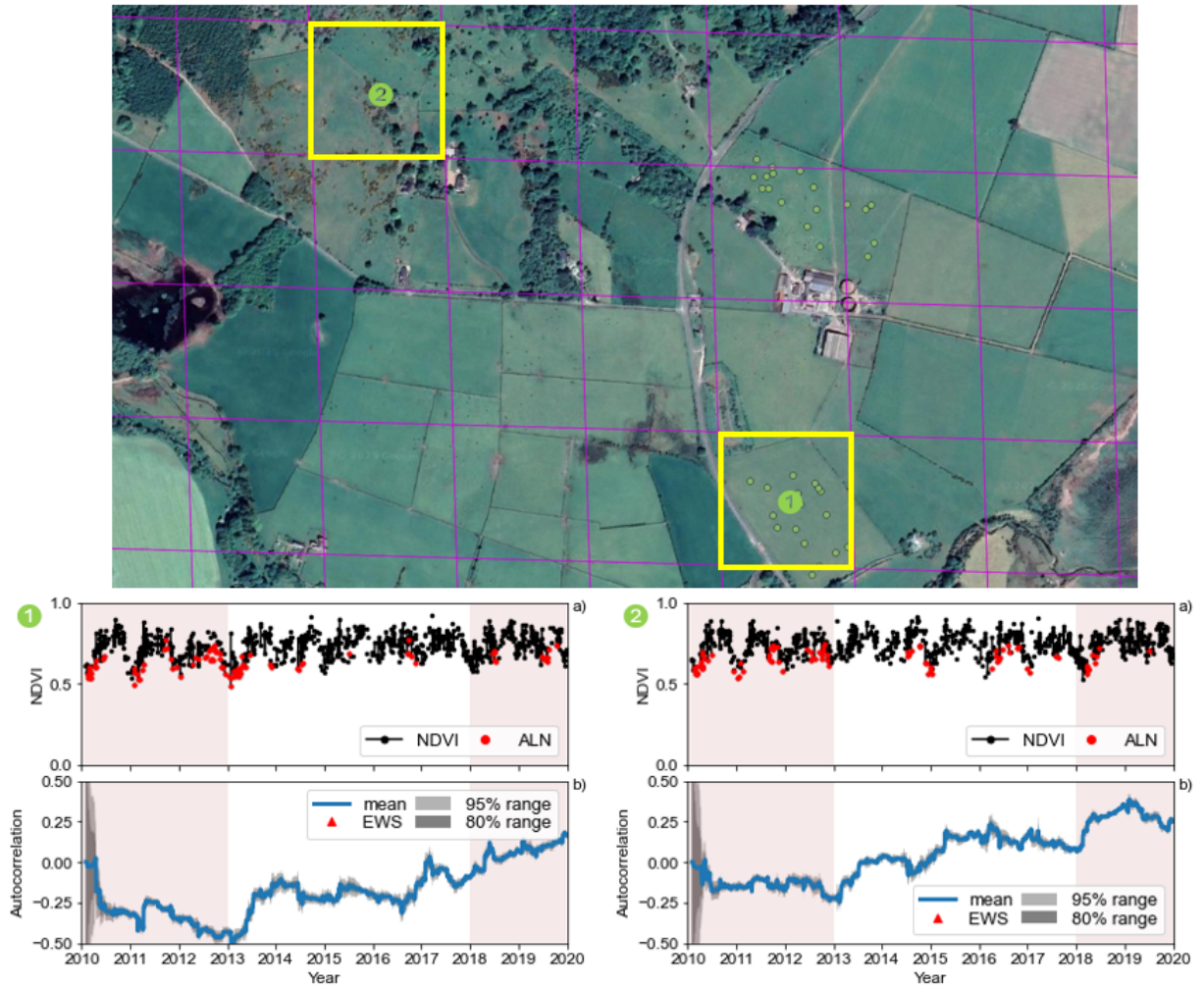


Figure 3-5 Dumfries grassland sites of: 1) improved pasture and 2) semi-natural managed grasslands. The yellow-lined area represents the spatial resolution 250x250 meters grid with site coordinates (lat: 54.85174, lon: -3.87127). Filtered daily NDVI time series, observations identified as valid using the algorithm are plotted in black series for different types of grassland sites (1,2), b) Mean and uncertainty of lag-1 temporal autocorrelation evaluated using the DLM, using component discounting, the dashed lines symbolize the threshold for an EWS, the shaded areas periods of drought. The Abnormally Low NDVI (Normalized Difference Vegetation Index)-ALN typically indicating poor vegetation health or sparse vegetation cover.

Yorkshire Study Sites

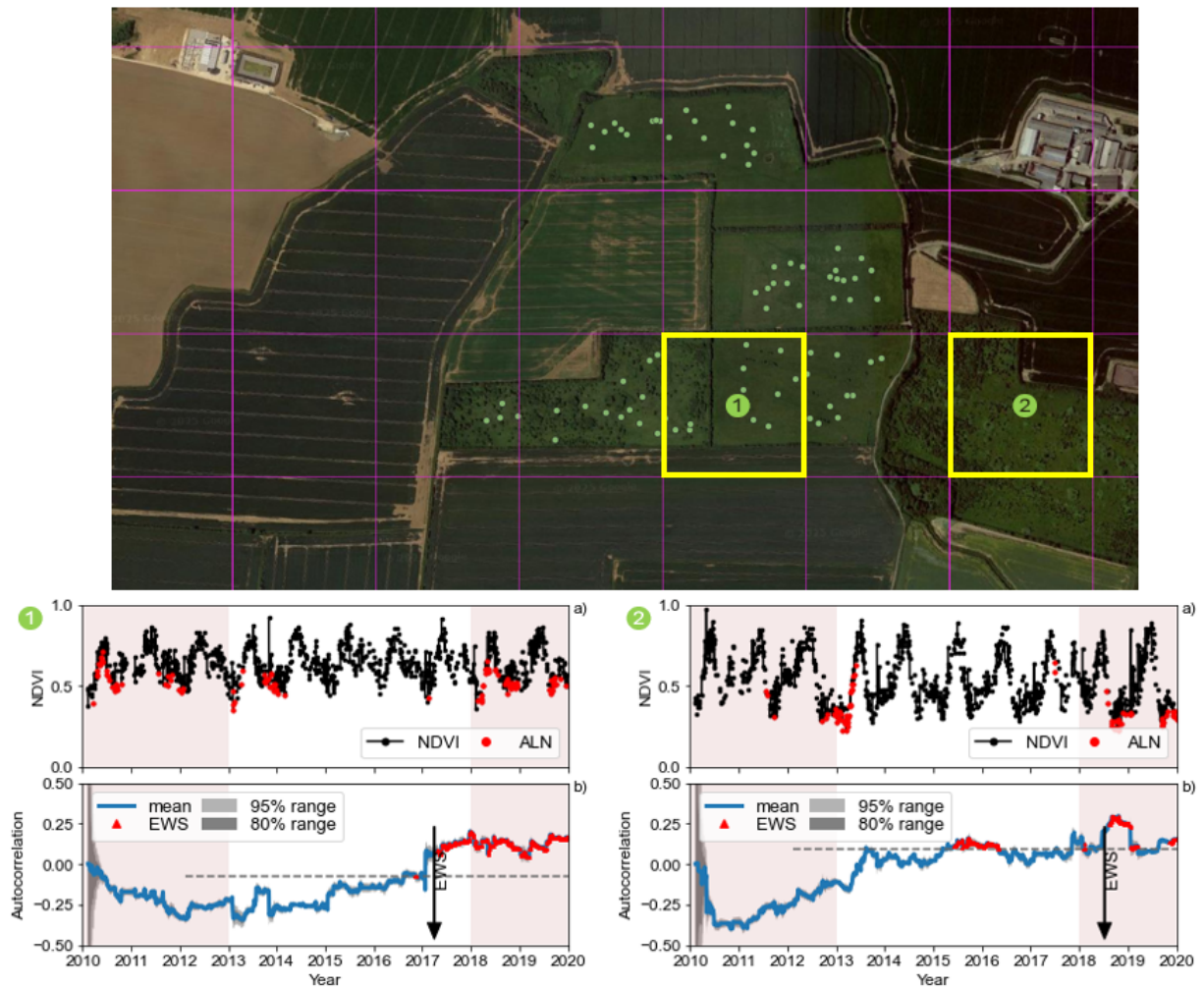


Figure 3-6 Yorkshire grassland sites of: 1) improved pasture and 2) semi-natural managed grasslands. The yellow-lined area represents the spatial resolution 250x250 meters grid with site coordinates (lat: 53.66502, lon: 0.07883). Filtered daily NDVI time series, observations identified as valid using the algorithm are plotted in black series for different types of grassland sites (1,2), b) Mean and uncertainty of lag-1 temporal autocorrelation evaluated using the DLM, using component discounting, the dashed lines symbolize the threshold for an EWS, the shaded areas periods of drought. The Abnormally Low NDVI (Normalized Difference Vegetation Index)-ALN typically indicating poor vegetation health or sparse vegetation cover.

Leicester Study Sites

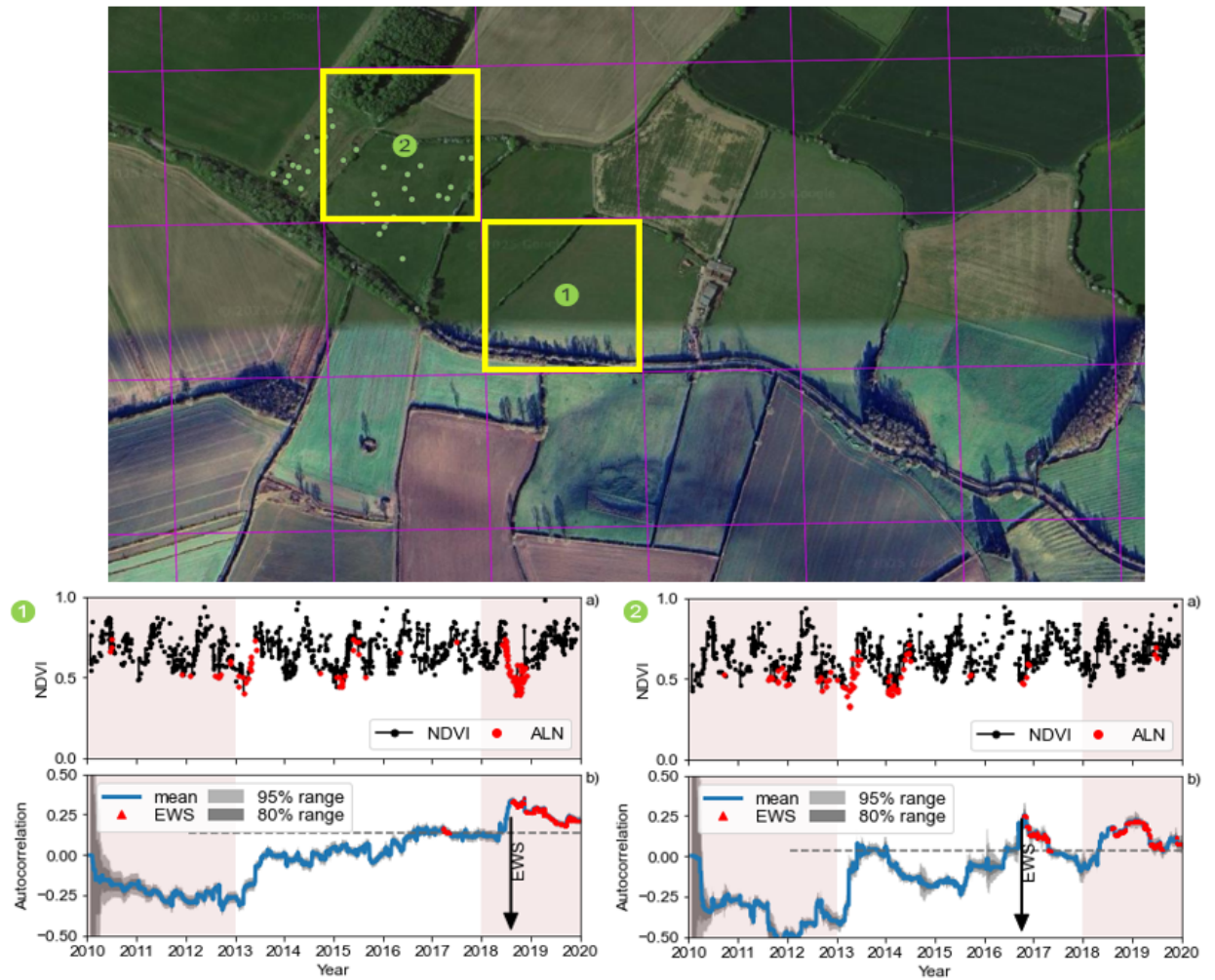


Figure 3-7 Leicester grassland sites of: 1) improved pasture and 2) semi-natural managed grasslands. The yellow-lined area represents the spatial resolution 250x250 meters grid with site coordinates (lat: 52.61556, lon: -0.83237). Filtered daily NDVI time series, observations identified as valid using the algorithm are plotted in black series for different types of grassland sites (1,2), b) Mean and uncertainty of lag-1 temporal autocorrelation evaluated using the DLM, using component discounting, the dashed lines symbolize the threshold for an EWS, the shaded areas periods of drought. The Abnormally Low NDVI (Normalized Difference Vegetation Index)-ALN typically indicating poor vegetation health or sparse vegetation cover.

Woburn Study Sites

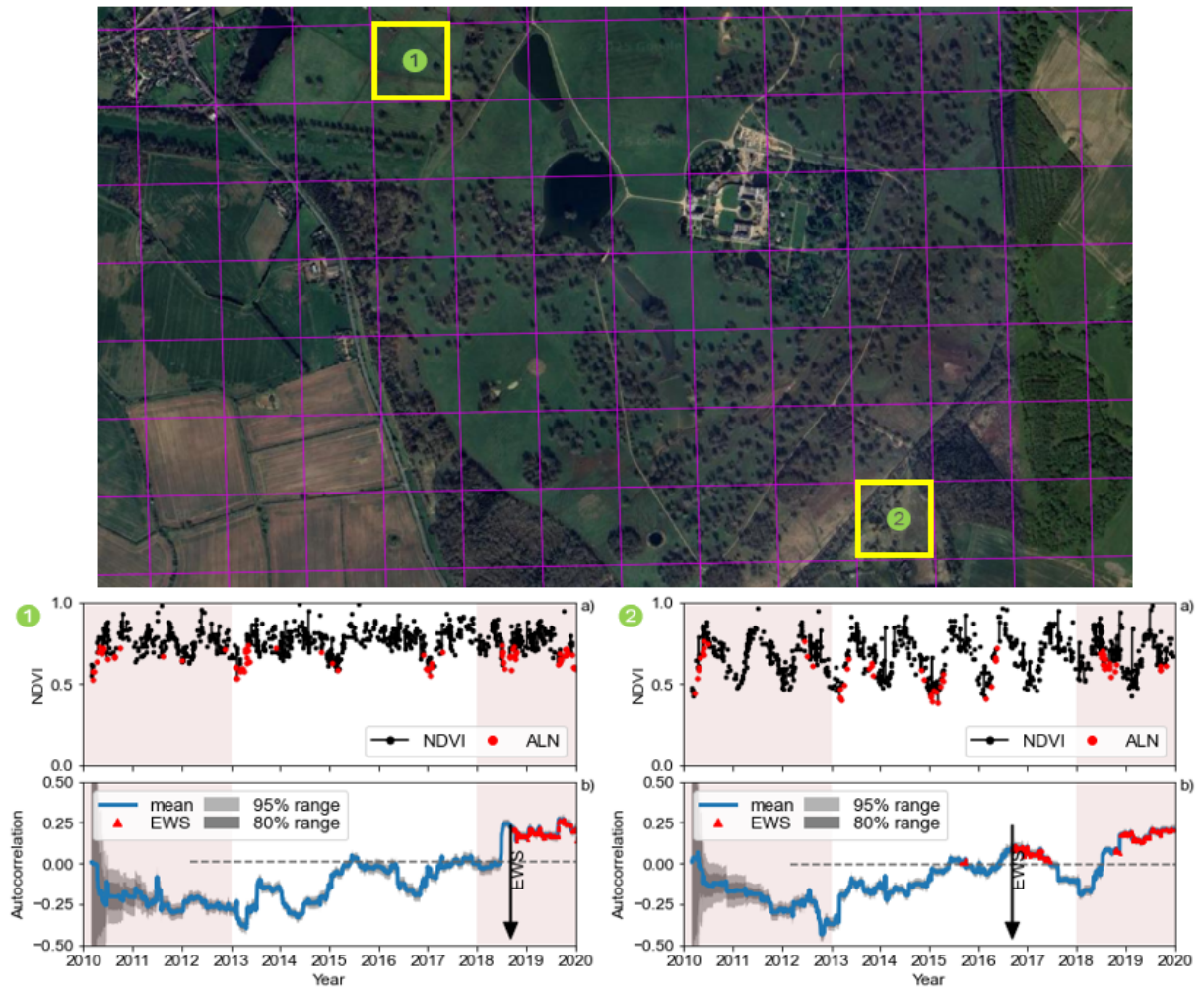


Figure 3-8 Woburn grassland sites of: 1) improved pasture and 2) semi-natural managed grasslands. The yellow-lined area represents the spatial resolution 250x250 meters grid with site coordinates (lat: 51.98686, lon: -0.60901). Filtered daily NDVI time series, observations identified as valid using the algorithm are plotted in black series for different types of grassland sites (1,2), b) Mean and uncertainty of lag-1 temporal autocorrelation evaluated using the DLM, using component discounting, the dashed lines symbolize the threshold for an EWS, the shaded areas periods of drought. The Abnormally Low NDVI (Normalized Difference Vegetation Index)-ALN typically indicating poor vegetation health or sparse vegetation cover.

Somerset Study Sites

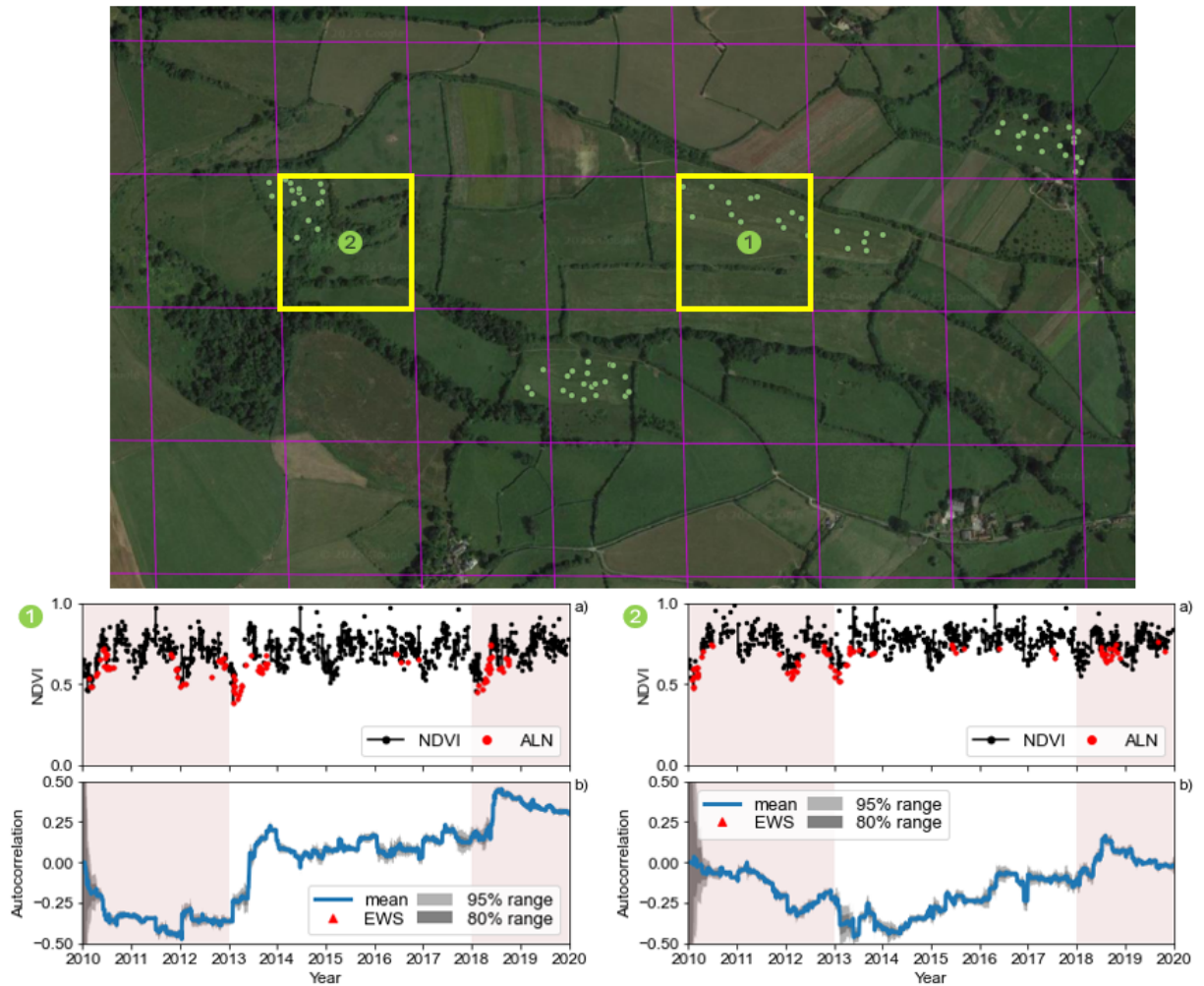


Figure 3-9 Somerset grassland sites of: 1) improved pasture and 2) semi-natural managed grasslands. The yellow-lined area represents the spatial resolution 250x250 meters grid with site coordinates (lat: 51.42648, lon: -2.38603). Filtered daily NDVI time series, observations identified as valid using the algorithm are plotted in black series for different types of grassland sites (1,2), b) Mean and uncertainty of lag-1 temporal autocorrelation evaluated using the DLM, using component discounting, the dashed lines symbolize the threshold for an EWS, the shaded areas periods of drought. The Abnormally Low NDVI (Normalized Difference Vegetation Index)-ALN typically indicating poor vegetation health or sparse vegetation cover.

Berkshire Study Sites

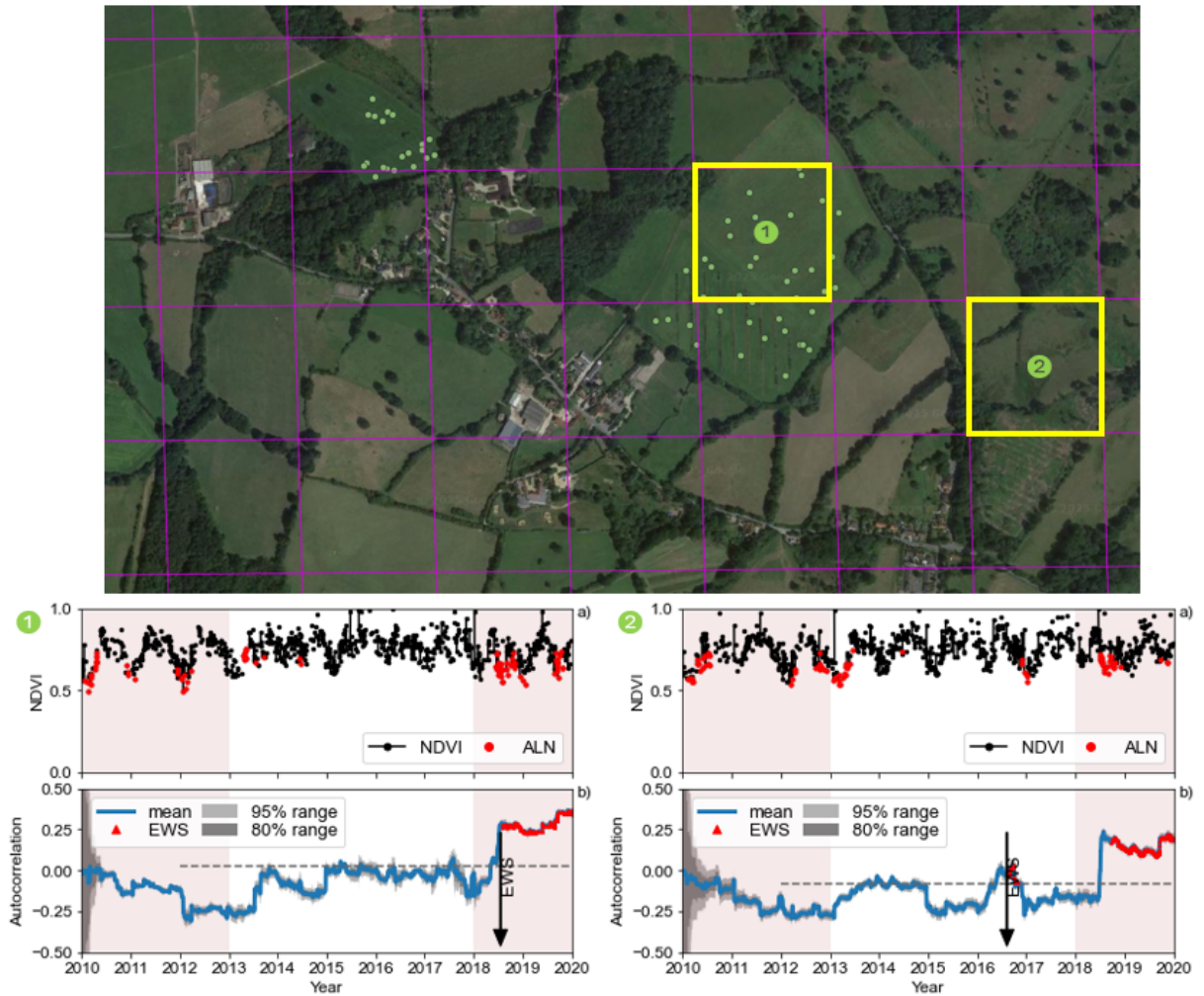


Figure 3-10 Berkshire grassland sites of: 1) improved pasture and 2) semi-natural managed grasslands. The yellow-lined area represents the spatial resolution 250x250 meters grid with site coordinates (lat: 51.39044, lon: -1.41083). Filtered daily NDVI time series, observations identified as valid using the algorithm are plotted in black series for different types of grassland sites (1,2), b) Mean and uncertainty of lag-1 temporal autocorrelation evaluated using the DLM, using component discounting, the dashed lines symbolize the threshold for an EWS, the shaded areas periods of drought. The Abnormally Low NDVI (Normalized Difference Vegetation Index)-ALN typically indicating poor vegetation health or sparse vegetation cover.

Dorset Study Sites

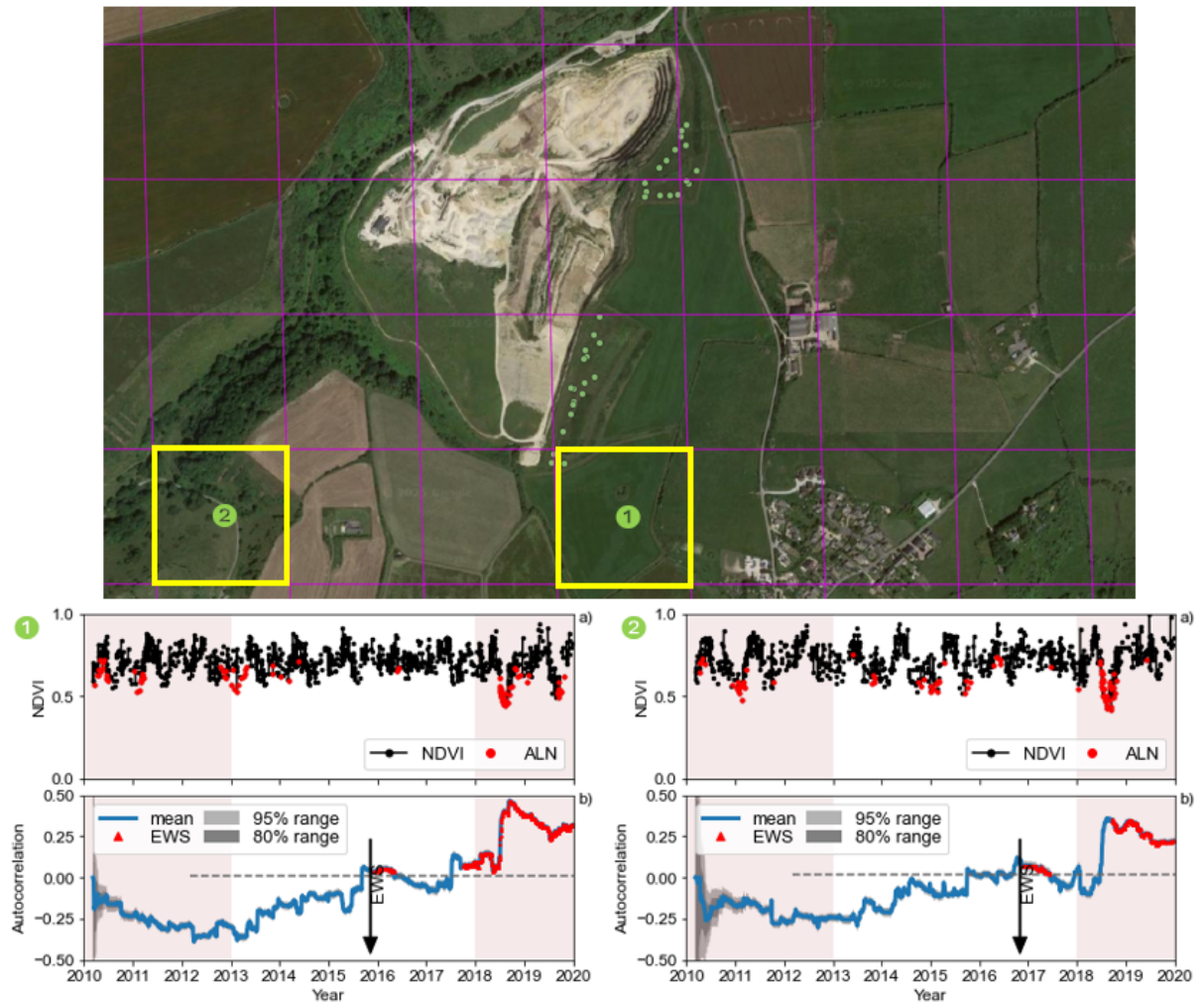


Figure 3-11 Dorset grassland sites of: 1) improved pasture and 2) semi-natural managed grasslands. The yellow-lined area represents the spatial resolution 250x250 meters grid with site coordinates (lat: 50.60199, lon: -2.04202). Filtered daily NDVI time series, observations identified as valid using the algorithm are plotted in black series for different types of grassland sites (1,2), b) Mean and uncertainty of lag-1 temporal autocorrelation evaluated using the DLM, using component discounting, the dashed lines symbolize the threshold for an EWS, the shaded areas periods of drought. The Abnormally Low NDVI (Normalized Difference Vegetation Index)-ALN typically indicating poor vegetation health or sparse vegetation cover.

Using NDVI and its autocorrelation patterns as a proxy for grazing intensity and grassland types is a clever approach. Grazing pressure in improved pasture grasslands likely introduces more variability and frequent vegetation recovery cycles, which could be reflected in stronger or faster-decaying autocorrelation at specific temporal *lags*. Meanwhile, calcareous, ungrazed semi-natural grasslands might exhibit more consistent or stable vegetation patterns with longer-lasting autocorrelation due to minimal disturbances.

3.7 Discussions

This case study delves into the intricate interplay between natural and anthropogenic factors in shaping grassland resilience. By identifying how droughts and increasing autocorrelation highlight the vulnerability or adaptability of ecosystems, we are touching on a critical aspect of environmental stability. Factoring in the potential role of disturbances, such as forest management and land use changes, adds a layer of complexity to understanding recovery dynamics. Applying the model to UK different types of grasslands, while accounting for the challenges of overcast conditions and leveraging remotely sensed data, is a clever and practical approach. The UK's climate indeed makes this a challenging yet highly relevant case study.

Recent modelling studies have identified predictors of upcoming regime shifts that can be used to issue early warning signals for transitions. Tracking key environmental indicators is essential for detecting these transitions; however, their effectiveness may be limited by a lack of relevant data. Empirical examples of how these indicators function in ecosystems are also scarce. Currently, approximately 8% of the territory of the European Union and the UK is experiencing 'very high' or 'high' levels of land degradation and desertification. Extreme changes in dynamic environmental factors can lead to permanent alterations in sensitive ecosystems, such as lakes, marshes, and forests. These

alterations are referred to as "regime shifts" or "critical transitions." When an ecosystem's resilience capacity reaches a "tipping point," it may sustain irreparable damage. Statistical metrics have been developed to indicate impending regime shifts, which can serve as early warning signals. However, regular monitoring of significant environmental variables is hindered by a lack of appropriate in-situ measurements and data, making it challenging to distinguish between these shifts. To assess ecosystem resilience to climate change, existing data can be compared with Earth Observation (EO) data. If high autocorrelation detection analysis is to be effectively implemented, the identification of these periods must be automated across the UK. From plotting the time series, it is evident that information about the establishment year of each grassland site has been provided.

In recent years, numerous studies have examined long-term trends and discounting methods in Dynamic Linear Models (DLMs). The findings from these studies provide valuable insights into the functionality of the component discounting approach. In our research, we applied the DLM using Python to UK-filtered datasets, modifying its structure to incorporate component discounting.

In the case of the Aberdeen (CBS) grassland site, the first EWS signal appears in the improved pasture-managed pixel, but a significant increase was observed during the drought period for the semi-natural pixel. An unusual increase of first-appear EWS indicated an improved pasture-managed pixel, and an increased anomaly for EWS of semi-natural pixel during the drought, as it concerns the Yorkshire (SKF) site (Table 3-3)

The EWS signal was initially observed for the Leicester (LOD) site at a semi-natural pixel with an abrupt drop of autocorrelation values, but also the EWS shows an unusual drop shift during the drought period of improved pasture-managed pixel. In the Woburn (WBN) grassland site, a slow decrease in tension for the first-appeared EWS of semi-natural pixel, as well as stable behaviour of EWS for the drought period, are indicated regarding improved pasture pixel. Regarding the Berkshire (ELM) grassland site associated with the semi-natural

pixel, the first EWS shows high values of a structural break in the time series with an increased tension for the improved pasture-managed pixel of the drought period. The first EWS indication for Dorset (DST) appeared marginal to the threshold of improved pasture-managed pixel, and an abrupt drop of autocorrelation values was indicated in semi-natural pixel concerning the drought period.

No EWS is observed for Somerset (MAN) and Dumfries (TOR). Only a slight increasing tension during the drought period for the improved pasture managed Somerset (MAN) grassland site and a slight increasing tension during the drought period for the semi-natural Dumfries (TOR) grassland site. The EWS (Early Warning Signal) appears initially for the improved pasture-managed pixels and for the cases of Aberdeen (CBS), Yorkshire (SKF), and Dorset (DST). As it concerns the Leicester (LOD), Woburn (WBN) and Berkshire (ELM) appear in the semi-natural pixels. We observed EWS inside the drought period 2018-2020 for the cases of Aberdeen (CBS)-Yorkshire (SKF) in semi-natural pixels and for the cases of Leicester (LOD)-Woburn (WBN)-Berkshire (ELM) in improved pasture-managed pixels (Table 3-3).

Somerset and Dumfries have shown resilience in early warning systems for drought and water scarcity, but the connection to groundwater and drought periods is nuanced. In Dumfries and Galloway, for instance, the Scottish Environment Protection Agency (SEPA) has highlighted the importance of monitoring groundwater levels as part of their climate resilience strategy. While groundwater levels in some areas have dipped due to insufficient winter recharge, regions like Moray have benefited from higher-than-average rainfall, which supports resilience. This suggests that groundwater plays a critical role in buffering against drought, but its effectiveness depends on consistent replenishment.

Somerset, on the other hand, has historically faced challenges with flooding rather than drought. However, its resilience could stem from integrated water management practices that balance flood prevention with water conservation,

ensuring a more stable groundwater supply. Both regions emphasize the importance of early warning systems and sustainable water management to adapt to changing climate patterns (Peng, 2021).

Table 3-3 Correspondence of the main Early Warning Signals (EWS) appearance and description across the improved pasture managed and semi-natural grassland sites, regarding the date of the first detection in each of the eight UK sites (summary table). The blue highlighted area indicates the existence of the EWS in terms of month/year of the event, and the red highlighted area the EWS observed during the drought period 2018-2020 accordingly.

Grassland Sites	Date of EWS first presence in autocorrelation plots		EWS inside of Drought Period '2018-2020'		Description
	Improved pasture	Semi-natural	Improved pasture	Semi-natural	
Aberdeen (CBS)	Jun 2016	Feb 2018			The first EWS signal appears in the improved pasture-managed pixel, but a significant increase is observed during the drought period for the semi-natural pixel.
Dumfries (TOR)	—	—	—	—	No EWS is observed, but a slight increasing tension during the drought period for the semi-natural grassland.
					An unusual increase of first-appear EWS is indicated at

Yorkshire (SKF)	Apr 2017	Jul 2018			improved pasture-managed pixel, and an increased anomaly for EWS of semi-natural pixel during the drought.
Leicester (LOD)	Aug 2018	Oct 2016			The EWS signal was initially observed at a semi-natural pixel with an abrupt drop of autocorrelation values, but also the EWS shows an unusual drop shift during the drought period of improved pasture-managed pixel.
Woburn (WBN)	Sep 2018	Oct 2016			A slow decrease in tension for the first-appeared EWS of semi-natural pixel, as well as a stable behaviour of EWS is observed for the drought period regarding improved pasture pixel.
Somerset (MAN)	—	—	—	—	No EWS is observed, but a slight increasing tension during the drought period for the improved pasture managed grassland.

Berkshire (ELM)	Aug 2018	Jul 2016			The associated with semi-natural pixel, first appeared EWS , shows high values of a structural break in the time series, with an increased tension for the improved pasture-managed pixel of the drought period.
Dorset (DST)	Nov 2015	Dec 2016			The first EWS indication appeared marginal to the threshold of improved pasture-managed pixel, and an abrupt drop of autocorrelation values indicated at semi-natural pixel concerning the drought period.

The detailed information corresponding to the periods of drought in 2010-2013 and 2018-2020, is presented in Figure 3-4 until Figure 3-11 along with the increases in autocorrelation. However, increases in NDVI were also discovered in other fields across the UK grasslands (see Appendix C). A long-term trend of increasing autocorrelation has been shown for the daily time series of the period 2010-2018 which is more responsive to localised shifts, whereas the daily time series from the middle of the period 2018 until 2020 has shown an explicit long-term trend. We also observe a connection of the increase of autocorrelation with the period of drought as well as an intensification of the phenomenon with the

weather events of the respective time period. On 16 October 2017 Ex-Hurricane Ophelia brought very strong winds to the west of the UK and Ireland. The Great Storm of 1987 was exactly on 30th anniversary on this day. A spell of hot-sunny weather from 17 to 21 June 2017 led to the UK's highest June temperature since 1976. On 15 to 16 December 2018 Storm Deirdre brought strong winds and freezing rain to western and northern parts of the UK (see Figure 3-4, Figure 3-5 Aberdeen-Dumfries). On 11 to 13 October 2018 Storm Callum brought strong winds and persistent heavy rain to western parts of the UK with South Wales particularly badly affected by flooding (see Figure 3-9, Figure 3-10, Figure 3-11, Somerset, Berkshire and Dorset). On 19 to 21 September 2018 Storm Ali brought very strong winds and heavy rain to Scotland and 14 June 2018 Storm Hector with unseasonably strong winds.

On 28 December 2019 18.7°C was recorded at Achfary (Sutherland), the UK's highest December temperature on record. Severe flooding affected parts of South Yorkshire and Derbyshire on 7 November 2019 after a whole month's average rain fell in 24 hours. An area of low pressure brought very strong winds to South Wales and the south coast with a gust of 95Kt (109mph) at Needles Old Battery, Isle of Wight on 2 November 2019 and a persistent of wet weather from late October. On 26 to 27 December 2020 storm Bella was a large and deep area of low pressure in the North Atlantic that affected UK bringing heavy rain and strong winds, whilst Storm Aiden was part of spell of turbulent wet and windy affecting the UK from the late October to early November. Also, Storm Alex on 2 to 4 October 2020 rainfall with average rainfall of 31.7mm across the entire UK and Storms Helen & Francis 19-21 and 25 August 2020 respectively (see Aberdeen, Yorkshire, Leicester, Woburn, Berkshire and Dorset grassland sites).

We observe for the Aberdeen grassland site a slight increase in autocorrelation for the period 2018-2020 regarding the semi-natural managed grassland, indicating the early warning signal as compared with the improved pasture managed grassland, while the period 2010-2018 appears to be behaving normally (Figure 3-4).

As we note for the Dumfries grassland site a normality of the early warning signals with a minimum growth trend autocorrelation for the semi-natural managed grassland for the entire period 2010-2020 (Figure 3-5).

A different behaviour opposite to the previous two fields is presented in the Yorkshire Study Site with an increased tension of autocorrelation from February 2017 until 2020 for the improved pasture-managed grassland, while a sharp increase appears in the middle of the year 2018 inside the drought period (Figure 3-6).

Concerning the Leicester grassland site a slight increase in autocorrelation is noticed at the end of 2018 regarding the improved pasture-managed grassland, indicating the early warning signals, and compared with the semi-natural managed grassland, which has some warning peaks of EWS inside the period 2018-2020 (Figure 3-7).

Regarding for the Woburn grassland site the same behaviour is determined for the semi-natural and improved pasture-managed grassland with increased autocorrelation for the drought period 2018-2020 (Figure 3-8).

In relation to the Somerset grassland site an extreme increase in autocorrelation appeared without any early warning signals for the period 2014-2020 regarding the improved pasture managed grassland compared with the semi-natural managed grassland, which is behaving with a decreasing tension of autocorrelation for the period 2010-2014 (Figure 3-9).

Regarding the Berkshire grassland site we see to behave almost the same for both types of grasslands, improved pasture and semi-natural managed grassland, following the same tension from mid-2018 until 2020, but the early warning signal is more significant for the improved pasture grassland (Figure 3-10)

Finally, for the Dorset grassland site an extreme increase in autocorrelation from the beginning of the year 2018, with significant early warning signals we observe to appear in the autocorrelation plot regarding the improved pasture grassland

and a continuing also increasing tension for the semi-natural managed grassland. This indicates that the area of the Dorset Site needs more attention as it concerns the landscape resilience (Figure 3-11).

The presented framework could be tested and applied to live monitoring of resilience under drought and near-term prediction of climate-induced EWS in other forested regions of the world. Based on our investigations on the occurrence and effects of EWS at managed and annually grazed grassland sites, it does not guarantee that these trends in autocorrelation correspond with a loss of resilience or that they provide the occurrence of a critical slowing down and an impending critical transition to an alternative state in the ecosystem. The strengthened loss of resilience in regions closer to human land-use recommends that limiting deforestation will not just protect the parts of the forest that are directly threatened but also benefit forest resilience over much larger spatial scales (Esquivel-Muelbert et al., 2019). Therefore, in Californian forests where degradation has been observed due to desertification, found that the EWS could often be detected before tree mortality, but in our case in UK grassland sites, it is unlikely to have desertification effects in the absence of long-term monitoring of other ecosystem properties, so the impact of using a higher frequency product on the DLM is a little uncertain.

There has been a lot of interest in the extent to which biodiversity might support the stability of grasslands in the face of climate uncertainty, like an extensive summer drought (He et al., 2023). Research to date has revealed mixed findings, and it is still unclear how various grassland management methods affect how those areas react to drought. In a study setting, we associated intensive land management with the creation of an extended summer drought. In grasslands subjected to reduced summer precipitation, autocorrelation was used as a resistance indicator and resilience measure. Resilience is defined as the difference between drought treatments in the spring and summer of the following year.

As land management becomes more intensive (e.g., overgrazing, frequent mowing, or fertilization), ecosystems may face greater disturbance, reducing their ability to recover from shocks like droughts or extreme weather. Lower autocorrelation often suggests greater system stability and adaptability. As autocorrelation decreases, it may indicate faster recovery and reduced susceptibility to persistent disruptions, leading to higher resilience. During droughts, ecosystems are already under stress. Intensified land use can amplify these stresses, diminishing the system's capacity to bounce back and recover effectively. In this Chapter we have seen that more intensive land management practices might weaken an ecosystem's resilience, possibly due to habitat alteration or resource depletion. Thus, resilience might improve with reduced autocorrelation, meaning systems with less dependence on their own past states could recover more efficiently. The hypothesis points out that during droughts, resilience can decline even further if land management intensifies, implying a compounded effect of natural stress and human-induced pressures.

3.8 Conclusions

Recent advancements in data-assimilation methodologies have employed Fourier analysis to filter and enhance cloud-free NDVI composites, effectively minimizing noise and improving data quality. A critical challenge is managing cloud cover, which complicates modelling due to insufficient clear days; the newly developed algorithm addresses this issue. Autocorrelation, particularly at *lag1*, serves as a metric for evaluating system stability, indicating consistency in the system's state over time. This analysis outlines a systematic method for preparing simulated time series, estimating leading indicators, and assessing their significance. The availability of multiple time series facilitates the monitoring of grassland resilience, enhancing the capacity to detect ecological transitions. Despite this, decision-making remains uncertain due to inaccuracies in forecasts and data limitations, which our early warning signal framework seeks to address.

Previous methodologies have struggled with cloud-affected pixels, particularly in the United Kingdom. A thresholding algorithm has shown promise in mitigating these issues. It is essential to consider daily time series data and land management practices for effective implementation. Research indicates that increasing temporal autocorrelation is associated with slower recovery rates, especially as annual rainfall declines in tropical forests. While stochastic differential equations are suggested for monitoring ecosystem changes, validating early warning signals over vast areas presents challenges (Esquivel-Muelbert et al., 2019; West et al., 1997).

Dynamic linear models (DLM) reveal declining resilience in regions threatened by climatic adversities, necessitating comprehensive observational data to understand ecological resilience under climate change. Future studies should explore innovative vegetation indices and metrics to accurately represent grassland and forest states. The HadUK dataset can produce daily climate anomaly datasets for integration into MODIS processing via Google Earth Engine. The proposed model for UK grasslands must consider field management practices to yield valid results. Our research demonstrates that remotely sensed vegetation indices are effective indicators of transitions in grassland ecosystems. Semi-natural managed grasslands show greater species diversity, correlating with improved NDVI scores and reduced early warning signals, indicating a lag between increased plant diversity and soil health improvements. Effective management of UK grasslands with reduced intensity can enhance biodiversity and soil health while maintaining productivity. Resampling methods may further improve model performance. Our findings suggest that drought and resilience in grasslands depends on management practices, with frequent mowing adversely affecting resistance. Semi-natural grasslands maintain resilience across various management approaches under stress. Many ecosystem services currently demonstrate potential resilience; however, climate change may heighten transition risks, particularly for intensively managed grasslands focused on forage production. Future management strategies should incorporate environmental and

socioeconomic factors to address vulnerabilities in these ecosystems (Tasser et al., 2017; Stowe et al., 1991).

Chapter 4

4 Predicting the impacts of salinity intrusion by identifying early warning signs for conservation and restoration of Louisiana's coastal wetlands.

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This study examines the critical challenge of assessing and enhancing ecosystem resilience to salinity intrusion in deltaic regions. It introduces a framework focused on sensitivity to salinity increases, recovery from disturbances, and adaptive capacity. Utilising long-term data from the Coastal Reference Monitoring System (CRMS) in Louisiana, I analyse four transects with wavelet techniques to identify temporal-frequency variations in salinity levels. The findings indicate that inland CRMS stations, especially those located in northern freshwater swamps and marshes, demonstrate greater resilience and are better insulated from drought-induced degradation than their coastal, low-elevation counterparts in the south, such as salt marshes. Furthermore, the study highlights the importance of temporal autocorrelation, such as lag-1 dependence, in predicting salinity dynamics and recognising environmental disruptions like hurricanes and droughts. This methodological approach supports the development of early warning systems and promotes a proactive, resilience-based coastal ecosystem management strategy, by combining advanced monitoring, predictive modelling, and ecological indicators to anticipate salinity-driven changes before they become irreversible.

4.1 Abstract

Understanding and enhancing the resilience of ecosystems facing salinity intrusion in delta regions is a critical and multifaceted challenge. Focusing on components like sensitivity to increased salinity, recovery ability from disturbances, and adaptability through system diversions provides a comprehensive framework for assessing resilience. Extensive monitoring programmes such as The Coastal Reference Monitoring System (CRMS) stations in Louisiana, USA, are opportune datasets to explore resilience concepts. Within this data, this study reports on four representative transects from the CRMS dataset. Using wavelets the temporal-frequency patterns in adjusted salinity (ppt) were analysed to identify shifts in variance, and also to detect periodicity and recovery patterns. Across all four transects, we were able to determine significant changes in variance and establish a return time subsequent to a perturbation. The findings indicate that the northern region of the study area, away from the coastline, contained clusters of CRMS stations exhibiting higher resilience. Most of the lower-resilience CRMS stations were located along the coastline and at lower elevations, especially within transect groups in the south. This method reveals patterns of temporal dependence, specifically how past salinity levels influence future conditions, aiding in predictive modelling. For instance, high autocorrelation at lag-1 signals momentum in salinity trends, while sudden shifts in the time series data may indicate disruptive events such as hurricanes, droughts, or tropical storms. Developing robust early warning systems contributes to environmental monitoring techniques that can be applied to other coastlines (e.g. deltas and estuaries). This predictive lens shifts coastal management from reactive triage to strategic resilience-building.

Keywords: Autocorrelation analysis; resilience; salinity; variance; coastal ecosystems; estuarine systems; wetlands; tipping points.

4.2 Introduction

Deltaic environments like those of coastal Louisiana are ecologically complex and highly sensitive to salinity intrusion, a process exacerbated by climate-driven sea-level rise and hydrological variability. Even slight increases in salinity can destabilize wetland ecosystems by altering vegetation composition, disrupting food webs, and threatening keystone species (Goette, 2020). These wetlands, which serve as biodiversity hotspots and natural storm buffers, are particularly vulnerable to abrupt shifts resulting from compound events such as droughts and hurricanes, which can accelerate ecological degradation and push systems beyond recovery thresholds (Reed et al., 2020; Castagno et al., 2021).

The resilience of wetland systems must be understood not only in terms of ecological recovery but also in the maintenance of essential socio-ecological functions under stress. Salinity intrusion impacts ecosystem services critical to human communities—such as freshwater supply, agriculture, and fisheries—requiring that resilience frameworks integrate ecological, economic, and social dimensions (Kuenzer et al., 2012; Renaud et al., 2015).

In Louisiana, where wetland loss has been intensified by hydrological alterations such as levee construction, proactive restoration strategies like freshwater diversions are being explored to reintroduce sediment and reduce salinity intrusion. However, the effectiveness of such interventions hinges on spatial calibration and predictive accuracy, as benefits in one region may cause degradation in another (Renaud et al., 2015).

A robust resilience assessment framework involves evaluating **ecological sensitivity**, **recovery potential**, and **adaptive capacity** (He et al., 2024). Sensitivity can be tracked through vegetation shifts, soil salinity, and hydroperiod changes; recovery is measured by indicators like regrowth rates and sediment accretion; and adaptive capacity is informed by governance flexibility, infrastructure, and community engagement. Key to this framework is the

identification of **Early Warning Signals (EWS)**, notably rising variance and autocorrelation in ecological time series, that may precede regime shifts (Tahsin et al., 2018).

Monitoring programs are essential to this predictive approach. Initiatives such as the **Coastwide Reference Monitoring System (CRMS)** provide long-term data on water levels, salinity, vegetation, and soil parameters, enabling the assessment of restoration outcomes and facilitating anticipatory management (U.S. Geological Survey & Louisiana Coastal Protection and Restoration Authority, 2025). By integrating ecological, technological, and community-based observations, a multi-scalar strategy improves early detection of salinity-driven degradation and supports adaptive planning. Salinity intrusion, especially when combined with sea-level rise and extreme events, presents a slow-building yet severe threat. Anticipating tipping points through early indicators and strategically deploying restoration efforts can prevent irreversible wetland loss. This predictive, systems-based approach is vital for preserving the ecological integrity and socio-economic value of Louisiana's coastal wetlands.

Ecological resilience—the capacity to absorb disturbance without undergoing fundamental change—declines as systems approach **tipping points**. Indicators of this decline include **Critical Slowing Down (CSD)**, where recovery from perturbations slows, accompanied by rising variance and autocorrelation in time-series data. The Dakos framework, grounded in dynamical systems theory, uses rolling window analysis to detect such early warnings, providing a quantitative foundation for restoration planning (Holling, 1973; Dakos et al., 2024; Scheffer et al., 2009).

Despite growing recognition, key knowledge gaps persist. Hydrodynamic models vary in resolution and often lack integration of ecological feedbacks or biogeochemical responses to non-marine saline inputs (Roy et al., 2020; Cantelon et al., 2022). Many vulnerable regions also suffer from sparse monitoring networks, limiting real-time detection. Efforts are underway to integrate satellite and in-situ data for enhanced spatial coverage, though

challenges remain in standardizing models and improving micro-scale sensor technologies (White et al., 2021; Farzamian et al., 2024).

This study focuses on a coastal Louisiana site within the **Mississippi River Deltaic Plain**, a region experiencing high rates of wetland loss due to river leveeing and sediment deprivation. Using data from 2006 to 2024, it applies process-based statistical models and wavelet transforms to assess temporal and spatial salinity trends. Shallow estuarine systems, more vulnerable to salinity retention, are examined to evaluate the role of residence time in driving marsh loss. The study area is divided into transects. Transects allow tracking changes in beach profiles, sediment distribution, and vegetation over time. This helps in understanding erosion, deposition, and the impact of sea-level rise, assisting in mapping areas vulnerable to flooding or erosion (White et al., 2019).

Five core objectives guide the research: (1) assess salinity patterns over time; (2) evaluate ecological thresholds and resilience; (3) refine predictive models; (4) examine natural and human-mediated adaptability; and (5) translate findings into actionable policy recommendations (Matsoukis et al., 2021). Early warning detection systems grounded in critical threshold science can enable proactive strategies, such as targeted **freshwater diversions**, to delay or prevent regime shifts from freshwater to saline marshes (Grafius et al., 2016).

As climate oscillations like El Niño Southern Oscillation (ENSO) and increased precipitation variability further complicate salinity dynamics, a multi-scalar, integrated monitoring approach is essential. Identifying and acting upon early warning indicators will be key to conserving and restoring Louisiana's fragile wetland ecosystems.

4.2.1 Background: Spatial and Temporal Dynamics of Salinity Intrusion in Louisiana's Coastal Wetlands

Louisiana's coastal wetlands are among the most ecologically and economically vital ecosystems in North America, yet they are increasingly threatened by salinity intrusion. The spatial variability of salinity across these wetlands is shaped by a complex interplay of geographic and geomorphic factors. Marshes near the Gulf of Mexico experience greater salinity exposure, while more inland zones tend to maintain freshwater or brackish conditions. Variations in wetland type, distance from tidal channels, and landscape elevation further mediate the degree and extent of saltwater encroachment.

Temporally, salinity patterns exhibit both short-term fluctuations and long-term trends. Seasonal droughts and decreased river discharge often allow saline water to advance inland, while episodic storm events, such as hurricanes and storm surges, can rapidly elevate salinity levels across freshwater habitats. Over longer timescales, sea-level rise and land subsidence intensify salinity intrusion, weakening the natural buffering capacity of these ecosystems. Mechanistically, the process is driven by tidal forcing, diminished freshwater input due to anthropogenic modifications (e.g. levees, dams), and subsurface dynamics such as groundwater salinization. Additionally, storm-induced overwash events transport saline water deep into wetland interiors, altering vegetation loss and hydrological change further reinforce salinity dynamics, threatening the resilience and function of wetlands (Attia, M. et al., 2025).

Salinity intrusion has emerged as a critical driver of ecological transformation in Louisiana's coastal wetlands, with both historical records and future projections underscoring its intensifying impact. Long-term monitoring data from the Louisiana Department of Wildlife and Fisheries indicate that while some saline marshes have remained relatively stable, freshwater and intermediate marshes have experienced increasing salinity levels over the past several decades (Visser et al., 2012). However, early assessments were limited by the spatial distribution

of monitoring stations, many of which were located in already brackish or saline zones, potentially underestimating the extent of intrusion into fresher systems (Snedden et al., 2015).

Recent advances in geophysical techniques have revealed a more nuanced picture. Attia et al. (2025) used Airborne Electromagnetic (AEM) surveys to detect a subsurface seawater wedge extending into the Mississippi and Atchafalaya River basins, suggesting the saltwater intrusion is not only a surface phenomenon but also a significant subsurface threat. These findings align with broader concerns about the compounding effects of sea-level rise, land subsidence, and reduced freshwater inflows due to river engineering and climate variability (Day et al., 2007). Looking ahead, climate models project that Louisiana's coastal zones will face increased salinity stress due to more intense surges, rising sea levels, and altered precipitation patterns (IPCC, 2023). Restoration strategies such as sediment and freshwater diversions, like the Mid-Barataria Sediment Diversion, are expected to mitigate salinity in some areas by reintroducing riverine inputs but may also shift salinity gradients and affect wetland vegetation dynamics. At the regional scale, large-scale barrier island restoration projects, such as those at Scofield Island, Caminada Headland, and Caillou lake, have employed innovative sediment delivery systems and adaptive engineering to rebuild critical storm buffers (CPRA, 2023). Modelling studies suggest that critical salinity thresholds for marsh vegetation may be exceeded more frequently in the coming decades, potentially accelerating wetland loss and habitat conversion (Wang et al., 2020).

Extreme weather events such as hurricanes and droughts are among the most significant natural drivers of salinity intrusion (Vicente-Serrano et al., 2022). These events disrupt the hydrological equilibrium between freshwater and saline systems, often accelerating the inland migration of saltwater and altering ecosystem structure and function. Storm surges associated with hurricanes can rapidly transport saline water deep into freshwater marshes, breaching natural levees and depositing salt-laden sediments that persist long after the event (Delaune & Pezeshki, 2003). Conversely, droughts reduce river discharge and

freshwater inputs weakening the hydraulic gradient that typically resists saltwater encroachment. The 2023-2024 Mississippi river saltwater wedge crisis exemplifies how prolonged low-flow conditions can allow a dense saline layer to advance upstream, threatening municipal water supplies and wetland health. Anthropogenic perturbations further exacerbate salinity intrusion. Channel deepening and dredging for navigation have increased the capacity for denser saltwater to move inland, particularly in the Mississippi River system (Attia et al., 2025).

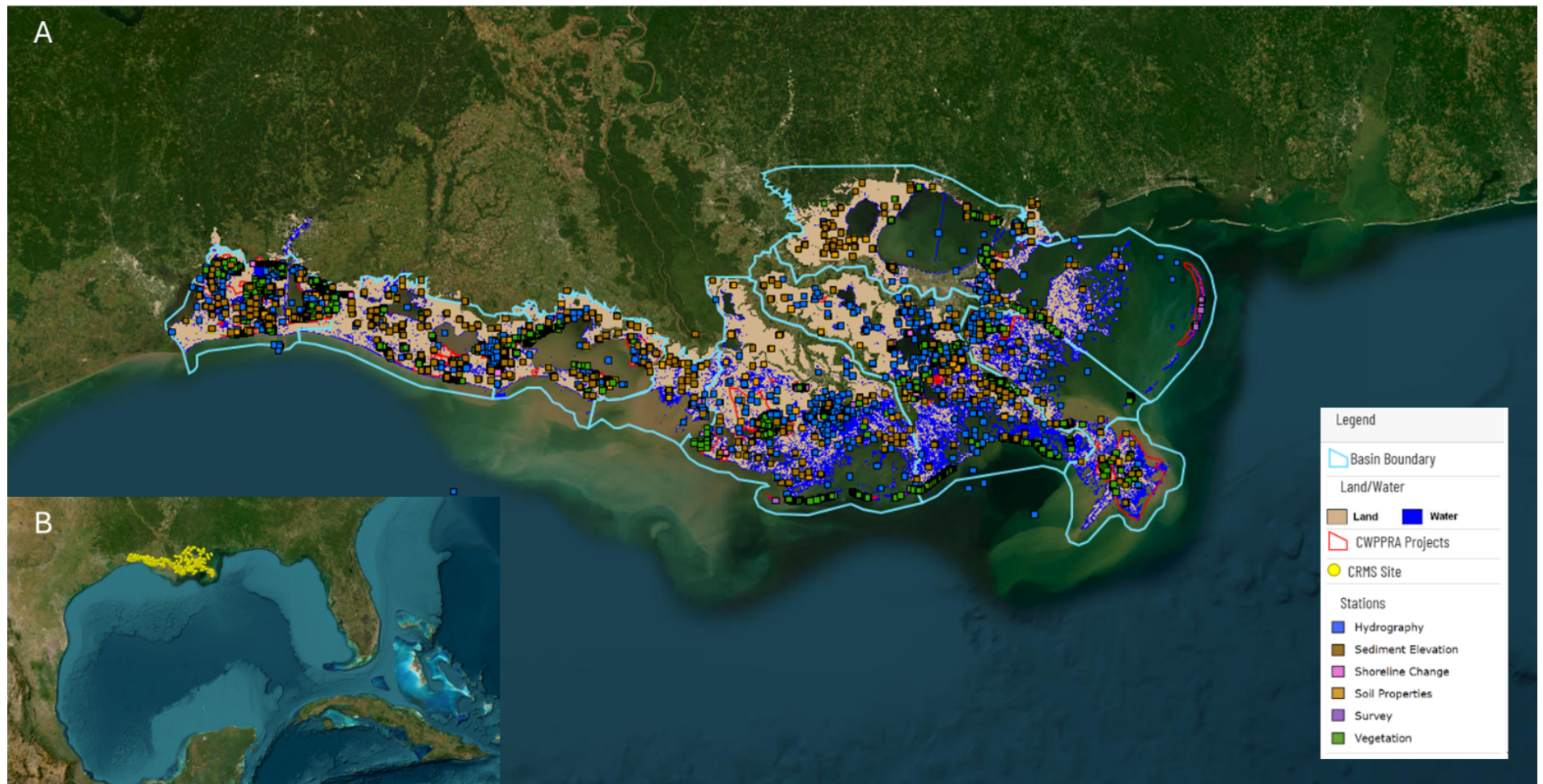


Figure 4-1 Locations of the CRMS stations in Louisiana estuary, USA indicating A) individual treatment basin boundaries and B) properties in response to Louisiana's land loss crisis (source: Coastwide Reference Monitoring System, CWPPRA).

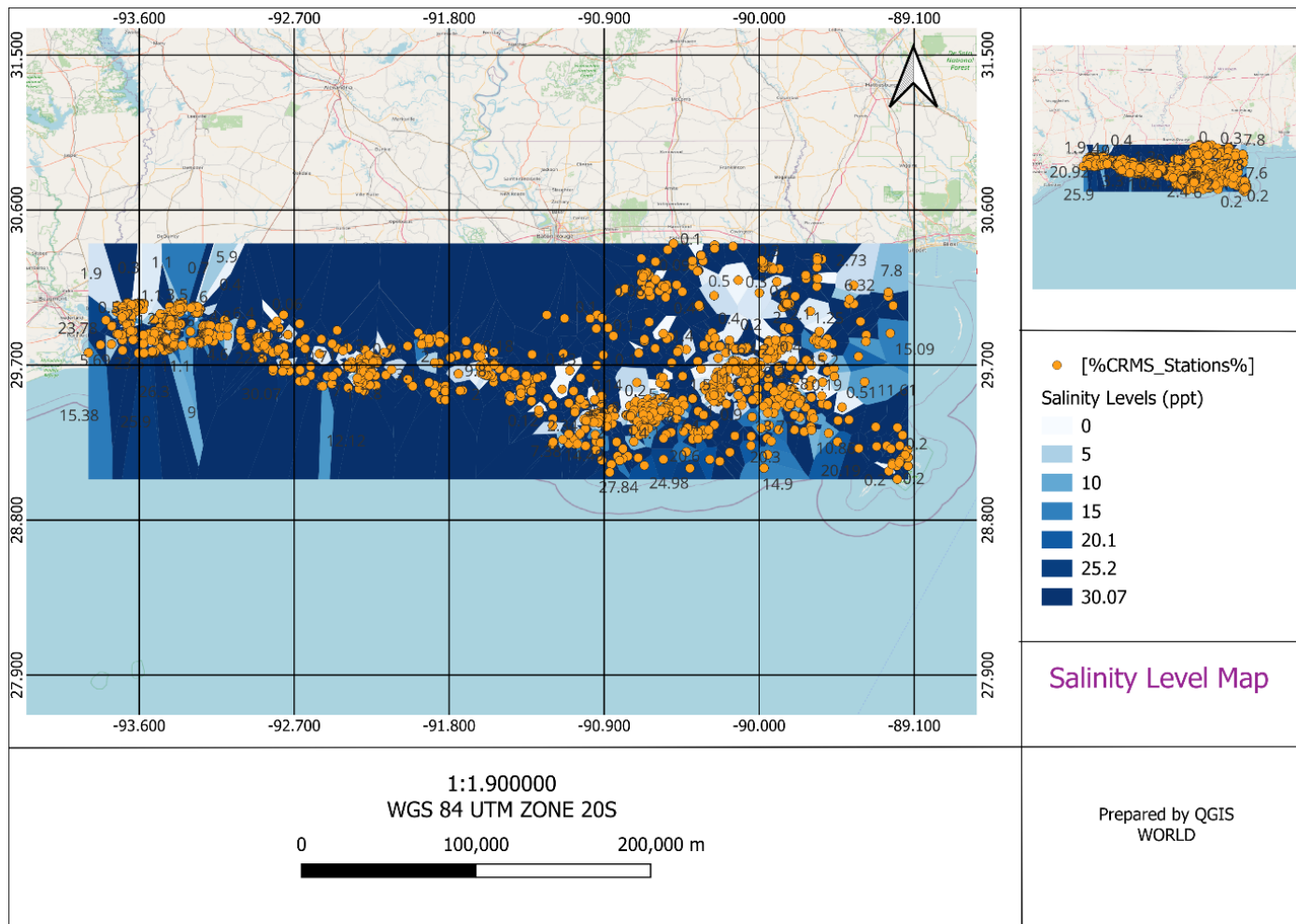


Figure 4-2 Mean salinity variation of CRMS stations in Louisiana.

Freshwater effect is negligible throughout the Gulf of Mexico coast of south Texas, where periodic freshwater pulses dictate the salinity structure (Irlandi et al., 1995; Tolan, 2007). The hypersaline estuary known as Baffin Bay, located in the South Texas region, had significant salinity changes in the study system in 2015 due to an extremely big rainfall event that followed a period of drought from 2010 to 2014 (Figure 4-2). These circumstances provide a singular chance to study significant salinity fluctuation. In order to better understand the ecosystem-scale implications of water quality variability, this study combines metrics related to water quality, namely salinity change. This paper aims to describe the following effects of extreme salinity change: 1) ascertain the impact of salinity variation on land loss, 2) the early warning signals in estuarine systems, and 3) the potential response of the shallow coastal basins of Louisiana region to diversions of nutrients from the Mississippi River in regard to saline influence.

River hydrology as well as wave and tidal forcing from the ocean shape river deltas, which are extremely dynamic systems. The stability of the deltas around the world is in jeopardy due to the ongoing rise in sea level. Nutrients from agricultural practices, atmospheric deposition, rainfall runoff, and wastewater inputs are currently enriching river systems globally. Large-scale coastal system restoration is being undertaken by the state of Louisiana utilising a range of approaches that differ in terms of cost, impact, and scale in terms of both space and time. One restoration strategy that has the potential to affect significant areas of the coastal basins is the diversion of the Mississippi River to re-connect it with the basins. Significant nutrient loads, particularly nitrate, are also directed into estuaries and coastal bay waters by diversion of river water containing land-building material (DeLaune et al., 2003).

In reaction to Louisiana's land loss crisis, the United States Congress passed the Coastal Wetlands Planning, Protection, and Restoration Act (CWPPRA) in 1990. The CWPPRA is a collaborative federal-state initiative that has given Louisiana's wetlands restoration a consistent and recurrent financial source. The CWPPRA programme has approved 218 projects related to coastal preservation and

restoration between 1990 and 2018. Diversion of freshwater and sediment, placement of dredged material for marsh development, protection of shorelines, terracing, hydrologic restoration, barrier island restoration, and vegetative planting are some of the restoration strategies employed.

In order to provide the services that humanity requires; large floodplain-river ecosystems are frequently heavily shifted. However, these modifications might make an ecosystem less resilient in response to changing environmental conditions. An ecosystem's general resilience, or adaptive capability, provides a conceptual framework for thinking about how a system will react to such changes. In order to better understand the structure and function of the floodplain-river ecosystem, we attempted to apply some ecological resilience principles. These principles highlight significant structural and functional elements of the ecosystem and most likely contribute to the ability of large rivers to withstand disturbance and change in the environment. Enhancing a system's capacity to react and adjust to both expected and unexpected changes and stress is the primary objective of incorporating resilience concepts into ecological restoration and natural resource management (Walker & Salt, 2012).

There are two complementary components to take into account when applying resilience concepts: the specific and the general. While general resilience takes into account the system's ability to adapt to a variety of shocks and disturbances in order to preserve ecological functions, specified resilience focusses on understanding the resilience of a single component of the system in response to a particular disturbance. The following generic concepts, which highlight the characteristics of ecological systems and aspects of ecological management that support these systems' overall resilience, have been presented: 1) In order to promote polycentric governance systems, it is important to maintain diversity and redundancy, manage connectivity, control variables, and feedbacks, foster an understanding of social-ecological systems as complex, adaptive systems, motivate learning and experimentation, broaden participation, and foster an understanding of how to manage controlling variables and feedbacks. 2) When these concepts are applied to a system, they can help identify how ecological

management actions might enhance the system's adaptive capacity, which is the system's ability to adjust to change. (Cosens et al., 2014).

4.2.2 Major variation in water quality (salinity) variables

Salinity is a critical parameter influencing aquatic ecosystem structure and function. Its variation is closely linked to both natural and processes and anthropogenic activities, and it significantly affects other water quality variables such as nutrient concentrations, dissolved oxygen, and biological productivity. Freshwater delivery fluctuations to estuaries are becoming more frequent globally and in South Texas specifically: In estuaries of several regions of Africa, Southwestern Australia, and Southern California in the United States, there have been cases of temporary or seasonal hyper salinity as well as increased salinity variation due to increased drought prevalence and anthropogenic water use. Communities in estuarine systems may experience disturbances due to salinity variations. Future hydrological variability is expected to rise due to changes in precipitation patterns, especially in the southwestern United States, according to climate models. In the semi-arid region of South Texas, USA, Baffin Bay is a mostly hypersaline system that sustains enormous populations of *Pogonias cromis*, black drum, a significant benthic predator for commerce. The most accurate indicator of changes in Baffin Bay's benthic macrofauna biomass, abundance, and diversity was salinity. Determining the ecosystem-scale implications of salinity variability requires an understanding of how salinity variation affects resilience dynamics (Breaux et al., 2019).

Baffin Bay is a subtropical lagoon that is a part of the Laguna Madre estuary complex and is situated on the coast of south Texas, USA. Due to its lack of a direct link to the Gulf of Mexico and low base freshwater intake, it frequently experiences hypersaline conditions and has lengthy residency durations (> 1 year on average). In south Texas, extended dry spells can extend up to five years, and

during these times, the salinity of the water can surpass seventy. But El Niño years also frequently have episodic heavy rainfall episodes, which lower salinities and shorten residency times to a few weeks or months. The phytoplankton *Aureoumbra lagunensis* has caused dangerous "brown tides" in Baffin Bay and Laguna Madre during the multi-year dry spells that have occurred between 1989 and the present.

While inflows into Baffin Bay are typically minimal, there are occasional major influx events that have the potential to significantly alter the system's salinity in a short amount of time and increase the amount of land-based nutrients and sediment. However, in the absence of an ocean link, nutrients introduced into the system are likely to be held for extended periods of time, increasing the risk of eutrophication. In fact, a number of indicators point to Baffin Bay's eutrophication, including elevated and rising levels of nutrients or chlorophyll during the previous three to four decades and new tracer research showing a notable signature of nutrients derived from humans. Forecasts indicate that the South Texas coast, home to Baffin Bay, may see warmer temperatures, more evaporation, and less average precipitation in the future due to global climate change. Freshwater inflows are therefore predicted to decrease as well. Decreased inflow could make the hyper salinity conditions worse and lengthen the residency durations even further. Temperature, precipitation, and evaporation rates directly influence salinity levels. For instance, arid and semi-arid regions experience higher salinity due to reduced freshwater inflow and increased evaporation. Water abstraction, damming, and land-use changes alter the salt balance in freshwater systems, often leading to salinization. Similar climate shifts are anticipated in other subtropical regions of the world with low-inflow estuaries, such as Australia, South Africa, and the Mediterranean. The South Texas coast is expected to have more severe storm events despite forecasts of an overall drying trend (Beecraft et al., 2023).

4.3 Materials and methods

4.3.1 Study site

To evaluate ecological resilience in southeast Louisiana's Lower Mississippi River Basin, the study examined relationships between key environmental variables—biodiversity, vegetation cover, and water quality—and ecosystem response to coastal hazards. Salinity intrusion was assessed using transects spanning freshwater to saltwater zones, enabling spatial and temporal analysis of salinity gradients (Corstanje et al., 2004). Salinity concentration data (ppt-parts per thousand) were analysed using wavelet analysis, allowing classification of transects based on resilience traits through frequency decomposition. The resulting resilience index underwent empirical validation to support its practical utility.

In parallel, data from the Coastwide Reference Monitoring System (CRMS) were integrated to assess broader-scale ecological dynamics. CRMS encompasses approximately 390 sites across Louisiana's coastal wetlands, with standardized sampling procedures capturing data on hydrology, vegetation, elevation change, sediment accretion, and land-to-water ratios. Observations were recorded at two spatial scales (200 m² and 1 km²), with aerial imagery and field transects providing insights into long-term ecological change. Data were quality-checked and archived in the Coastal Information Management System (National Academies of Sciences, Engineering, and Medicine, 2017).

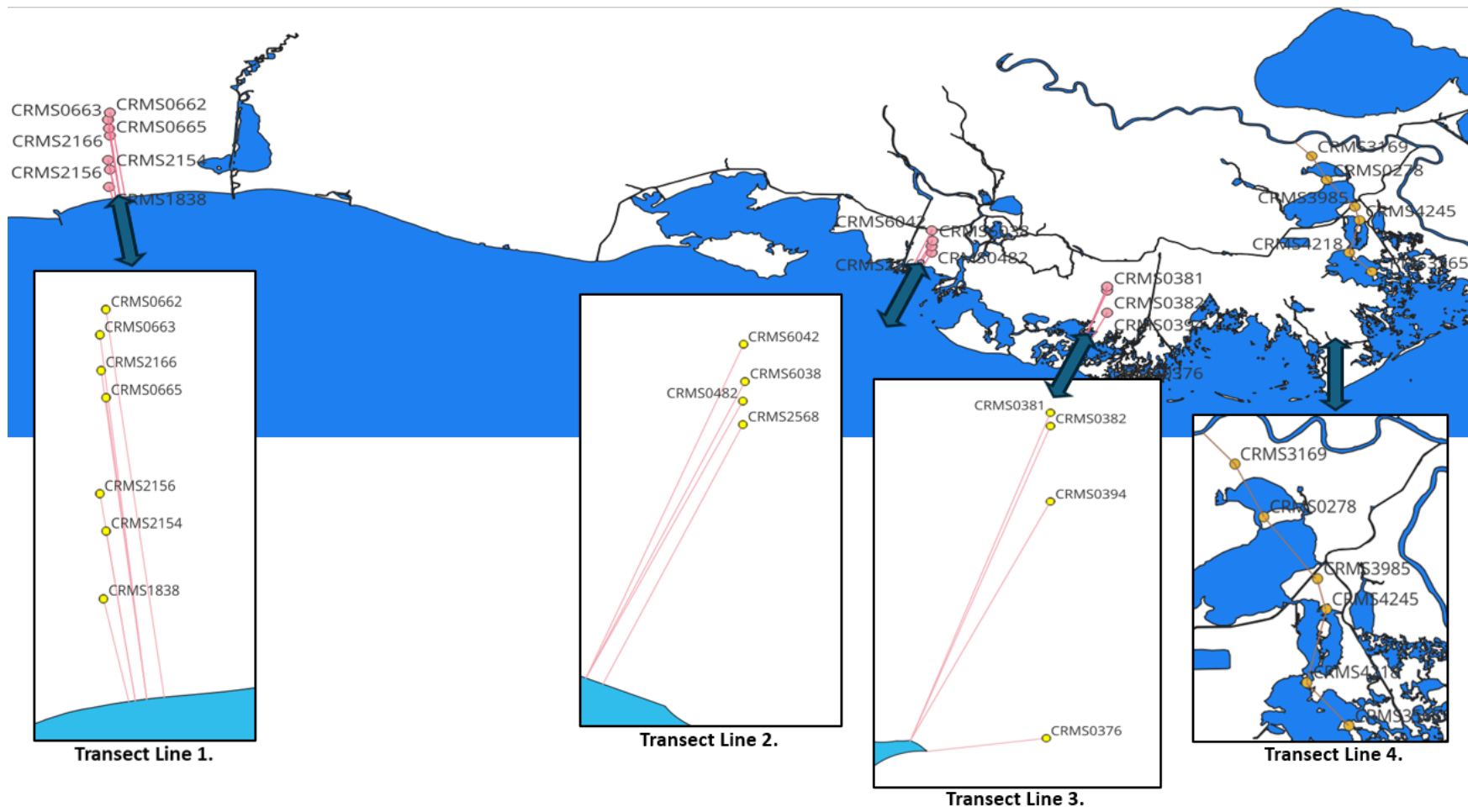


Figure 4-3 Locations of the Transects 1,2,3,4 along the coastline of Barataria Bay. In the deltaic plain, the coastal basins are separated by current and abandoned river channels.

Twenty-one CRMS sites at variable distances, of which fifteen stations divided into 3 Transects along the coastline structure and another six stations located close to the Mississippi river diversion (Transect 4) were chosen (Figure 4-3).

Next, a set of numerical analysis is conducted to investigate the effects quantitatively of different salinity levels. To quantitatively assess the spatial relationship between monitoring stations and coastal influences, the Euclidean distance from each CRMS (Coastwide Reference Monitoring System) station to the nearest point along the Louisiana coastline was calculated using QGIS and ArcGIS software. This spatial metric served as a proxy for coastal proximity and was integrated into the broader analysis of salinity stratification, freshwater forcing, and estuarine dynamics. Given the influence of Mississippi River outflow, rainfall events, and proposed freshwater diversions (such as the Mid-Barataria sediment diversion), proximity to the coast plays a key role in determining local salinity regimes. Incorporating Euclidean distance enabled more nuanced interpretation of salinity gradients and improved the spatial resolution of salinity intrusion modelling across the estuarine landscape. When continuous salinity perturbation is added with the red regions in the power diagram to the results we could easily conclude if every single CRMS station is resilient or not, under the current climate. (Hu et al., 2023).

Tables of the hydrographic data were created (**Table 4-1, Table 4-2**) in order to select the best stations for analysis (best date period of years(>10years) min, max of the date) along the coastline and from the coastline with the longer period of data and less missing values. Salinity distribution maps were generated using Voronoi polygons, with each monitoring point assigned a unique polygon representing its zone of influence. These zones were delineated based on the relative proximity between monitoring locations, enabling a spatially explicit visualization of salinity variation across the study area. The method basically uses its computation algorithm to fill in for these unknown areas so we can see pixel value. We are looking to use the data associated to CRMS stations, in particular the salinity and conductivity to do a time series analysis decomposition, trying to

identify where we may detect signals of change at stations that are located at varying distances along the coastline and from the coastline. Plotting time series creating graphs with mean salinity over time (months-days) we analyzed the points interpolating the distance of the CRMS station's points from the Louisiana coastline.

4.3.2 The Wavelet Analysis Method

A wavelet is an asymmetrical wave feature with a limited time span that can be translated and rescaled in tandem with the time series under analysis. To examine the time frequency distribution, the Wavelet Transform (WT) breaks down a time collection into its time and frequency additives.

There is a requirement of a framework that data or observations to be collected at consistent intervals, with no gaps, in order to analyse changes in variance across varying scales. This approach is often used in statistical analyses, time series studies, or even signal processing where regular data sampling is critical to identify trends, anomalies, or patterns. The data from the CRMS stations was examined using Wavelet Analysis in an attempt to gauge their resistance using the "WaveletComp" R package, examining notable shifts in variance across different scales. The program "WaveletComp" uses a small waveform called a wavelet to determine the intensity of various periodicity lengths along any kind of continuous data—in this case, time-series data. This robust methodology facilitates the examination of variation changes across multiple scales. By calculating the wavelet power of the Adjusted Salinity time series, measured in parts per thousand, the analysis provides an in-depth understanding of the temporal and frequency-based dynamics of salinity. The resulting power diagram serves as a visual representation of the energy distribution of periodic components, effectively illustrating scale-specific variations in variance. The diagram indicates (in red) the dataset's regions with the largest variance changes.

Typically, wavelet analysis methods require that the time series compare a series of measurements that have been made at regular intervals in time, which proves particularly advantageous for identifying patterns, trends, and anomalies within complex ecosystems, such as the estuaries of Louisiana (Milne & Lark, 2009).

Mathematically, the wavelet transforms of a time series $x(t)$ is defined as:

$$W(a, b) = \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt, (4-1)$$

where: $-a$ is the scale parameter (related to frequency), $-b$ is the time translation parameter, $-\psi$ is the wavelet function, and $-\psi^*$ is the complex conjugate of ψ . The power spectrum is visualized as a 2D diagram where the x-axis represents time b , the y-axis represents scale a (inversely related to frequency), and the intensity of colour (e.g., red) indicates the magnitude of $P(a, b)$ (regions of high energy or variance).

The arches in the wavelet power spectrum represent areas where the signal has significant periodic components or high energy across specific time and scale combinations, representing the significant area in our measurements. These arches visually highlight the dominant frequency patterns within the time series data. Mathematically, the arches correspond to regions where the wavelet power, calculated as: $|W(a, b)|^2$ is strongest, indicating pronounced variations or oscillations at specific frequencies over time. This makes them excellent markers for analyzing and interpreting patterns, trends, or even detecting anomalies in complex datasets.

By calculating the daily total mean salinity (ppt) the data was effectively smoothed to focus on broader trends while still retaining key variability components. To investigate periodicity and estimate ecosystem recovery time, patterns of recurrence were identified by analysing graphs for cyclic trends and measuring the intervals between successive peaks and troughs (Figure 4-12). The time or interval between similar peaks was then estimated troughs, or features identifying one cycle of the periodic pattern (e.g., from one peak to the next peak, or one trough to the next trough).

To analyse the recovery phase of a graph, I start by identifying the Peak Point, which is the highest value on the graph. This peak indicates the beginning of the recovery phase. Next, I identify the Low Point, which is the lowest value that occurs after the peak. This marks the end of the recovery phase. After pinpointing these two points, I determine the period of recovery by calculating the time difference between the peak and the low point. Since the x-axis of the graph represents time in days, I can subtract the time at which the peak occurs from the time at the low point. The resulting time difference gives me the recovery time represented in the graph (Figure 4-13).

4.4 Results

Rates of salinity accretion determined from the 15 sites ranged from 0.18ppt to 19.84ppt (Table 4-1, Table 4-2 and Figure 4-2). The highest average rates of salinity were measured at sites CRMS0376 (Transect 3), CRMS2154 (Transect 1), which were nearest to the saltwater influence of the ocean. It is noticeable that Marsh sites in the upper portion CRMS0224, CRMS0226 of the sampling grid had significantly high salinity levels ($>8ppt$) of vertical accretion compared to salinity accretion at sites located at a greater distance from freshwater input (Mississippi river).

Table 4-1 A hierarchy of forcing mean salinity (ppt), pulsing Euclidean distance (m) from the coastline of the Gulf of Mexico (Barataria Bay) affecting the resilience formation of CRMS stations, according to mean raw water level (m) of Transect Lines 1,2,3 for the period 2006-2024.

Station_ID	Total_Mean_Salinity (ppt)	Longitude	Latitude	Mean_Raw_Water_Level (m)	Distance (m)
Transect Line 1					
CRMS1838	2.13	-93.69607	29.78543	0.71	10030
CRMS2154	4.77	-93.69388	29.84389	0.40	16381
CRMS2156	5.39	-93.6991	29.87614	0.31	19992
CRMS0665	4.16	-93.69392	29.95888	0.49	28993
CRMS2166	3.63	-93.69807	29.98224	0.48	31612
CRMS0663	4.11	-93.69908	30.01318	0.38	35030
CRMS0662	3.42	-93.69394	30.0349	0.40	37362
Transect Line 2					
CRMS2568	0.19	-91.35421	29.56401	0.79	29102
CRMS0482	0.18	-91.35418	29.5858	0.88	31324
CRMS6038	0.18	-91.35242	29.60381	0.66	33214
CRMS6042	0.19	-91.35359	29.63851	0.59	36729
Transect Line 3					
CRMS0376	19.84	-90.85775	29.12404	0.88	10108
CRMS0394	4.75	-90.8543	29.35896	0.40	28790
CRMS0382	0.89	-90.85424	29.43382	0.71	36523
CRMS0381	0.79	-90.85429	29.447	0.41	37906

Table 4-2 A hierarchy of forcing mean salinity (ppt), pulsing Euclidean distance (m) from the Mississippi river diversion (Transect Line 4.) affecting the resilience formation of CRMS stations, according to mean raw water level for the period 2006-2024.

Station_ID	Total_Mean_Salinity (ppt)	Distance (m)	Longitude	Latitude	Mean_Raw_Water_Level (m)
CRMS0276	6.02	2224	-89.94501897	29.61936079	0.27
CRMS0263	7.77	6190	-89.88885734	29.55324889	0.50
CRMS3601	7.02	6619	-89.94810901	29.57505163	0.55
CRMS0260	8.58	6733	-89.85422681	29.53410765	0.60
CRMS3617	8.18	7467	-89.91364609	29.54773115	0.49
CRMS0225	5.14	9936	-90.0095165	29.56317423	0.47
CRMS0226	9.14	10456	-89.88550016	29.51238918	0.64
CRMS0224	9.21	12667	-89.91767272	29.49967494	1.40
CRMS0251	6.49	14557	-90.01049609	29.51870615	0.33
CRMS3590	7.69	15282	-89.94905225	29.48427375	0.68
CRMS0232	7.06	16825	-90.01256228	29.49787383	0.53

Table 4-3 The CRMS Stations sorted by Transects 1, 2, 3, 4, and perturbation events (e.g. Hurricanes, Tropical Storms, Drought)
analysing the periodicity, the end date in years, and the recovery time in days for the period 2006-2024.

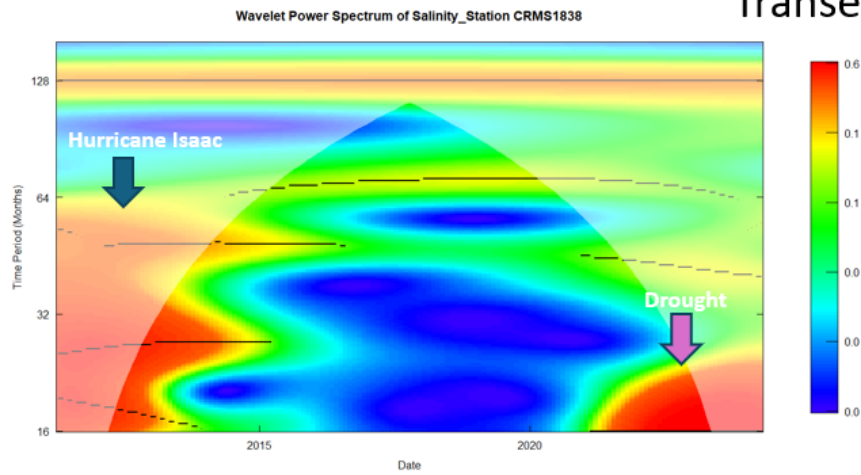
Transect Line 1	Hurricane Isaac (29th Aug 2012)			Hurricane Ian & Nicole (10th Oct-7th Nov 2022)			Tropical Storm Ida (10th Nov 2009)			Hurricane Humberto (13th Sep 2007)			Drought (June 2023)								
	Periodictiy (Months)	End Date (Years)	Recovery Time (Days)	Periodictiy (Months)	End Date (Years)	Recovery Time (Days)	Periodictiy (Months)	End Date (Years)	Recovery Time (Days)	Periodictiy (Months)	End Date (Years)	Recovery Time (Days)	Periodictiy (Months)	End Date (Years)	Recovery Time (Days)						
CRMS_1838	44	2014	65										7	2024	234						
CRMS_2154	18	2015	216										2	2024	130						
CRMS_2156	19		135										3	2024	154						
CRMS_0665	34	2015	111										6	2024	123						
CRMS_2166				6	2024	196							8	2024	207						
CRMS_0663	29	2014	158										2	2024	197						
CRMS_0662	8	2014	163																		
Transect Line 2	Hurricane Isaac (29th Aug 2012)			Tropical Storm Gustav (1st Sep 2008)			Hurricane Ida (29th Aug 2021)						Drought (June 2023)								
CRMS_2568				7	2013	96	30	2024	90												
CRMS_0482				39	2019	41	4	2024	90												
CRMS_6038				30	2018	33	1	2022	54												
CRMS_6042							3	2024	44												
Transect Line 3	Hurricane Ida (29th Aug 2021)			Hurricane Harvey (30th Aug 2017)			Tropical Storm Ida (10th Nov 2009)			Hurricane Humberto (13th Sep 2007)			Drought (June 2023)								
CRMS_0376				31	2024	45				34	2024	110	8	2024	110						
CRMS_0394	8	2024	193							31	2011	184	10	2024	123						
CRMS_0382	Tropical Storm Gustav (1st Sep 2008)						78	2016	194												
CRMS_0381	60	2012	213													58	2012	71			
Transect Line 4	Hurricane Ida (29th Aug 2021)			Hurricane Isaac (29th Aug 2012)			Tropical Storm Ida (10th Nov 2009)			Hurricane Barry (13th Jul 2019)			Drought (June 2023)								
CRMS_3169							6	2012	109				101	2024	67						
CRMS_0278							42	2011	115				98	2024	94						
CRMS_3985	68	2024	90										97	2024	118						
CRMS_4245	82	2024	64										12	2017	63	98	2024	70			
CRMS_4218										13	2011	85	50	2024	127	59	2024	55			
CRMS_3565													2	2024	123	54	2024	44			

The analysis indicated that the duration of disturbances for Transect 1 differed markedly across sites. The more resilient area, identified as CRMS0662, demonstrated a recovery period of 163 days following Hurricane Isaac on August 29, 2012. In contrast, the less resilient station, referred to as CRMS2166, required 403 days to recover from the impacts of both Hurricane Ian and Hurricane Nicole on October 10, 2022, as well as the subsequent drought event in June 2023, as depicted in Figure 4-4.

Concerning Transect 2, the more resilient station, designated as CRMS6042, experienced minimal disturbances and required only 44 days to recover from Tropical Storm Ida, which occurred on November 10, 2009. In contrast, the station referred to as CRMS2568 faced a significantly longer recovery duration of 186 days following both Tropical Storm Gustav on September 1, 2008, and Hurricane Ida on August 29, 2021, as indicated in Figure 4-5. Also, concerning Transect 3 with more resilient station CRMS0382 lasted 194 days to recover from the perturbation of Tropical Storm Ida (10th Nov 2009) but for the less resilient station CRMS0394 lasted 500 days to recover from Hurricane Ida (29th Aug 2021), Hurricane Humberto (13th Sep 2007), and Drought event (June 2023), (Figure 4-6). In Transect 4, the more resilient station observed the CRMS3565 with 167 days recovery time from the perturbations of Hurricane Barry (13th July 2019), and Drought (June 2023), as well as the less resilient station CRMS4218 with 267 days of recovery time of Tropical Storm Ida (10th Nov 2009), Hurricane Barry (13th July 2019), and Drought event (June 2023), (Figure 4-7). Generally, Transects 1, 3, 4 are more saline and Transect 2 is more freshwater dominated (freshwater intrusion by Mississippi river. Overall, the most resilient stations located in Transect Line 2 recover faster (448 days on average) than Transect Line 1 stations (2089 days on average) from the extreme events. The figures show the realizations of variance of the time series; the variance increases in red areas and decreases in blue areas.

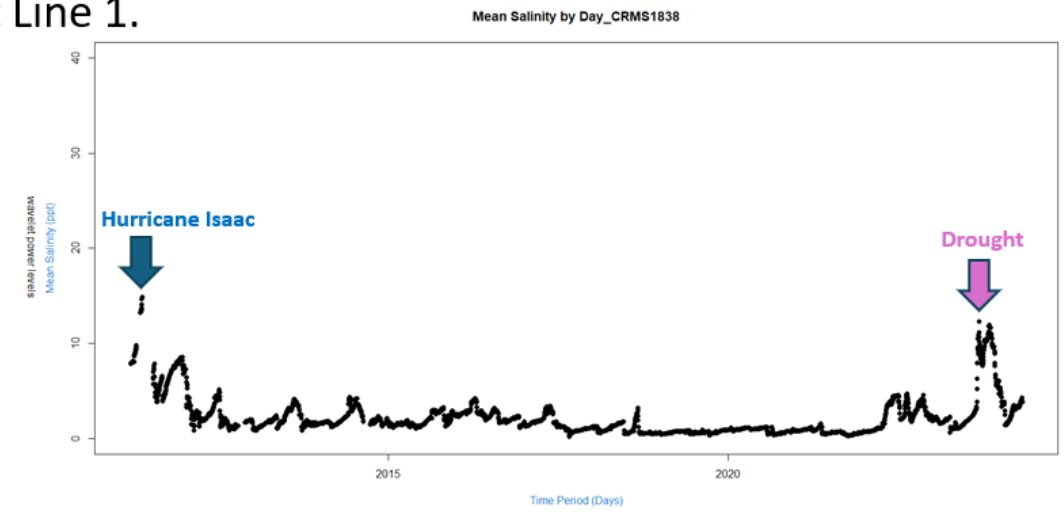
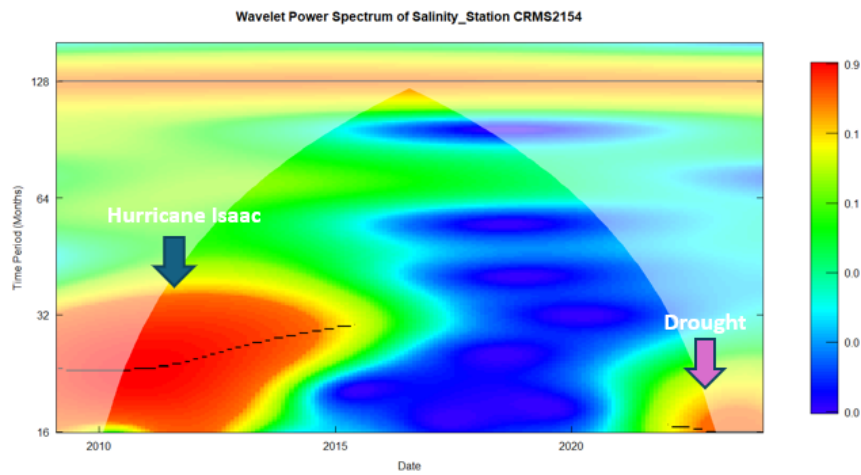
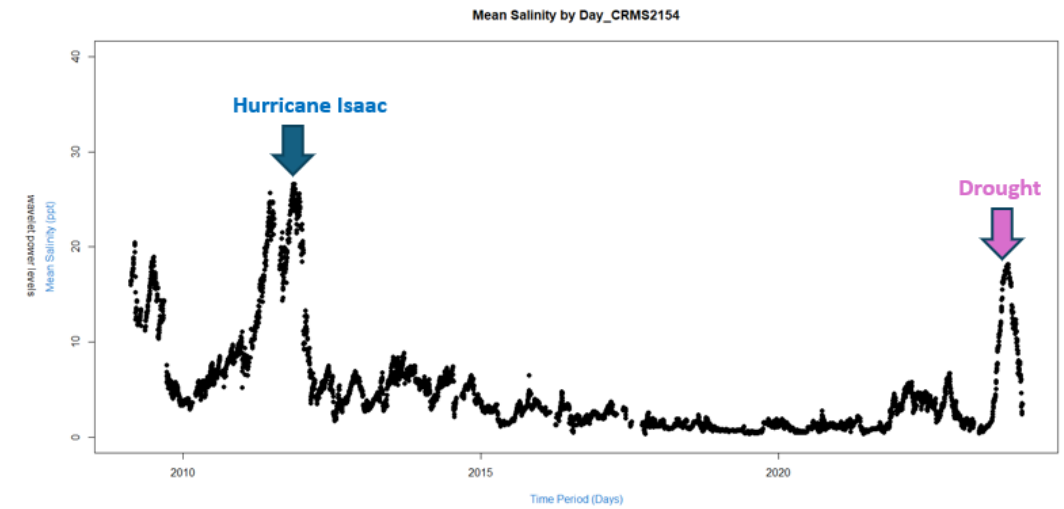
The blue arrows indicate the extreme events that occurred in CRMS stations, and the pink arrows indicate the major drought event of June 2023, for which the segment trend statistic is higher than the trend statistic prior to the event.

(a)

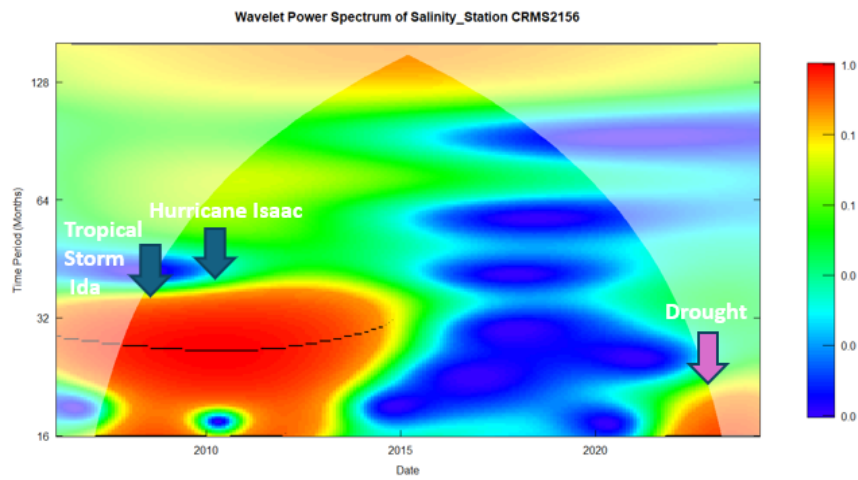


(b)

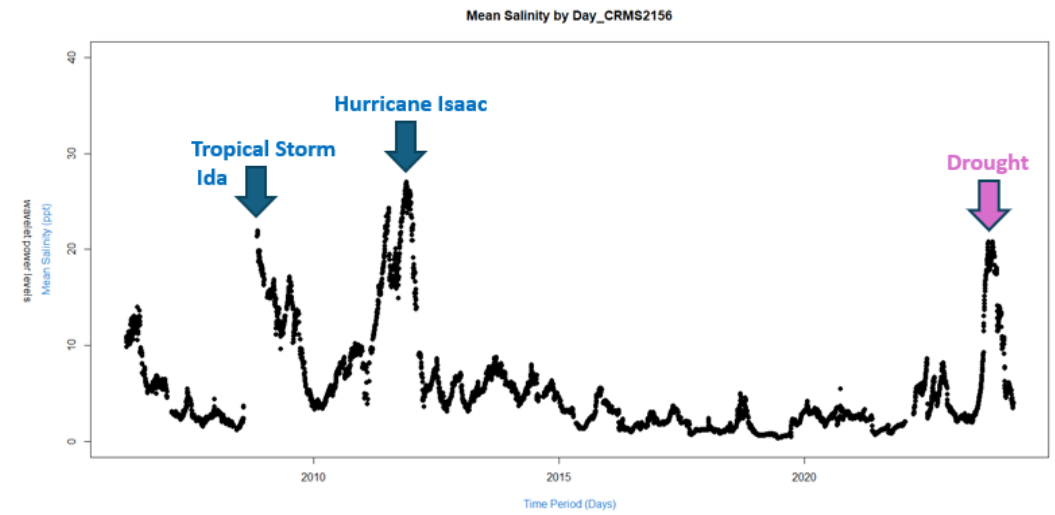
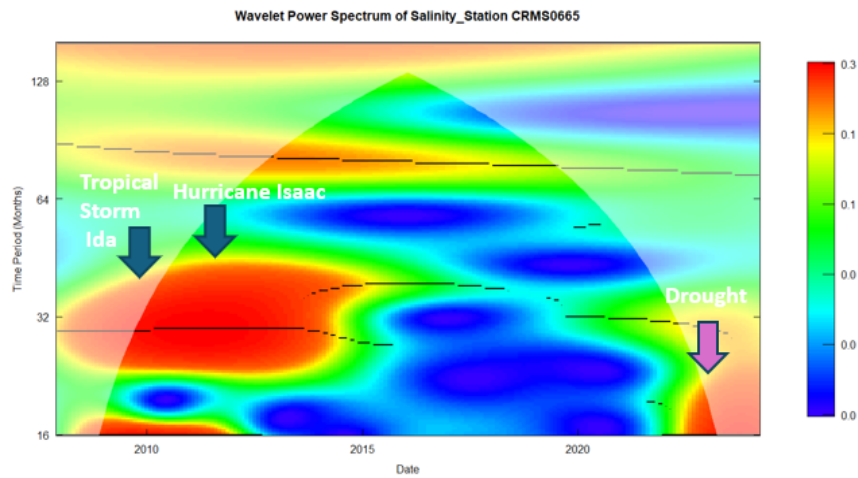
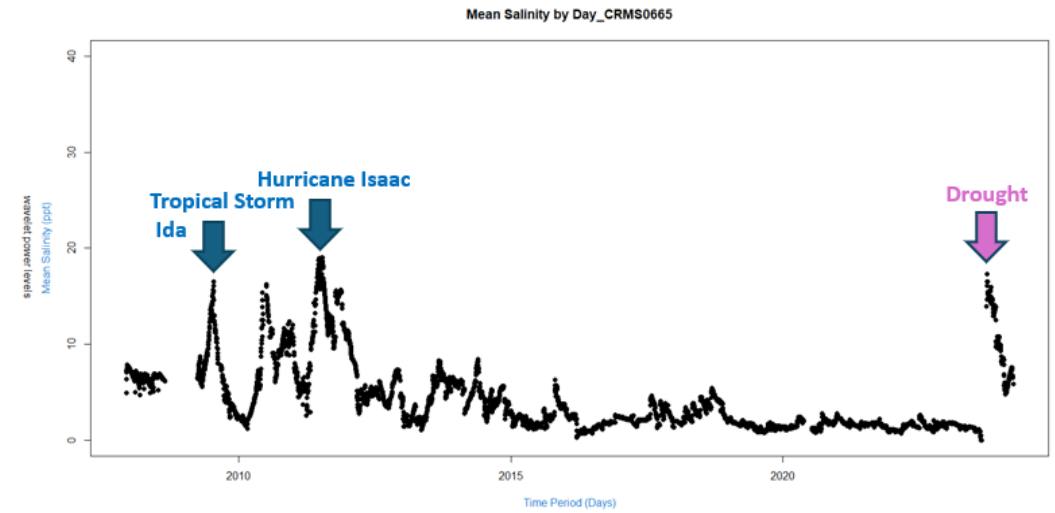
Transect Line 1.



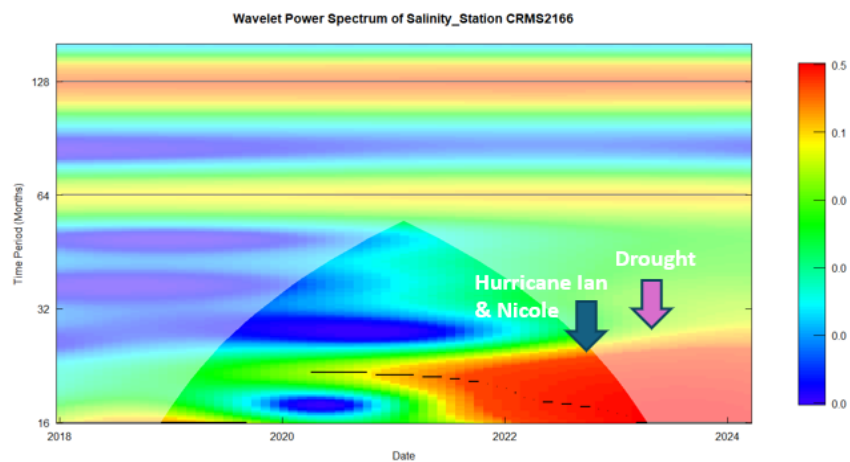
(a)



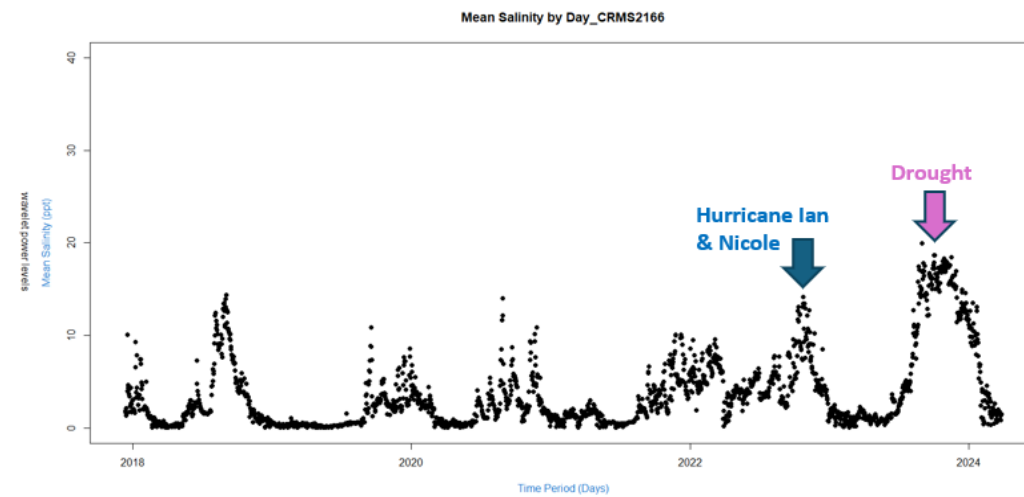
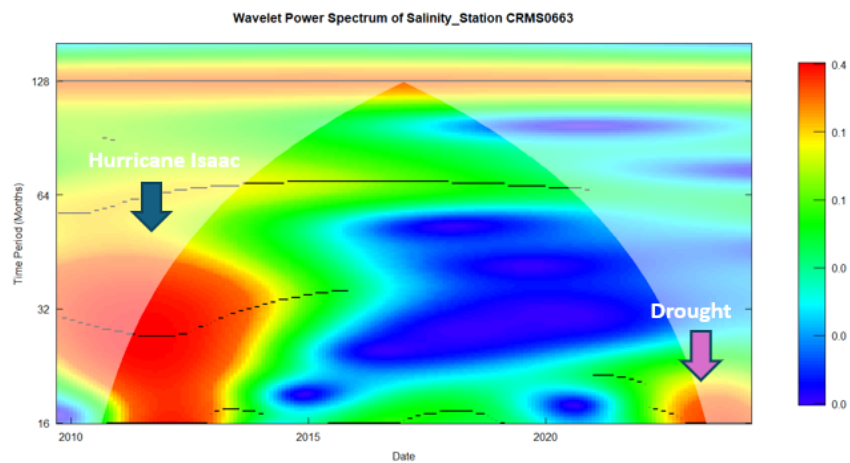
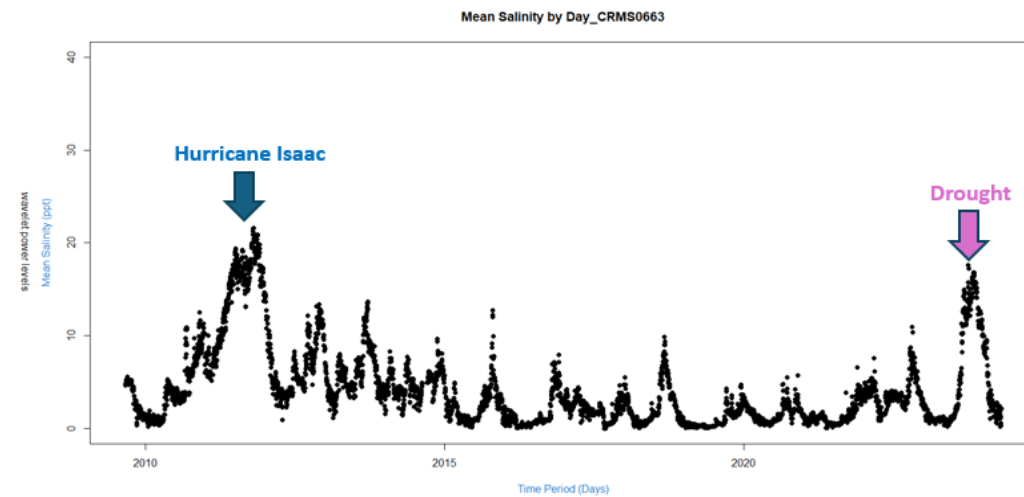
(b)



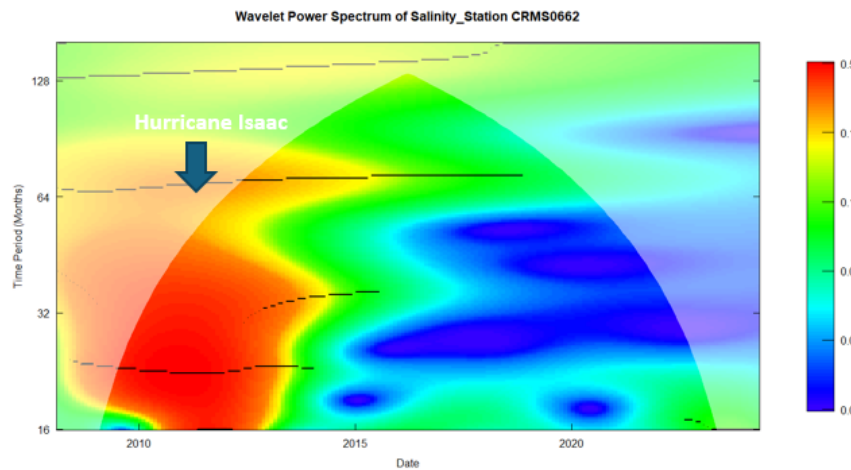
(a)



(b)



(a)



(b)

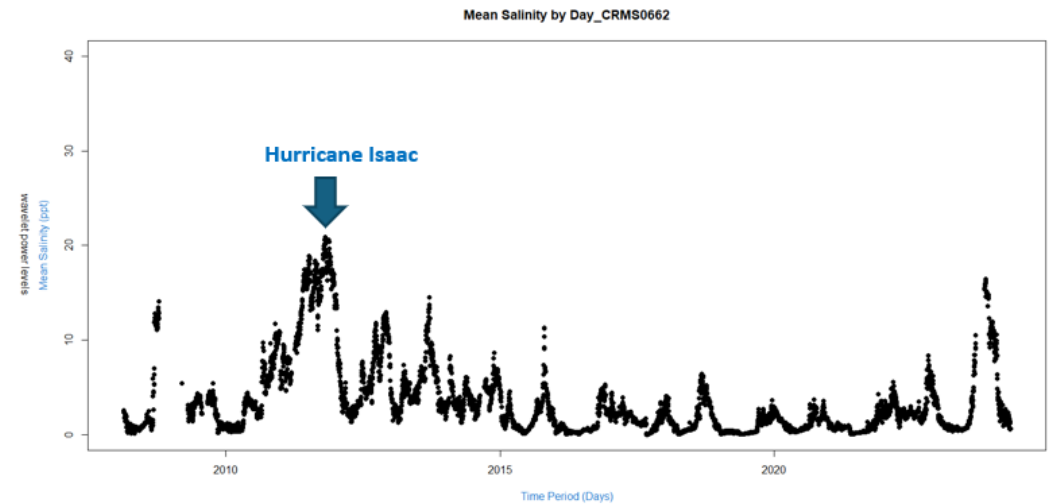
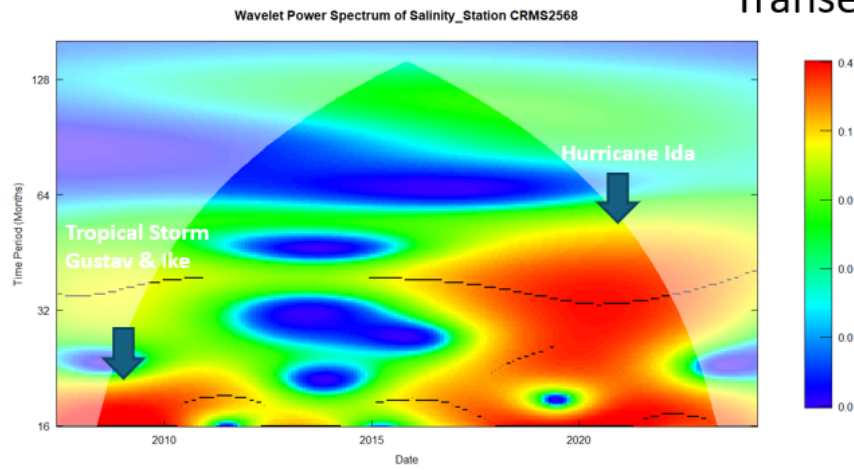


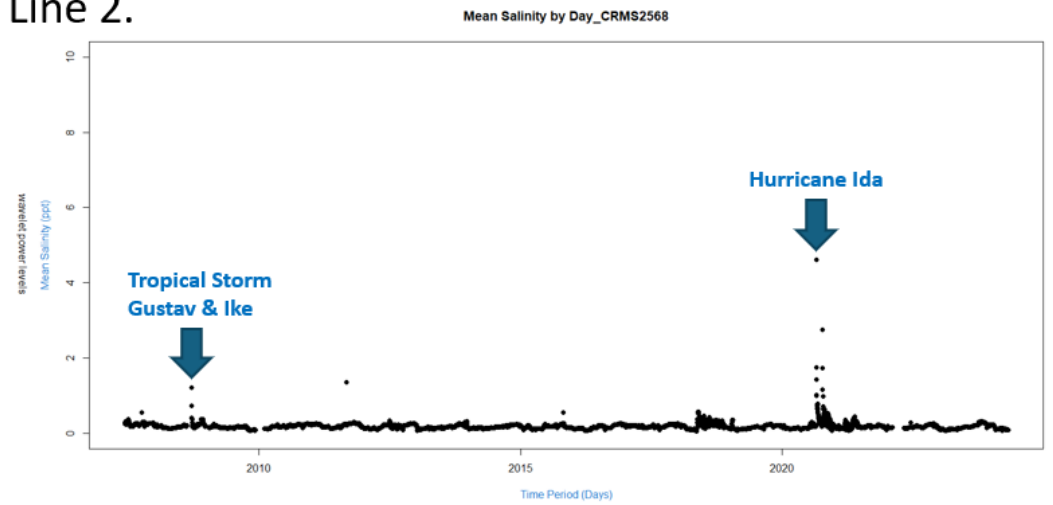
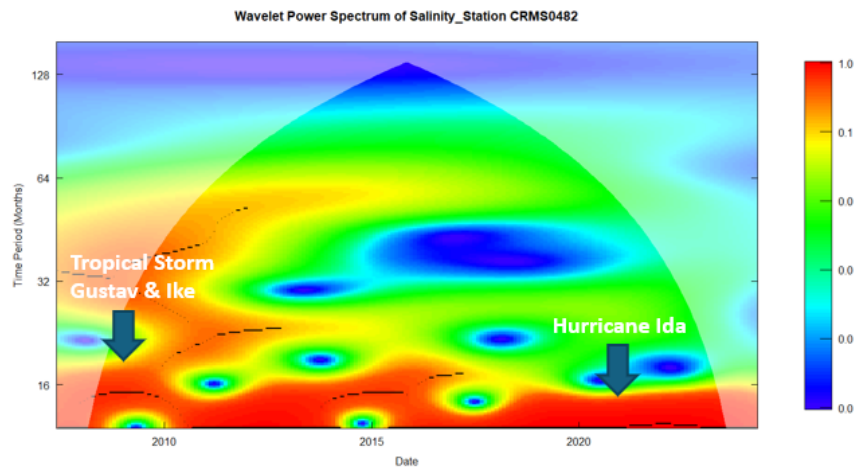
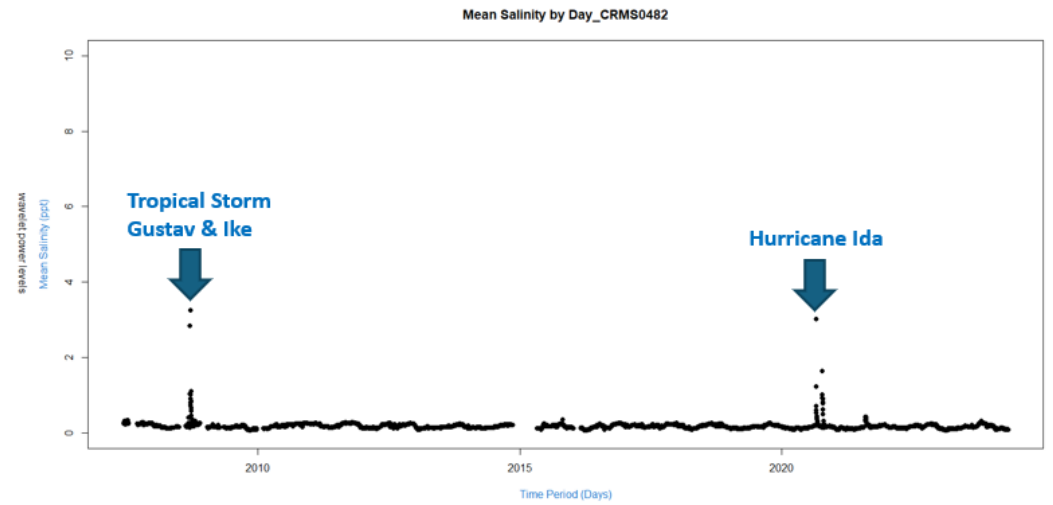
Figure 4-4 The Wavelet Power Spectra regarding Transect 1 as a function of time and frequency for the stations sorted from nearest to longest distance from the Louisiana's coastline. The more resilient is CRMS0662 station and less resilient CRMS2166 station according to the realizations of variance of the time series and the recovery time (days) after perturbation events. a) The graphs show that the variance increases in red areas and decreases in blue areas. b) The visualizations of total mean salinity (ppt) correlations with days for the period 2006-2024 of the time series respectively.

(a)

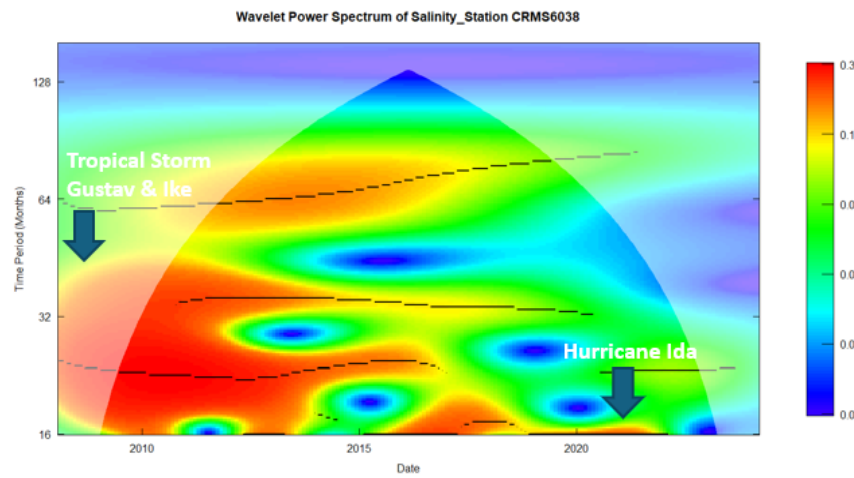
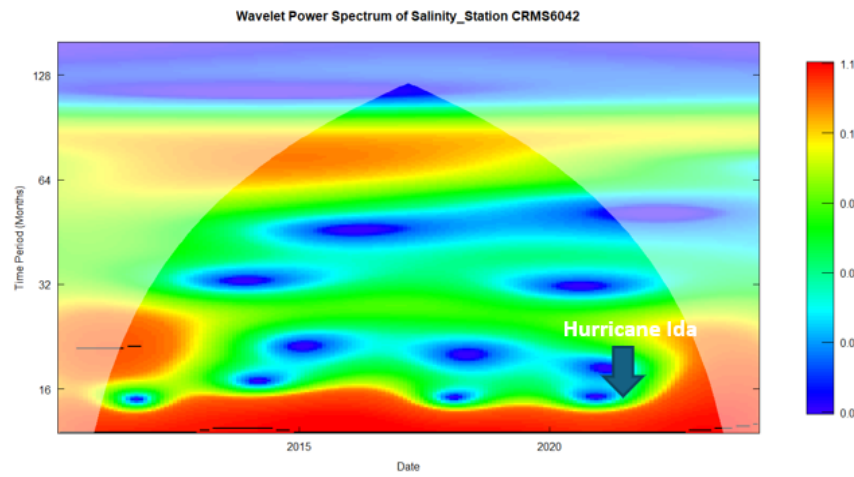


(b)

Transect Line 2.



(a)



(b)

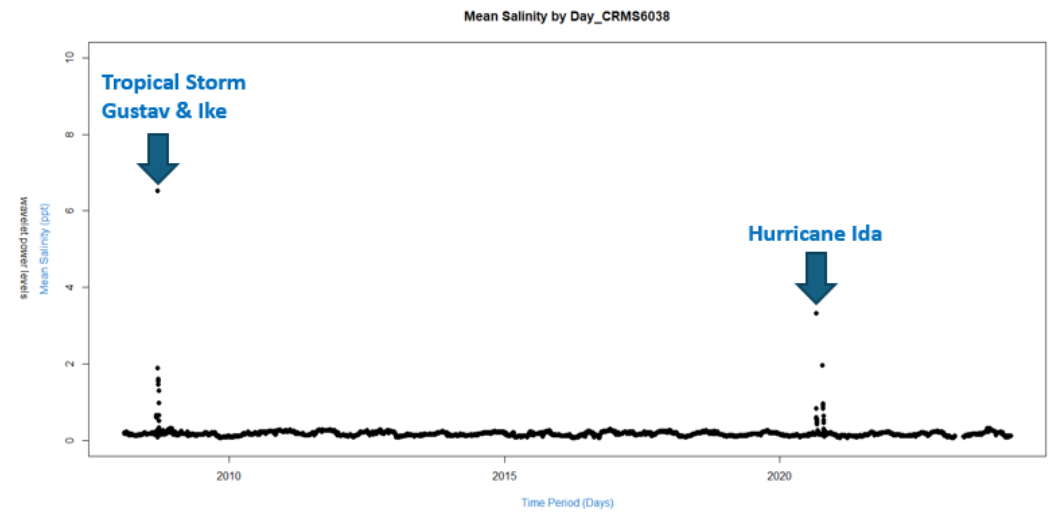
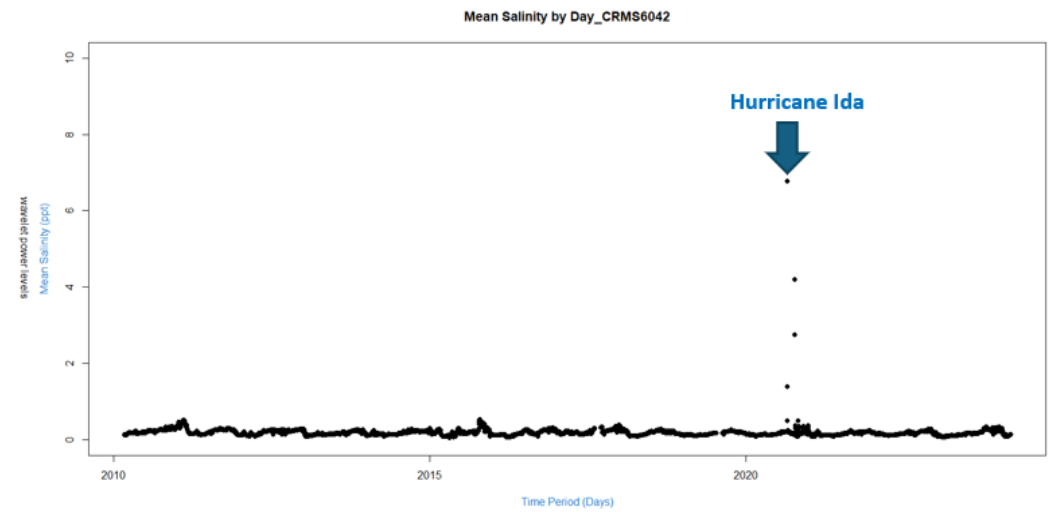
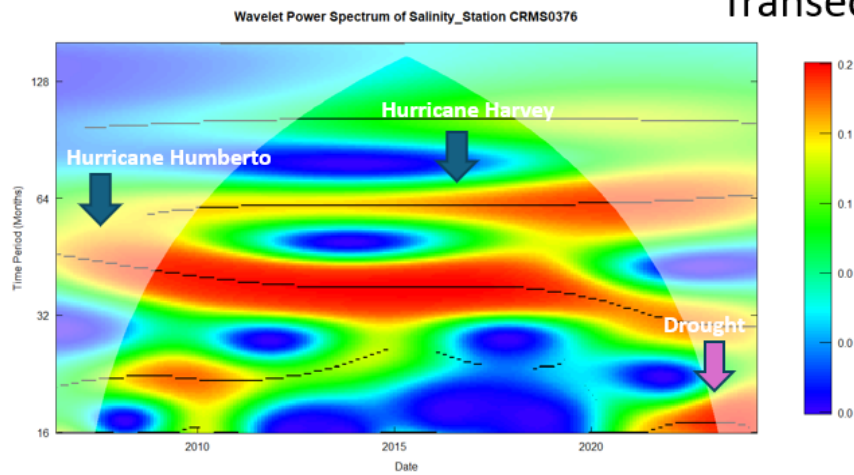


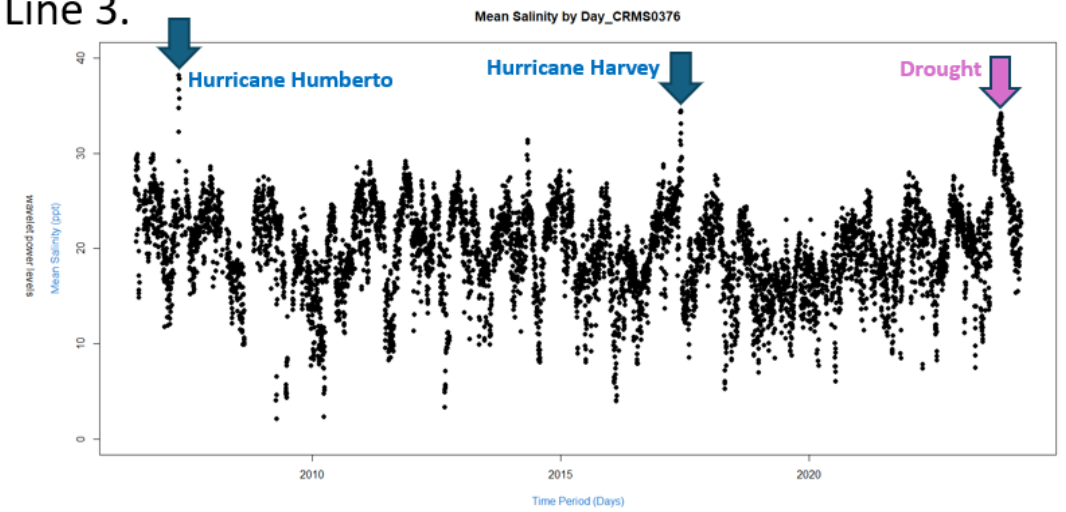
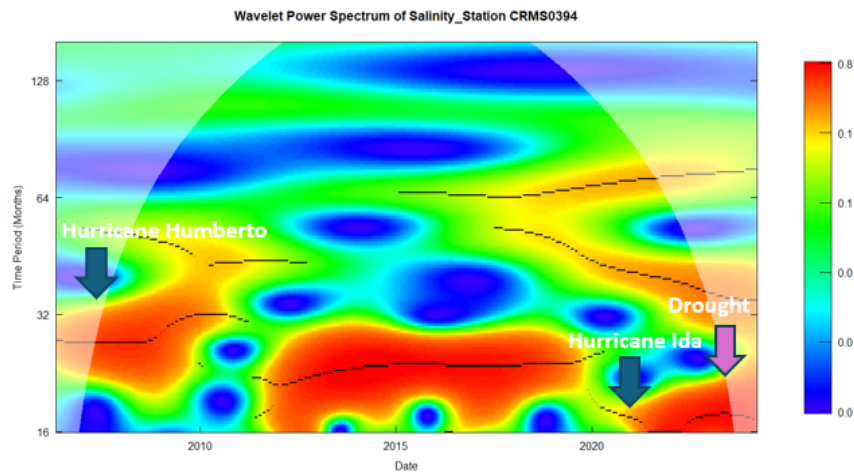
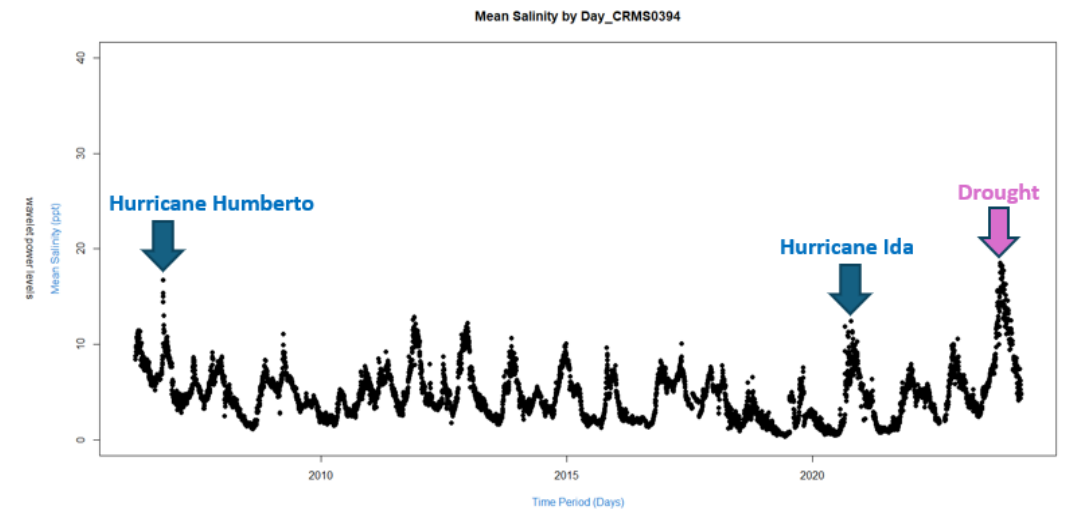
Figure 4-5 The Wavelet Power Spectra regarding Transect 2. as a function of frequency. The more resilient is CRMS6042 station and less resilient is CRMS2568 station according to the realizations of variance of the time series and the recovery time (days) after) after perturbation events. a) The graphs show that the variance increases in red areas and decreases in blue areas. b) The total mean salinity (ppt) correlations with days for the period 2006-2024.

(a)

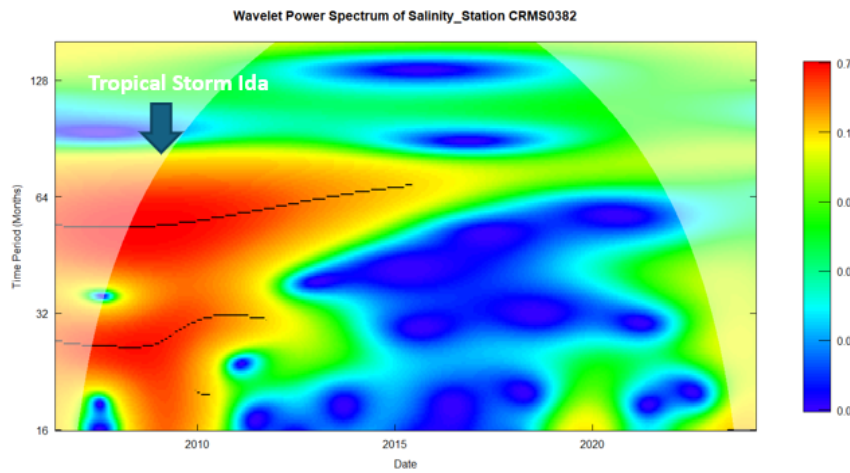


(b)

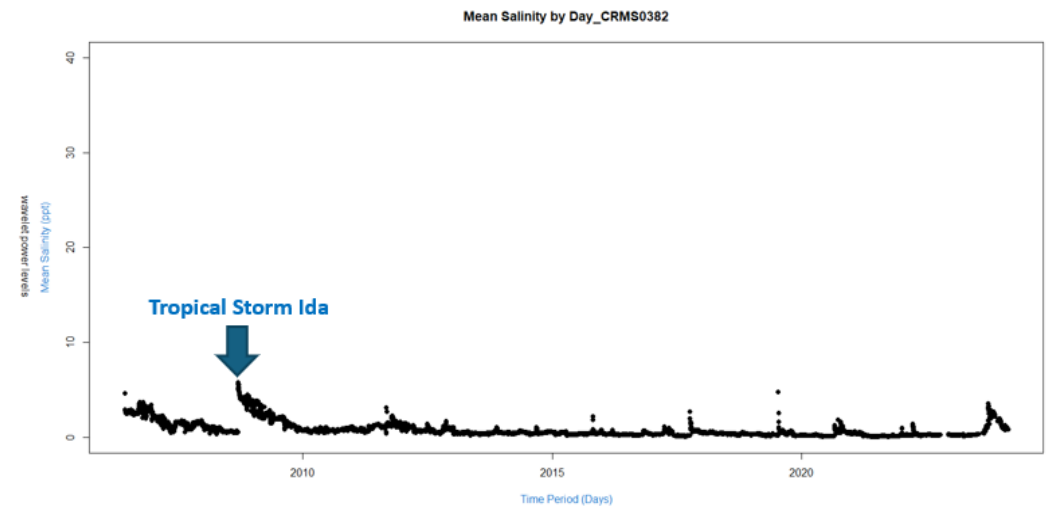
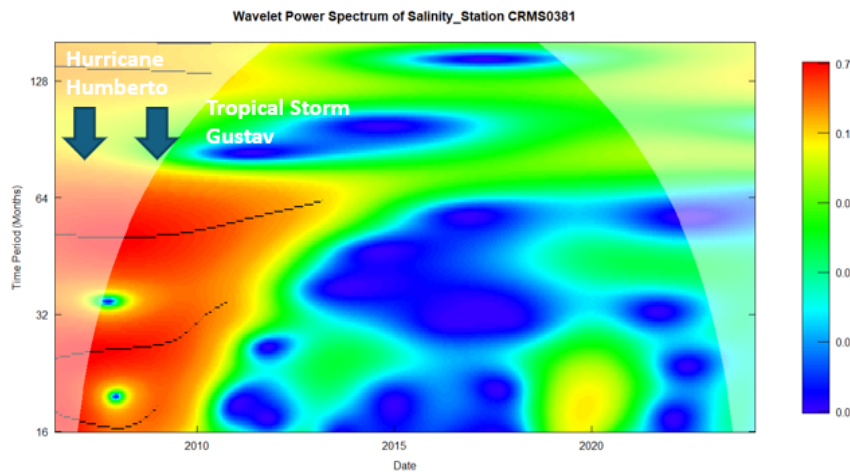
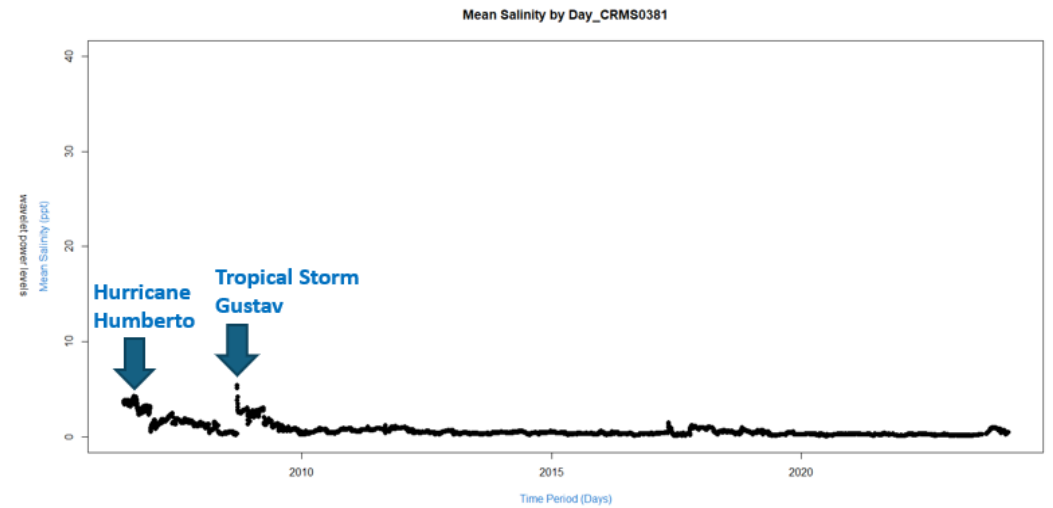
Transect Line 3.



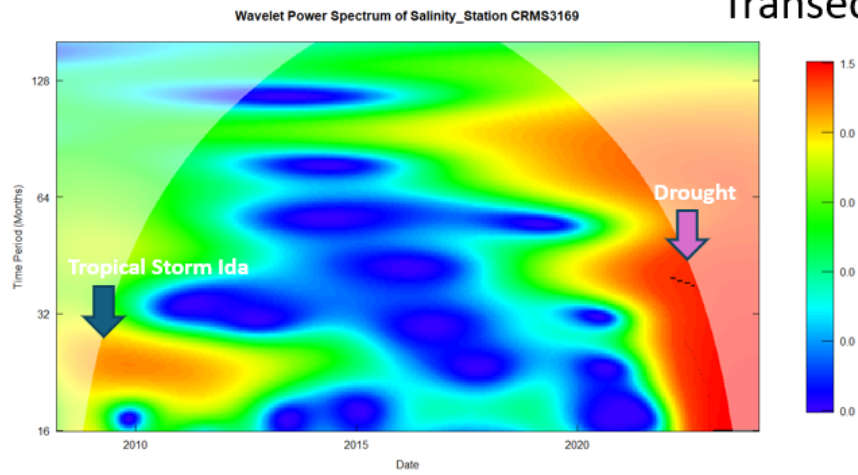
(a)



(b)



(a)



(b)

Transect Line 4.

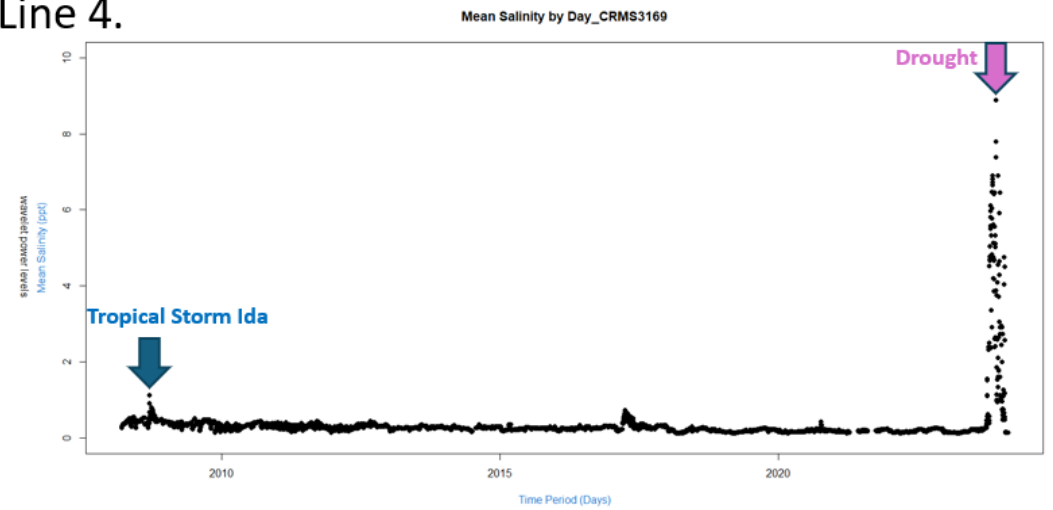
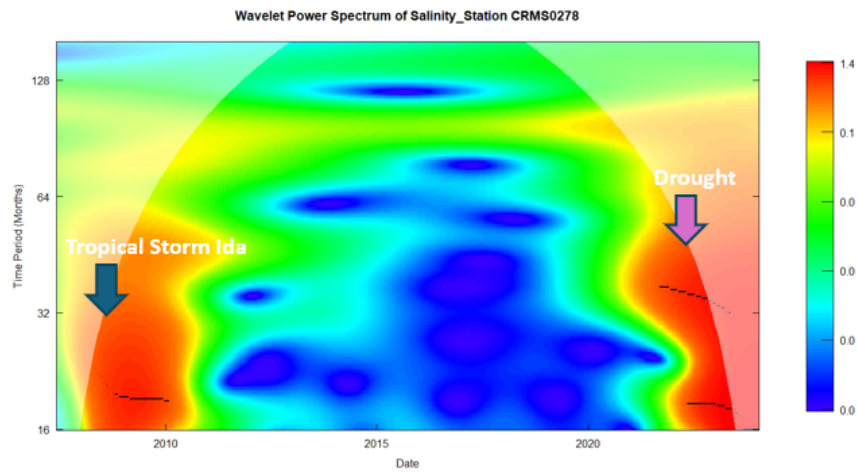
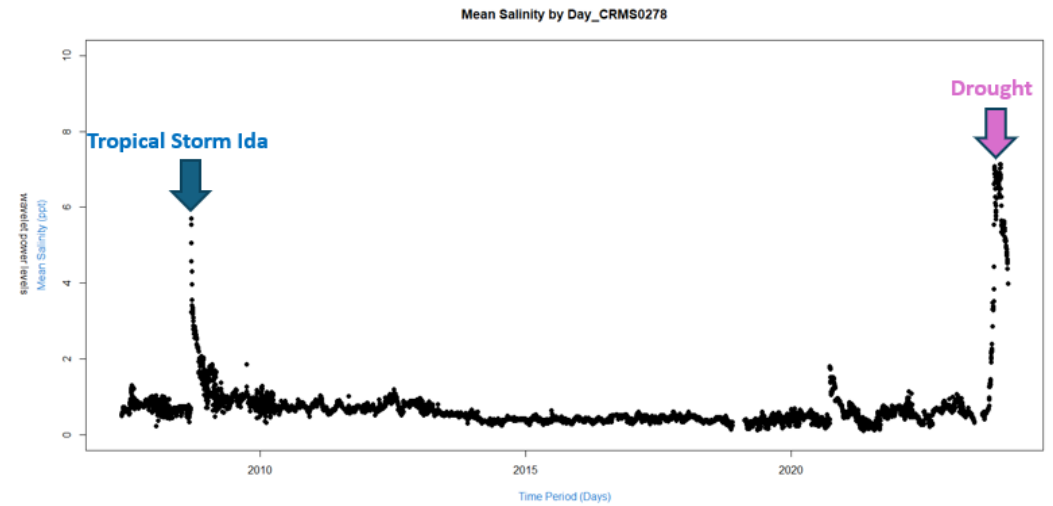
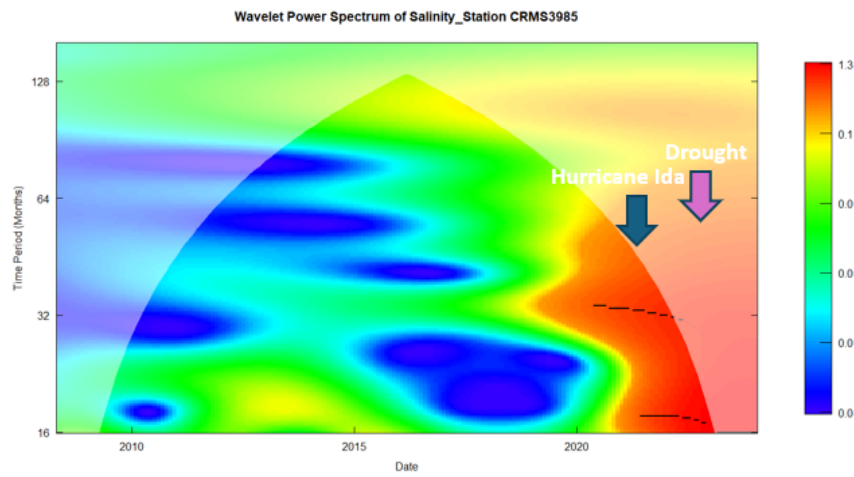
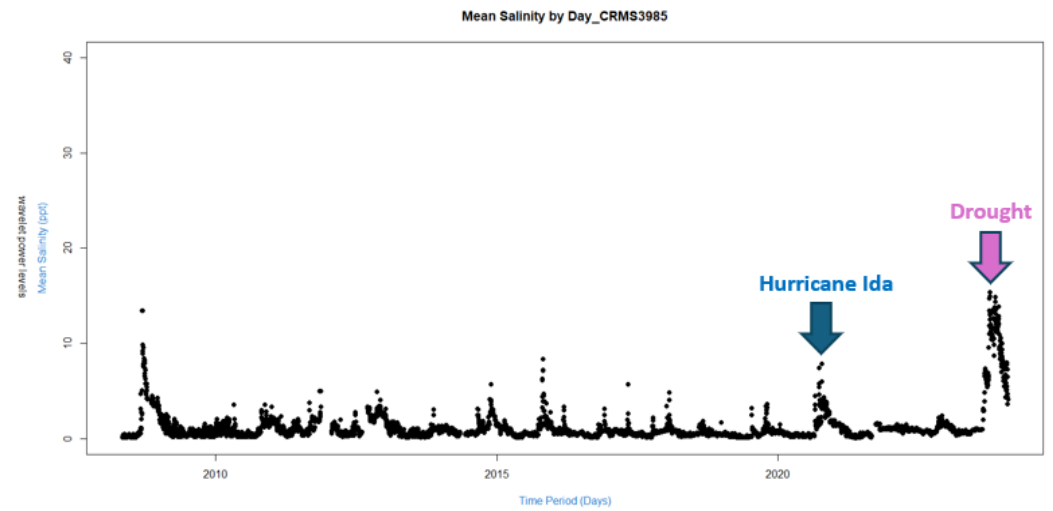
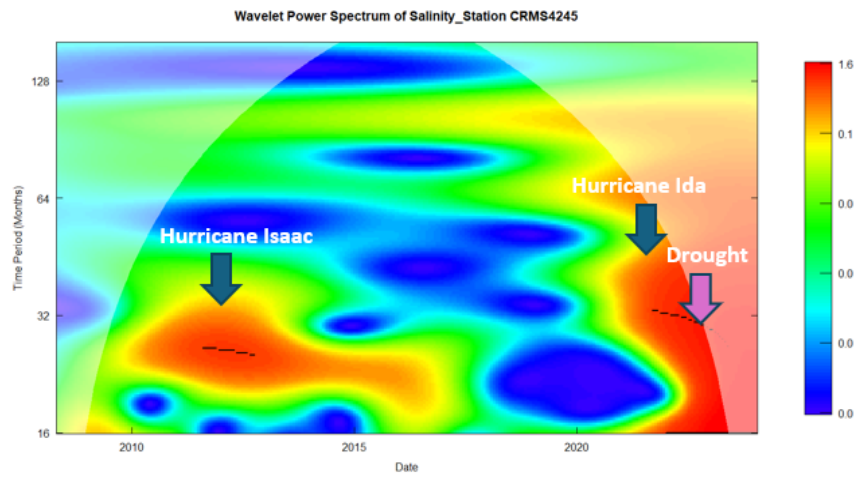
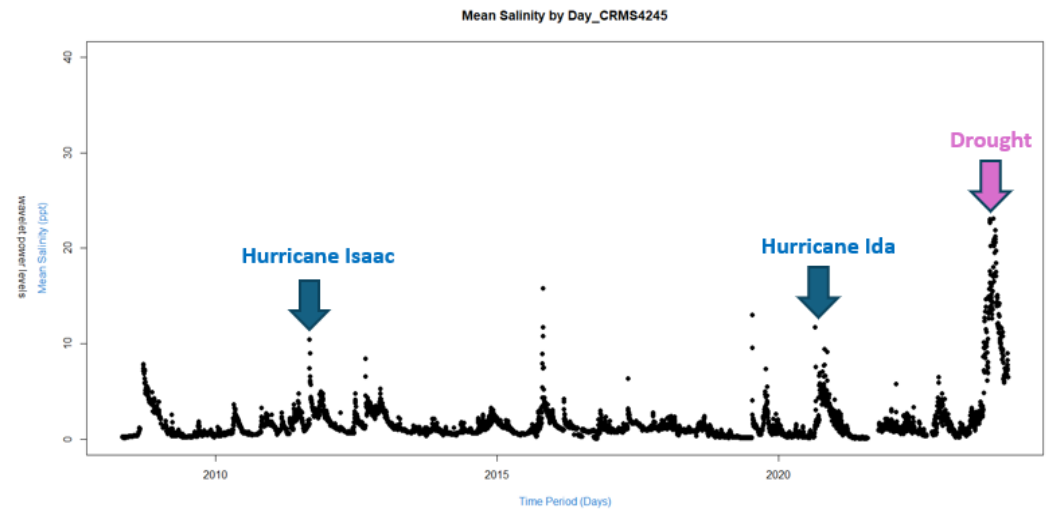


Figure 4-6 The Wavelet Power Spectra regarding Transect 3. as a function of frequency for the stations sorted from nearest to longest distance from the Louisiana's coastline. The more resilient is CRMS0382 station and less resilient CRMS0394 station according to the realizations of variance of the time series and the recovery time (days) after perturbation events. a) The graphs show that the variance increases in red areas and decreases in blue areas. b) The visualizations of total mean salinity (ppt) correlations with days for the period 2006-2024 of the time series respectively.

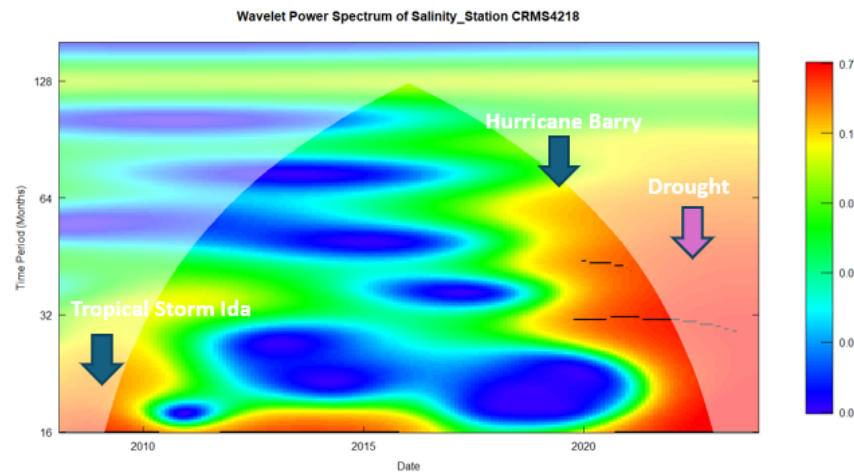
(a)



(b)



(a)



(b)

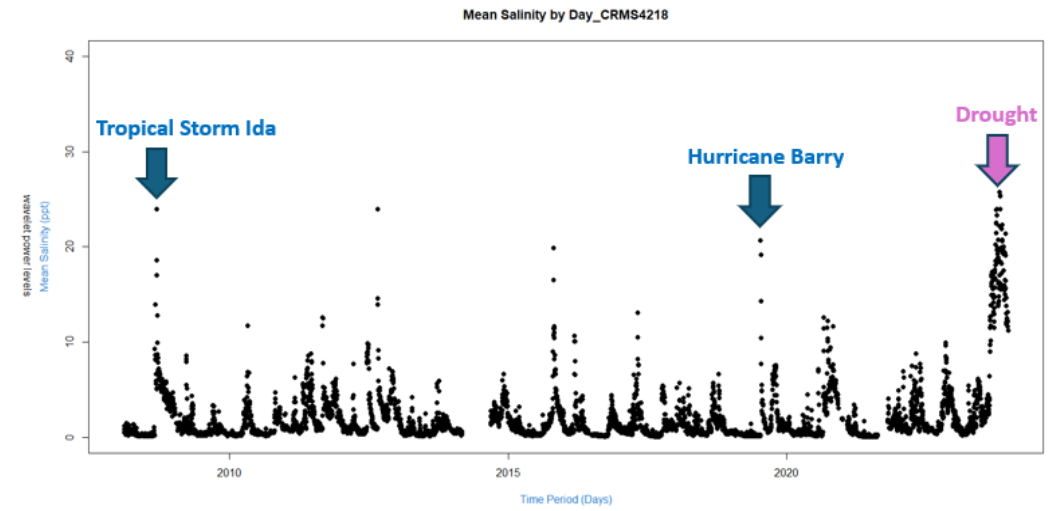
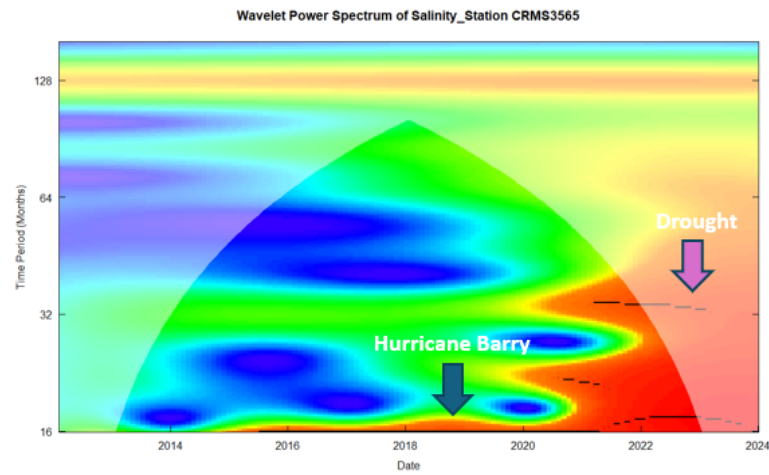
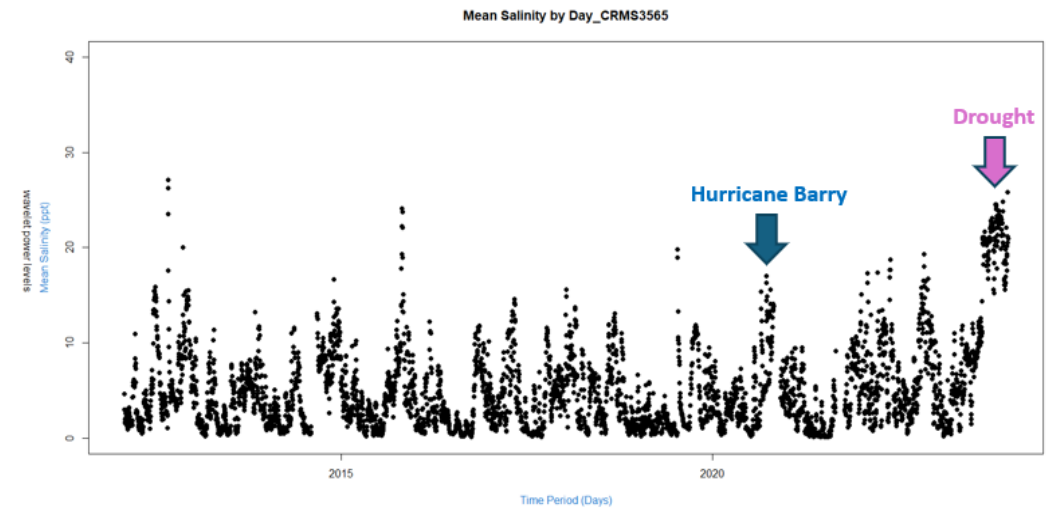
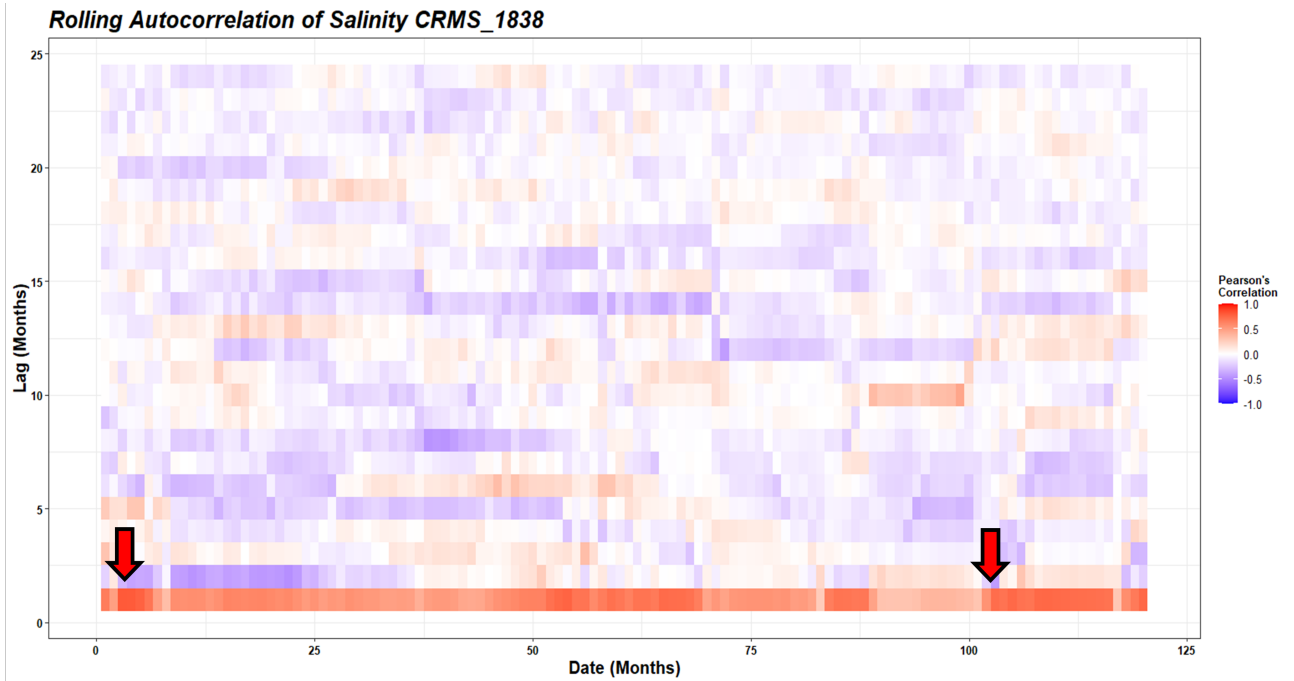
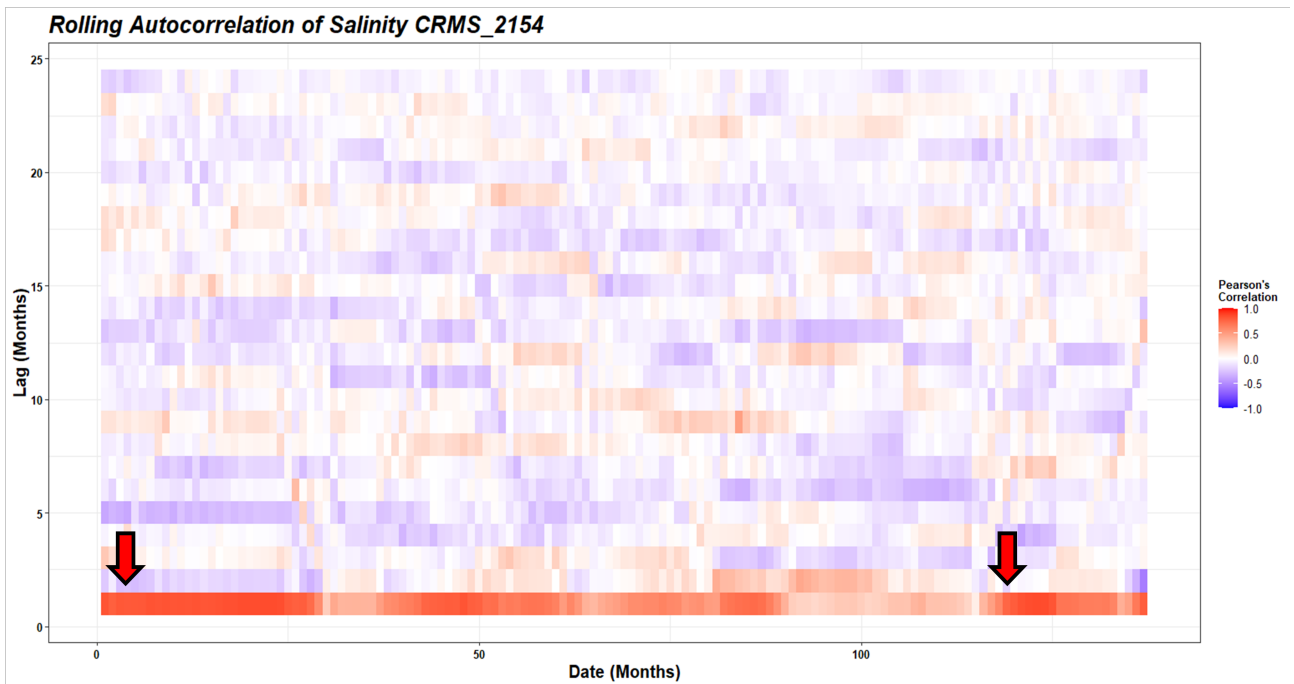
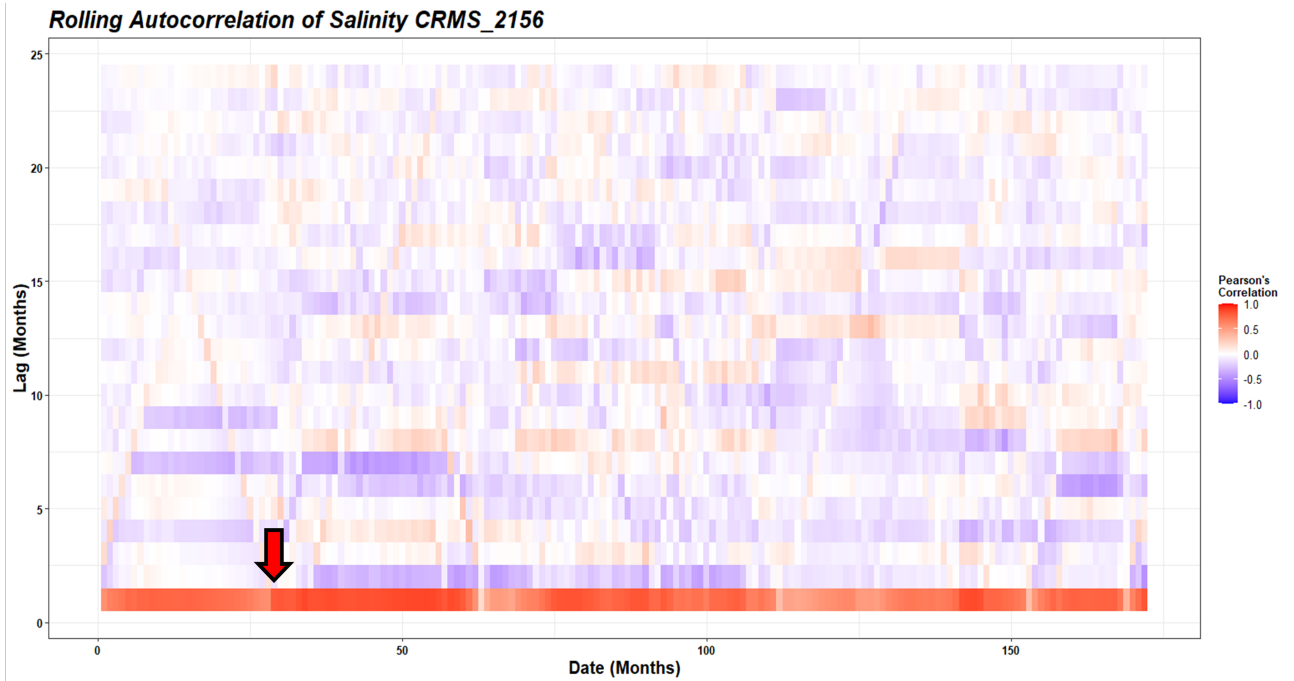
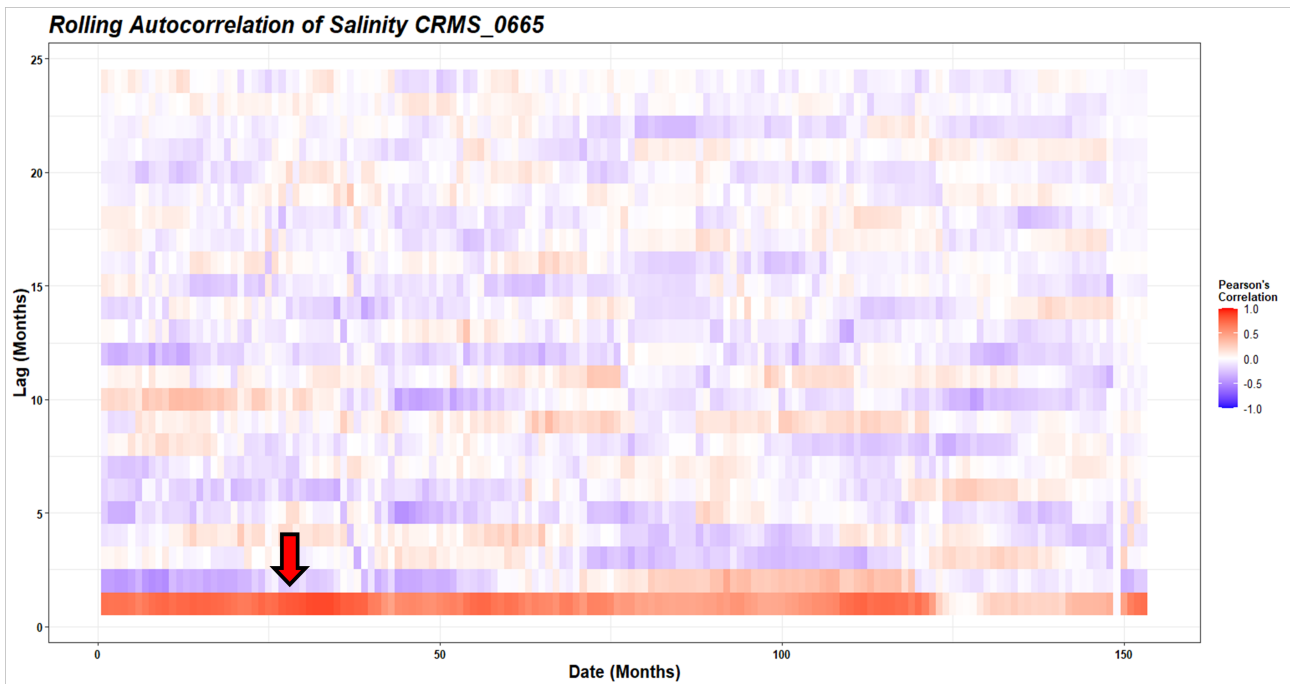


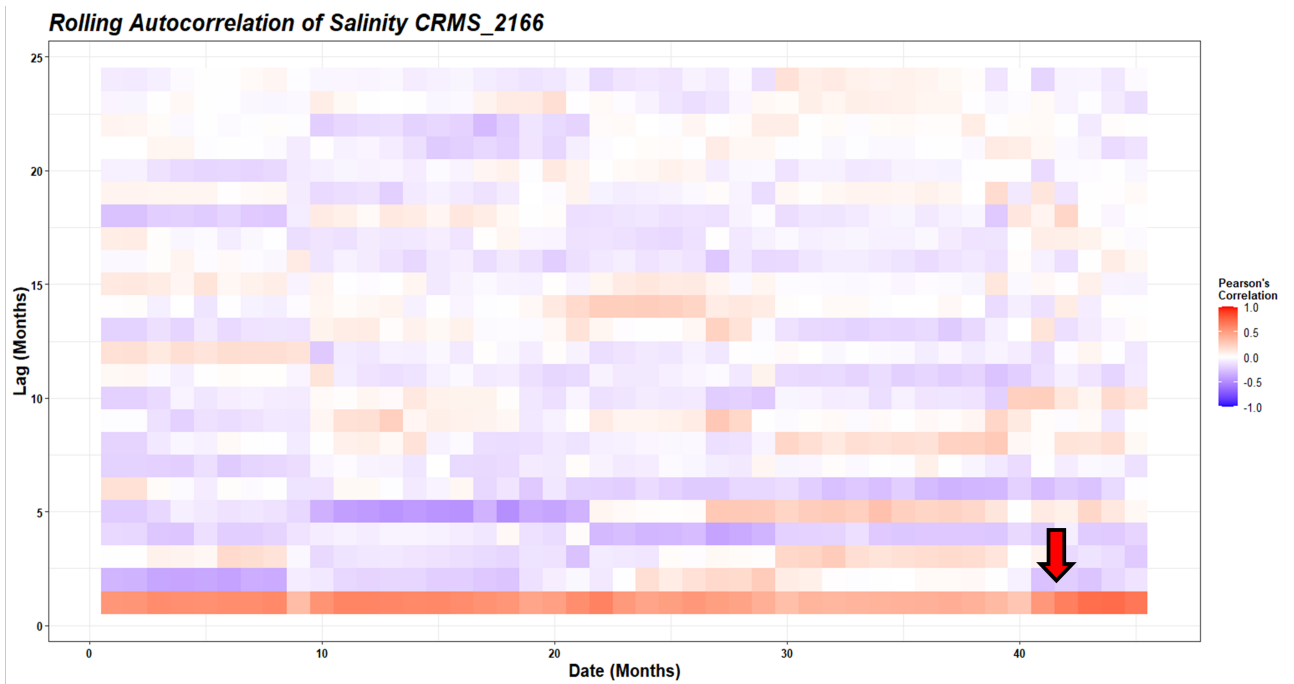
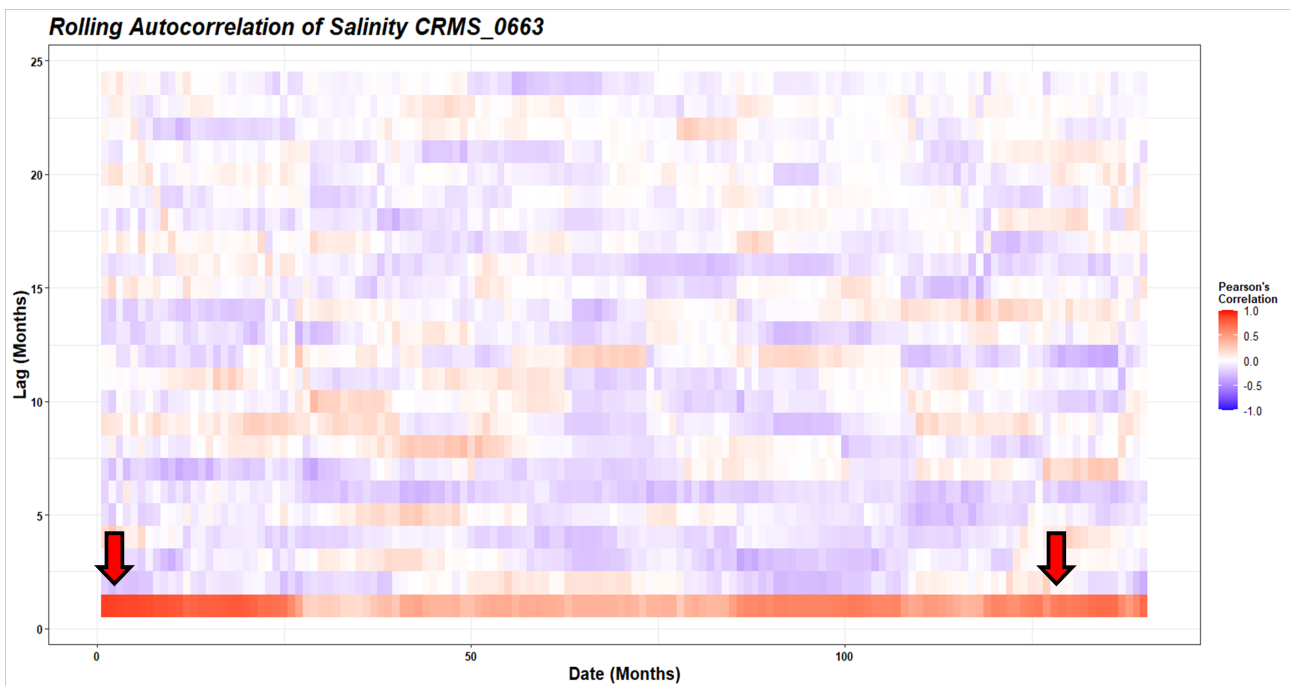
Figure 4-7 The Wavelet Power Spectrum regarding Transect 4. as a function of frequency for the stations sorted from nearest to longest distance from the Louisiana's coastline. The more resilient is CRMS3565 station and less resilient CRMS4218 station according to the realizations of variance of the time series and the recovery time (days) after perturbation events. a) The graphs show that the variance increases in red areas and decreases in blue areas. b) The visualizations of total mean salinity (ppt) correlations with days for the period 2006-2024 of the time series respectively.

Examining how the relationship between the variable of adjusted salinity in ppt (parts per thousands) and its lagged values changes over time I plotted the graphs for all the CRMS stations along the Transects (Figure 4-8, Figure 4-9, Figure 4-10, Figure 4-11). Essentially, it shows the autocorrelation of a time series data at different lags across moving windows of specified size. By applying a rolling autocorrelation, I can see how the correlation between a particular month and the previous months evolves over the time span of my dataset. Thus, determining accumulated autocorrelation at different lags, I can understand how past values of the series influence future values, a particularly useful for predictive modelling, where I need to identify which, past values are most relevant for forecasting future values. From the graphs a high positive autocorrelation value at *lag1* suggests that high values in my series tend to follow high values, indicating momentum. Sudden shifts or changes (e.g. dark red colour) in the plot can indicate events (hurricanes, tropical storms, drought) that have impacted the data.

Autocorrelation measures the correlation of a time series with its past and future values. The ACF plot is used to determine where in our time series data there is autocorrelation presence, allowing for a better interpretation of the observed temporal patterns as in Chapter 2. In Figure 4-8 to Figure 4-11, accumulated rolling autocorrelation analysis of adjusted salinity (ppt) is plotted with lagged months- at different lags with maximum lag of =24. In these figures, red arrows indicate the regions where the critical transitions were observed through time in the rolling autocorrelation plots. The colour bar graded from blue to red shows the correlation of the values. The CSD relationship and the points where disturbance events took place are represented by the direction of the red arrows. Whilst the ACF plots show some noise in the data, there are signs of autocorrelations in time indicated by horizontal stretches of pixels of the same hue. The highest positive autocorrelations occur for *lag* of first month which may indicate seasonality in adjusted salinity (ppt) input to the Transect Line.







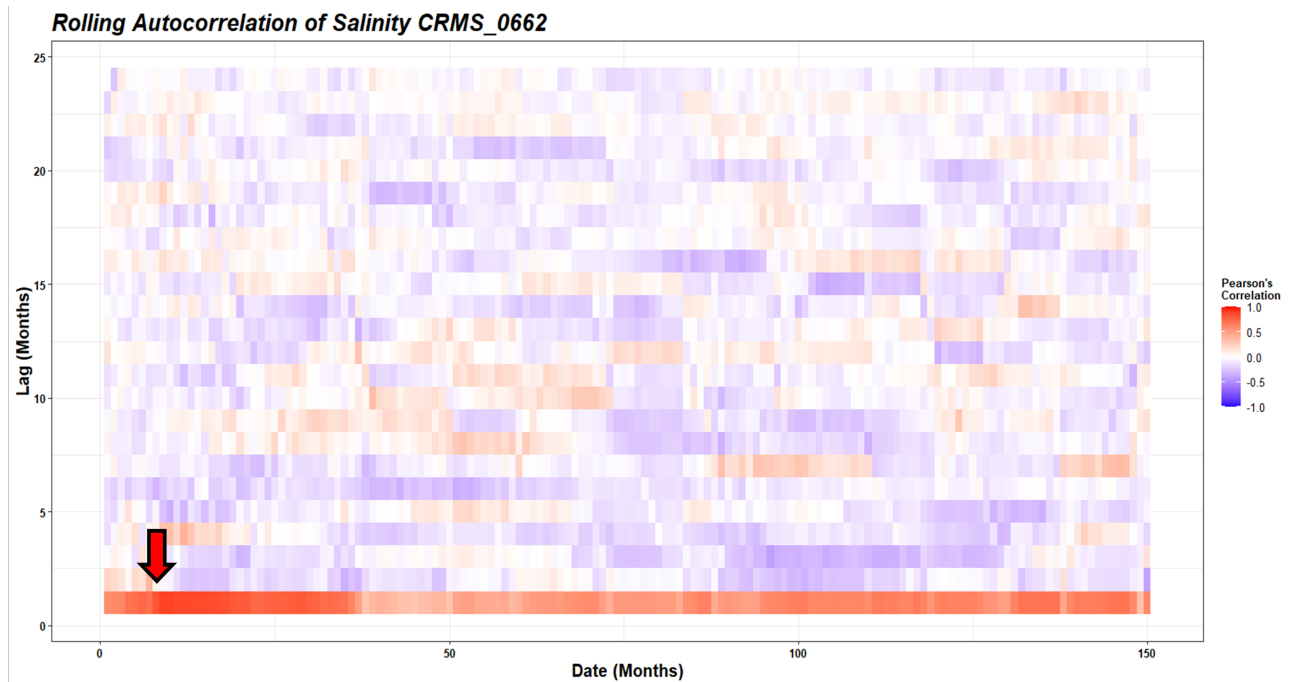
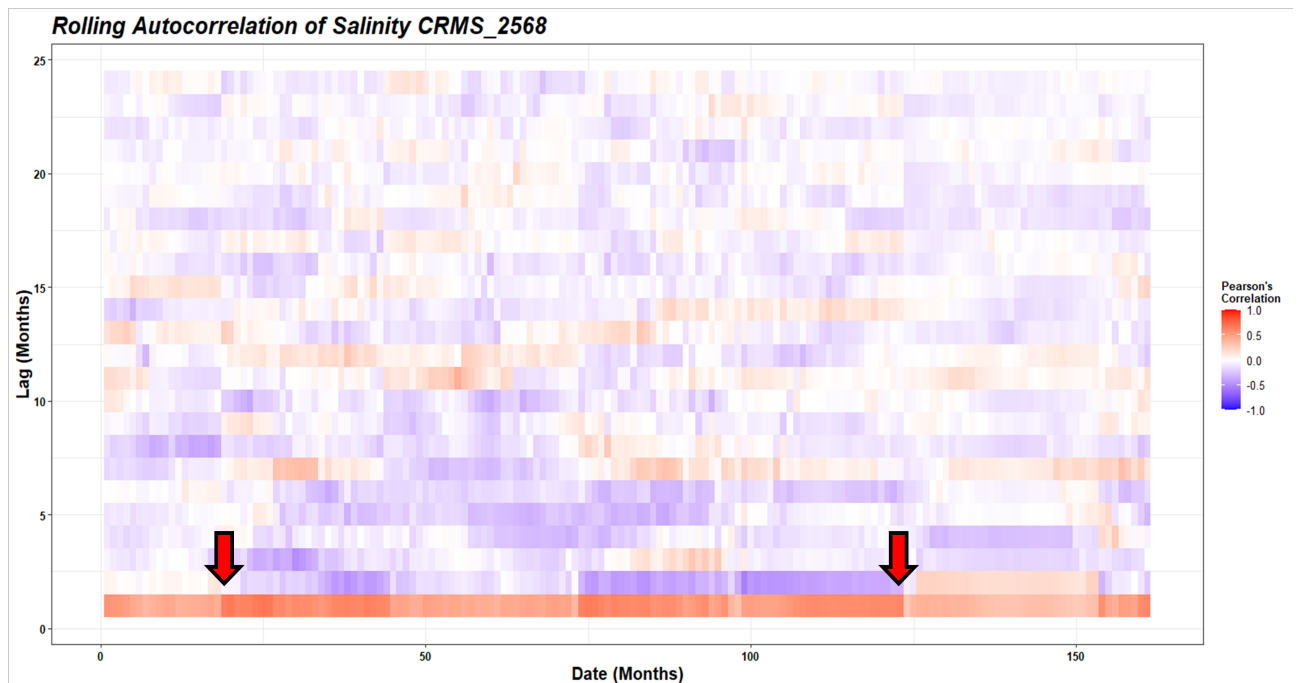
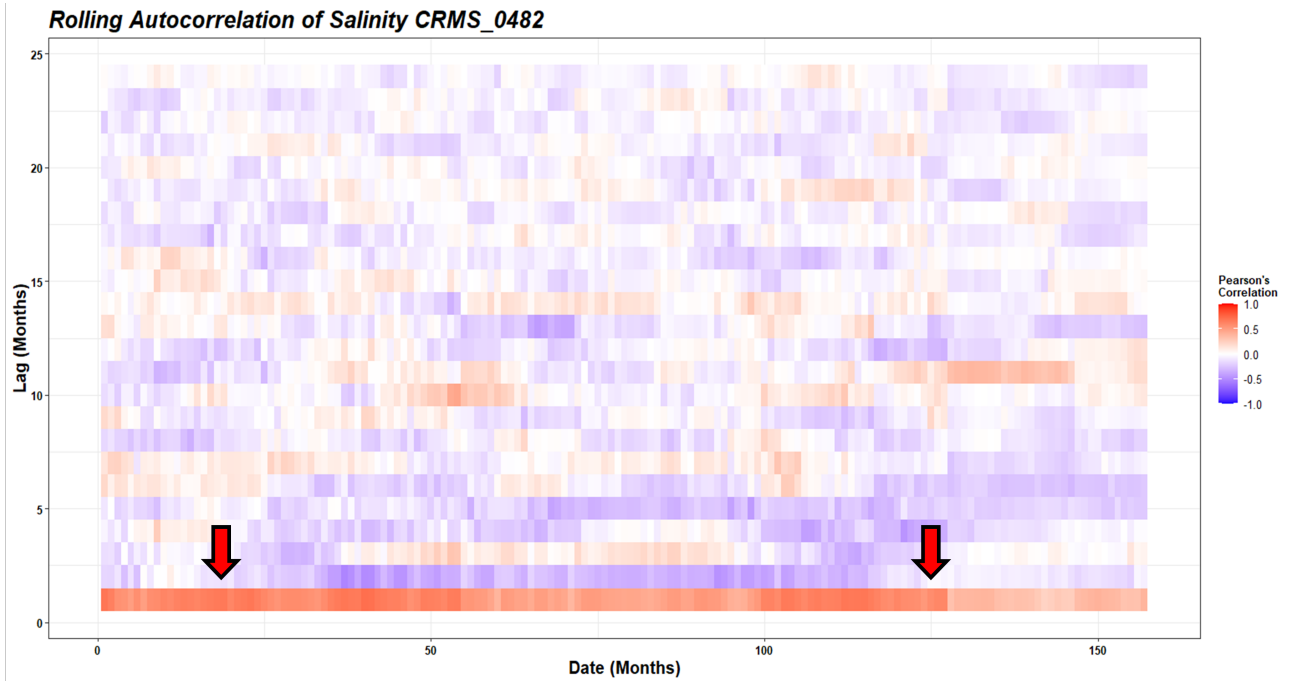
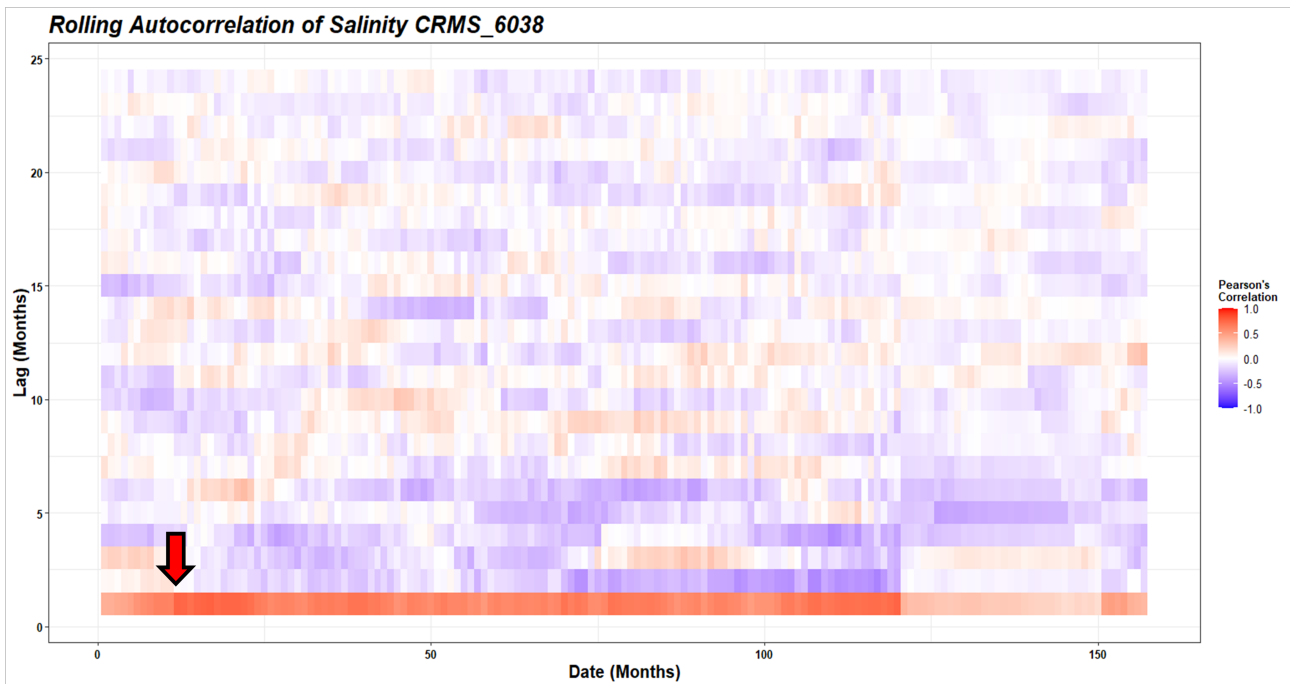


Figure 4-8 Transect Line 1. The Rolling autocorrelation plots for adjusted salinity (ppt) with lag(months) and date (months)-period 2006-2024. We indicated with red arrows the regions where the critical transitions observed through time in rolling autocorrelation plots and according to Pearson's method.





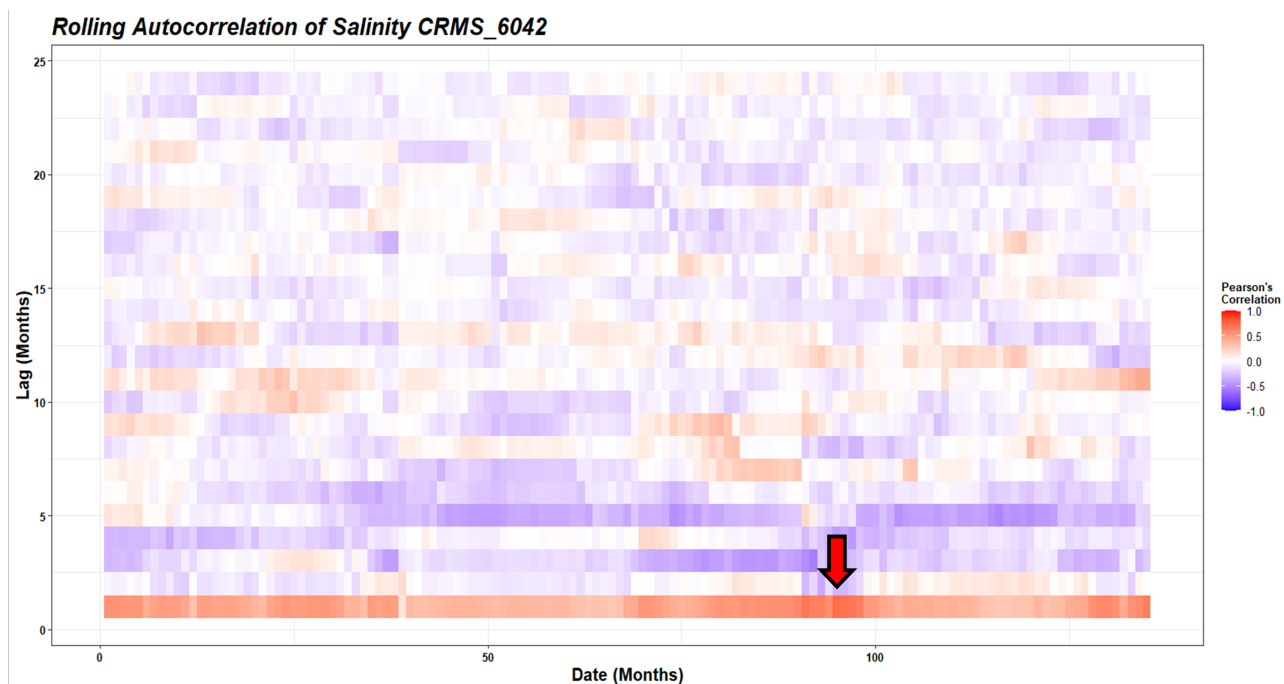
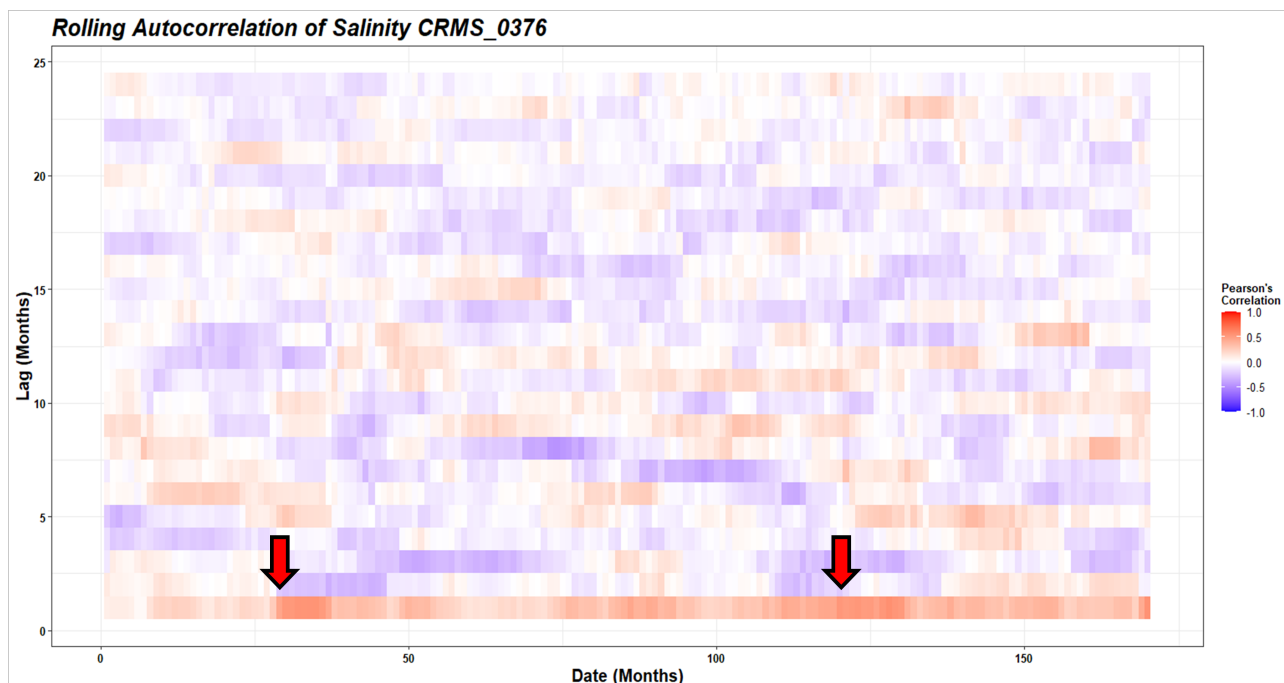
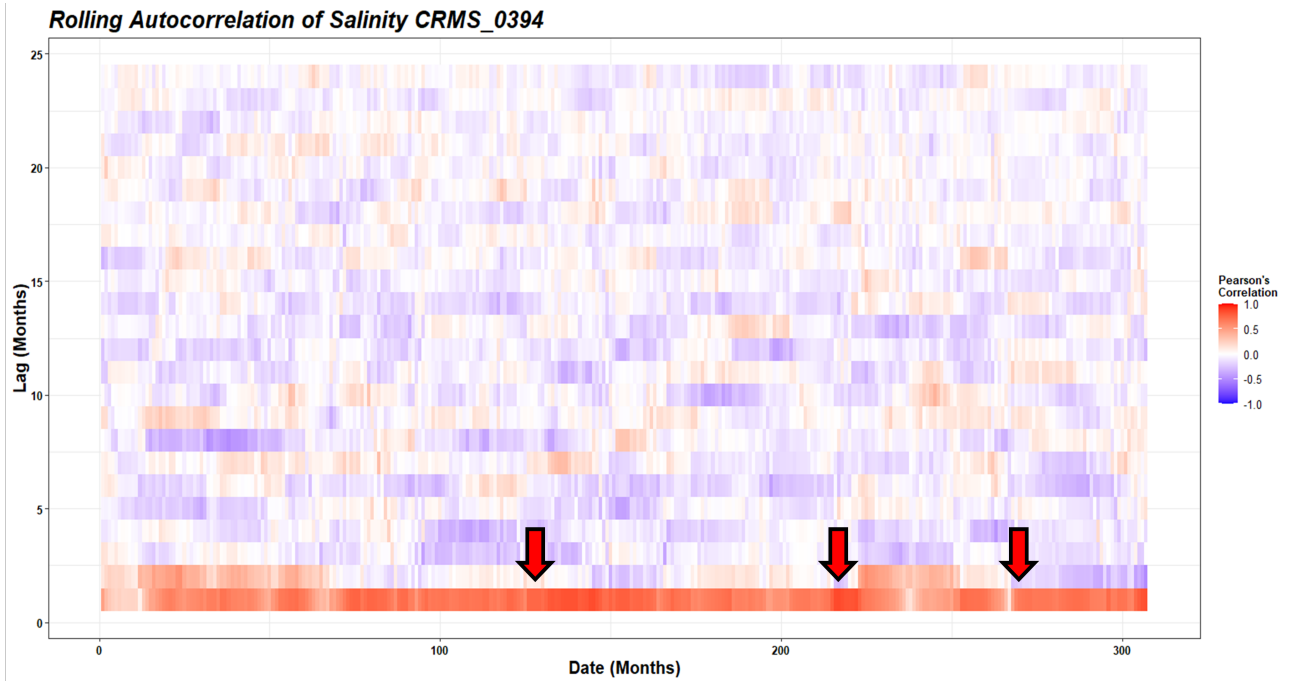
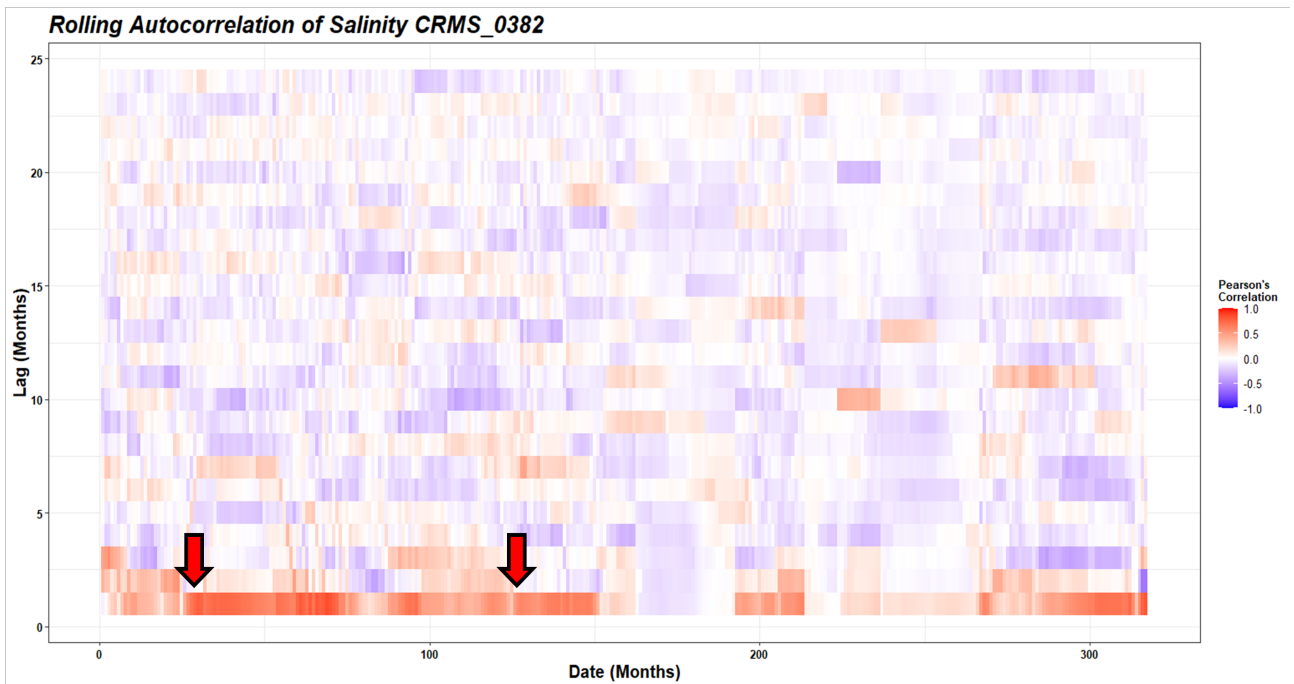


Figure 4-9 Transect Line 2. The Rolling autocorrelation plots for adjusted salinity (ppt) with lag(months) and date (months)-period 2006-2024. We indicated with red arrows the regions where the critical transitions observed through time in rolling autocorrelation plots and according to Pearson's method.





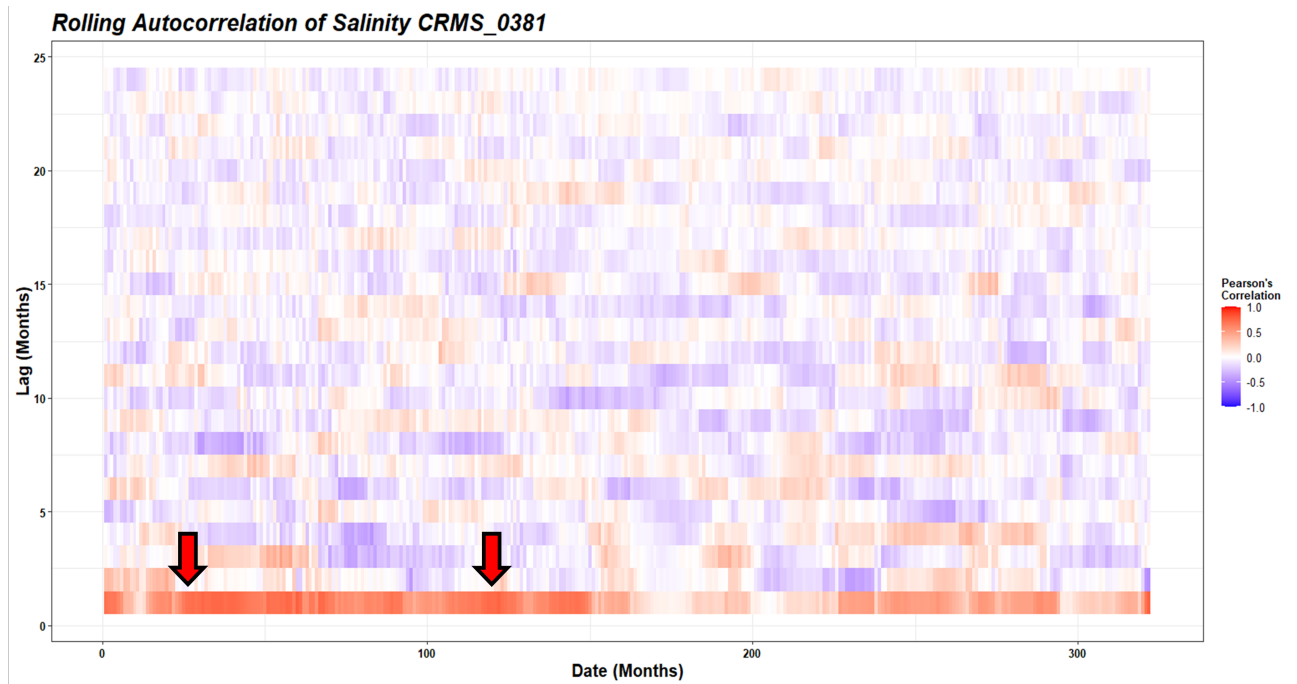
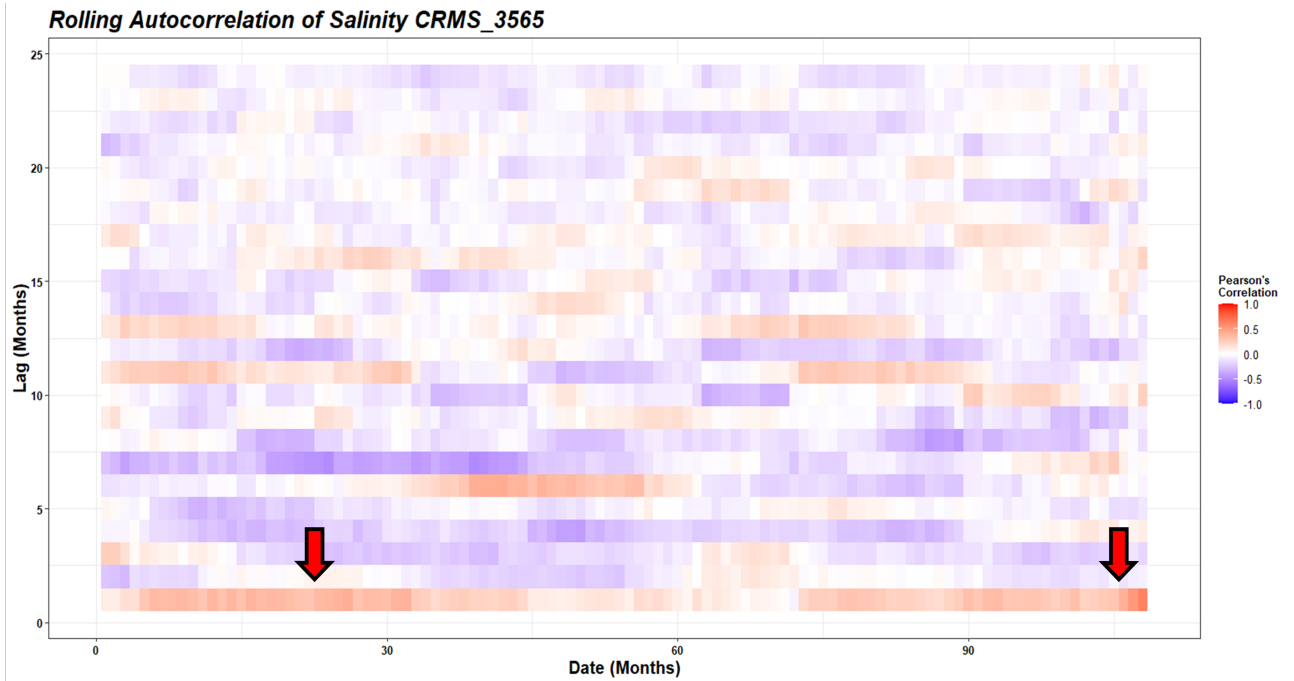
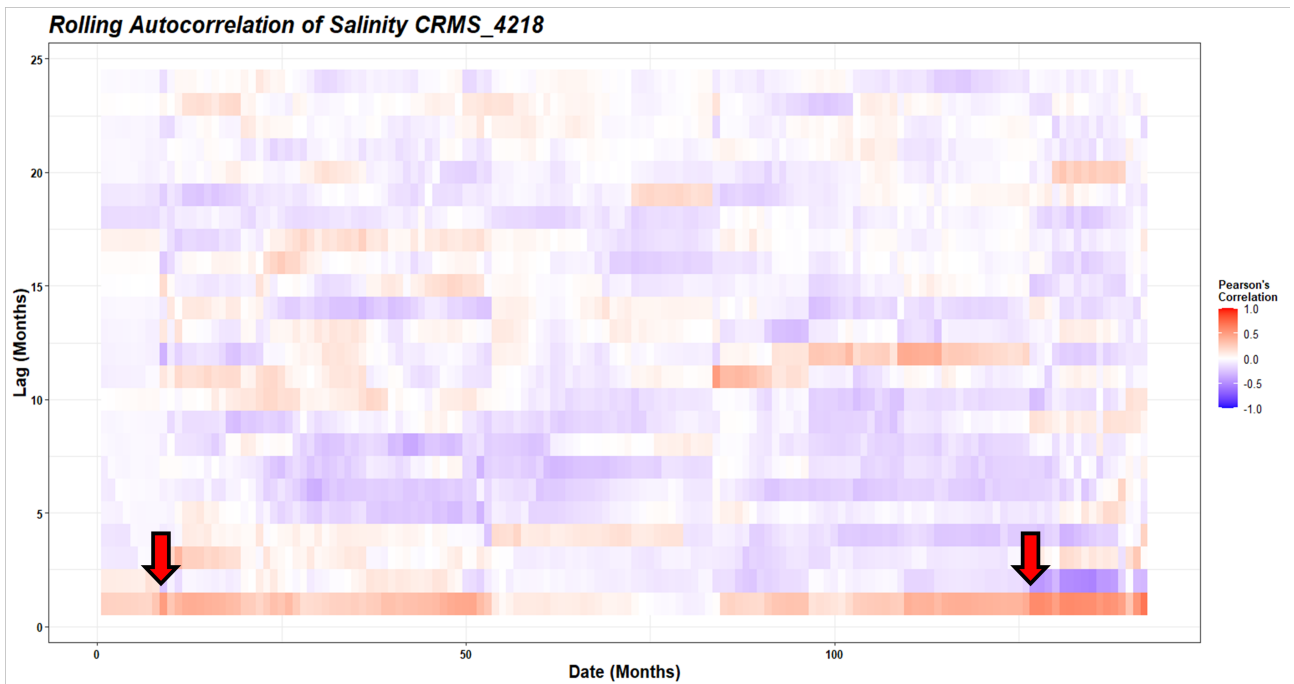
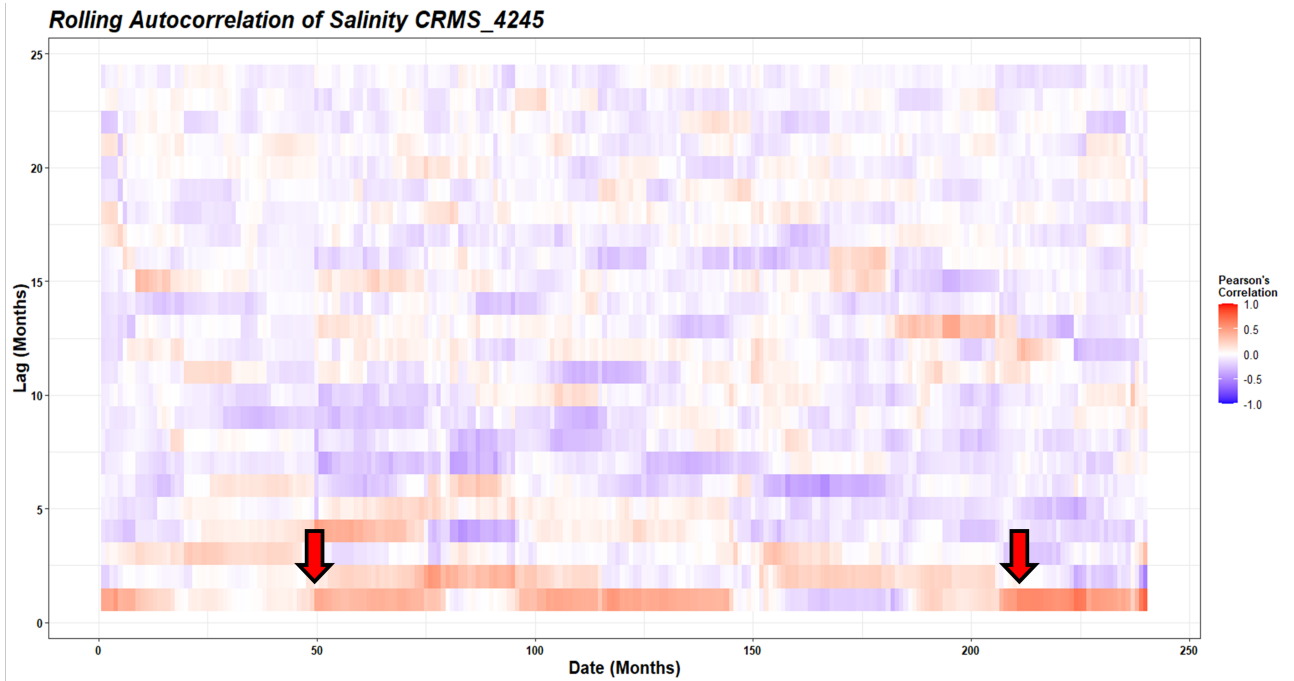
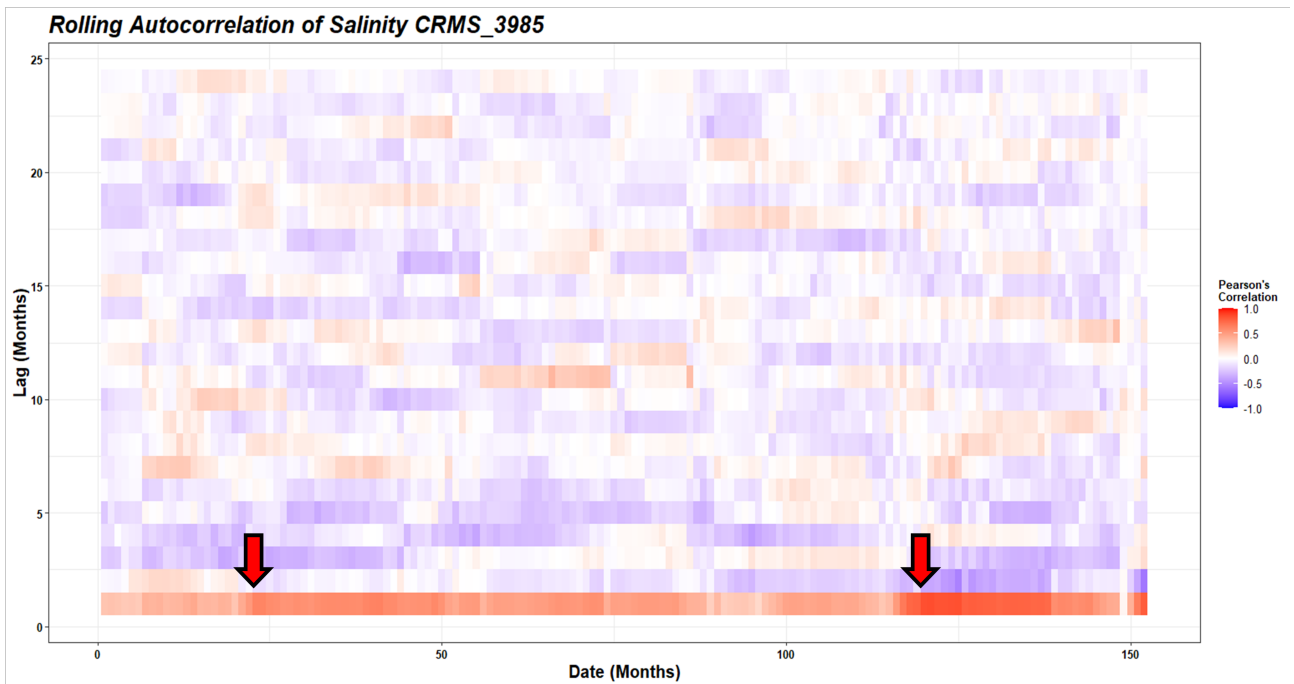


Figure 4-10 Transect Line 3. The Rolling autocorrelation plots for adjusted salinity (ppt) with lag(months) and date (months)-period 2006-2024. We indicated with red arrows the regions where the critical transitions observed through time in rolling autocorrelation plots and according to Pearson's method.





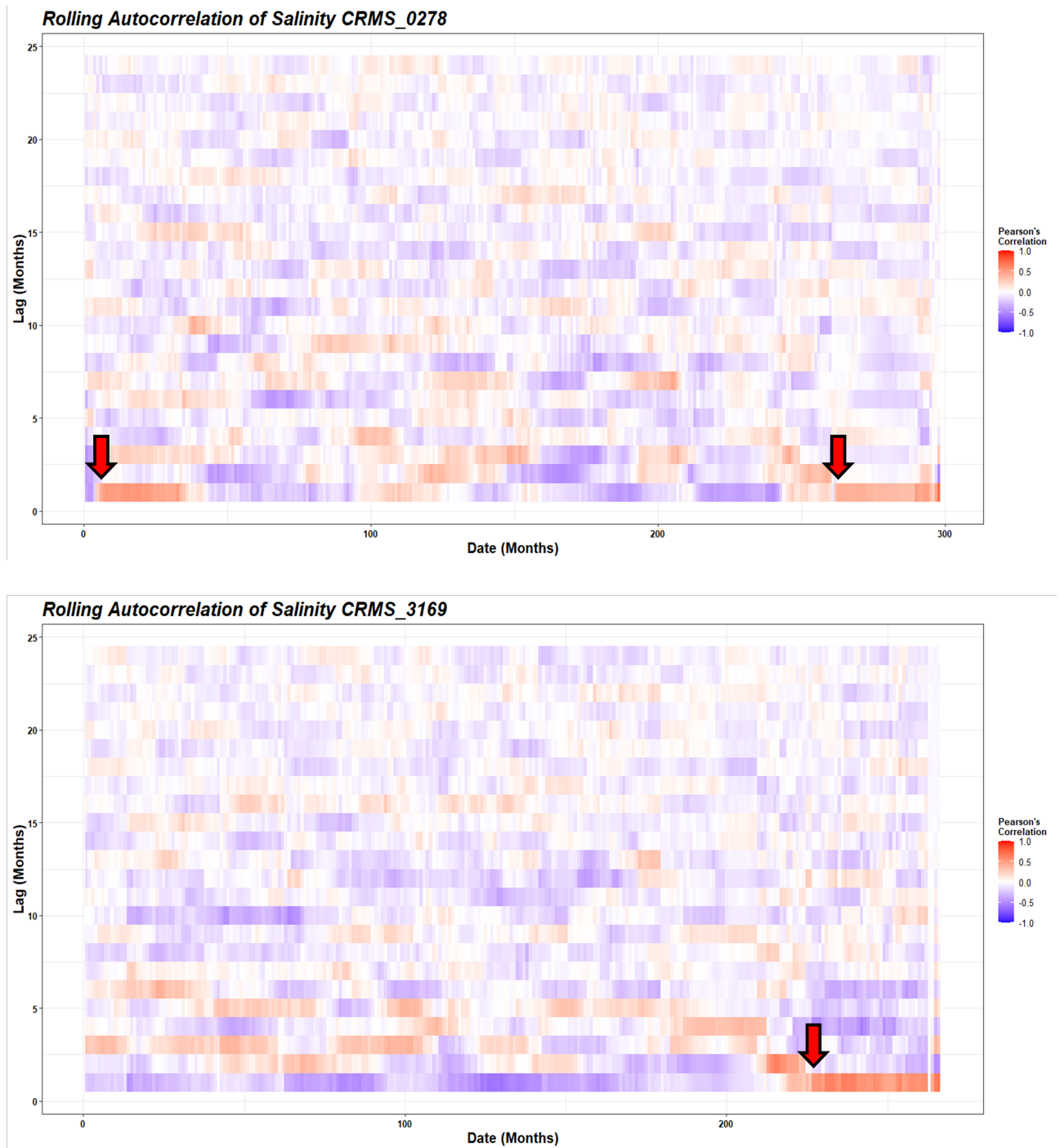
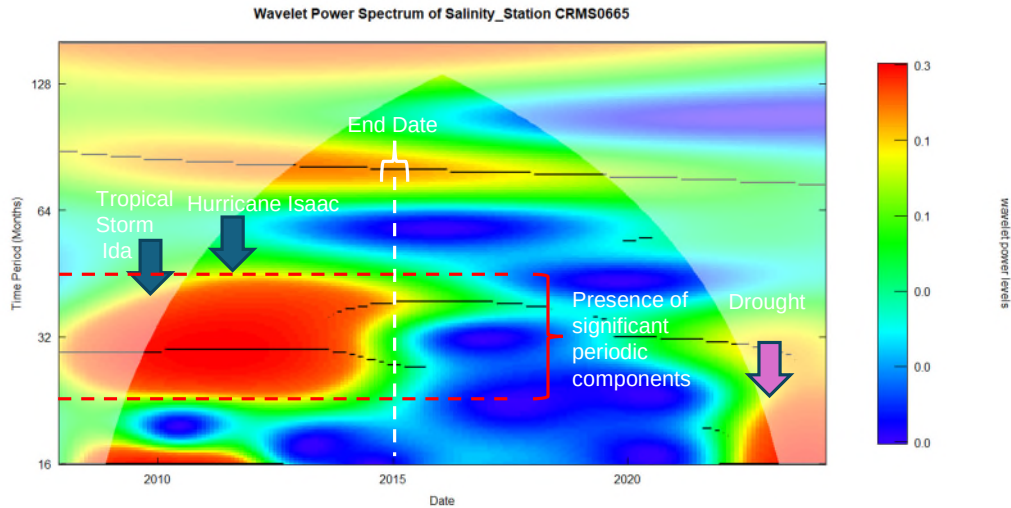


Figure 4-11 Transect Line 4. The Rolling autocorrelation plots for adjusted salinity (ppt) with lag(months) and date (months)-period 2006-2024. We indicated with red arrows the regions where the critical transitions observed through time in rolling autocorrelation plots and according to Pearson's method.

The Wavelet Power Spectrum serves as an effective metric for identifying dominant frequencies in a time series by decomposing it into time-frequency space. Peaks within the Wavelet Power Spectrum are indicative of periodic components. To evaluate recovery time from a wavelet power spectrum plot, I analyse the time-frequency representation of the data. Initially, I pinpoint the region in the plot where the power begins to decline following a peak, which marks the recovery period. I then establish a threshold for power levels that signifies the conclusion of this recovery phase. Typically, I set this threshold at 50% of the peak power value or utilize a specific value derived from the data. This approach proves useful when the recovery phase is proportional to the peak, and by knowing the baseline (or noise level), I can adjust the threshold to be slightly above this level, indicating a "recovered" state (Figure 4-12A).

Moreover, areas of significant periodicity are often highlighted with confidence contours. Next, I measured the time interval between the peak power and the point where the power drops below the threshold; this interval constitutes the recovery time. Recovery time is defined as the duration required for a system or process to return to its baseline or steady-state condition after experiencing a disturbance. It emphasizes the time needed for stabilization following an event rather than focusing solely on repetitive cycles.

A)



B)

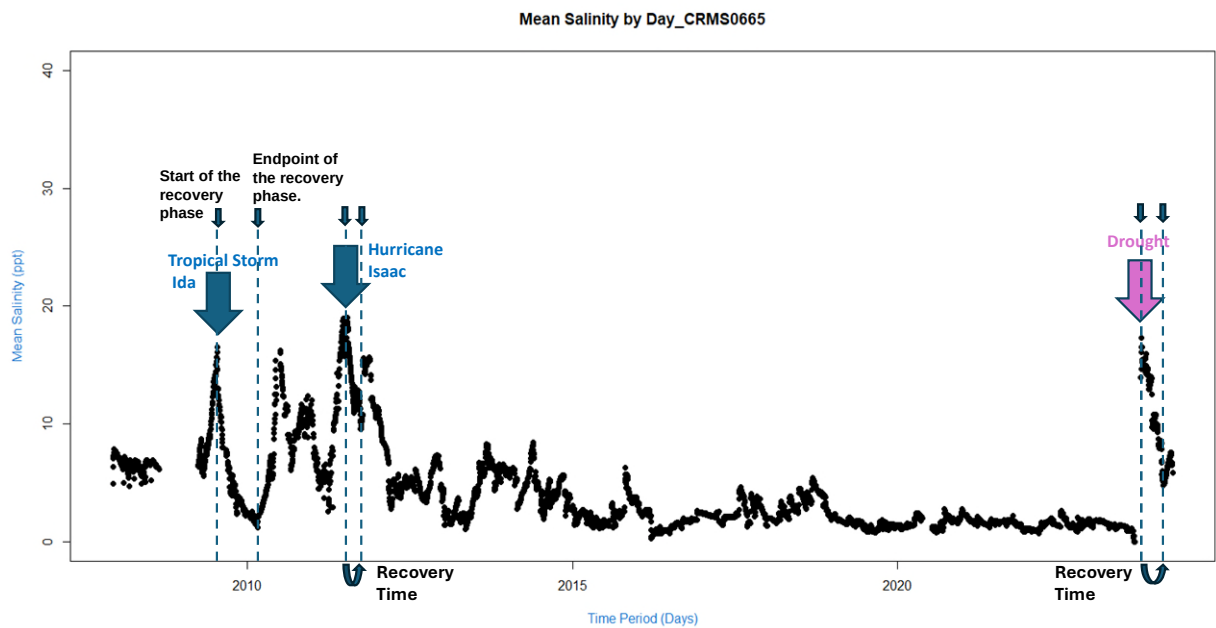


Figure 4-12 The Wavelet Power Spectrum of CRMS_0665 as a function of according to the realizations of variance of the time series and the periodicity (months) after perturbation events. The graphs show that the variance increases in red areas and decreases in blue areas, but also the presence of significant periodic components. b) The visualizations of total mean salinity (ppt) vs days for

the period 2006-2024 of the time series and the calculated recovery time between the dashed blue lines of every event occurred in that period of time.

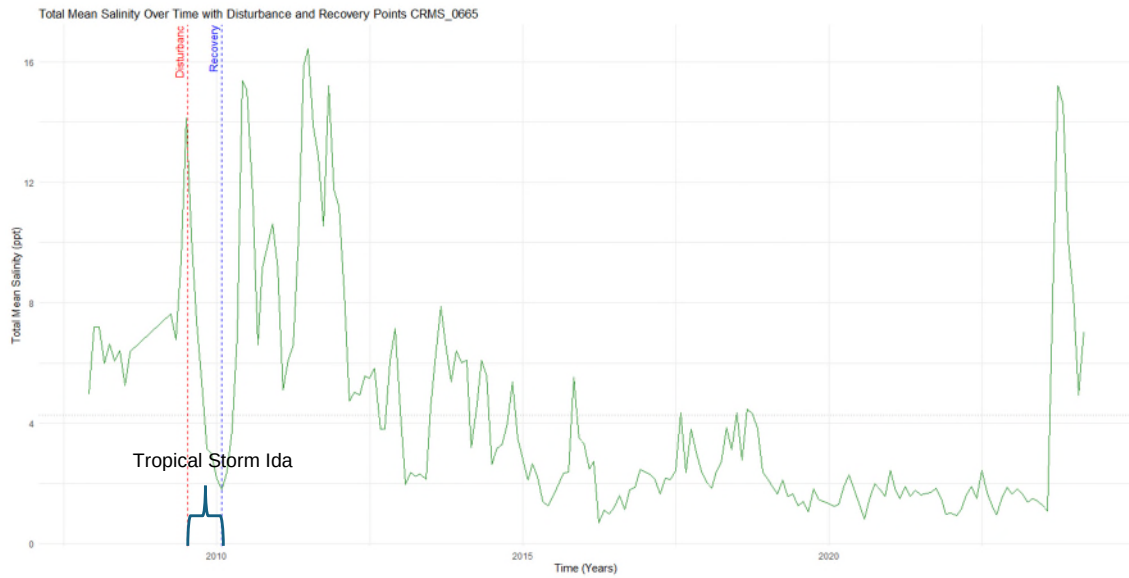
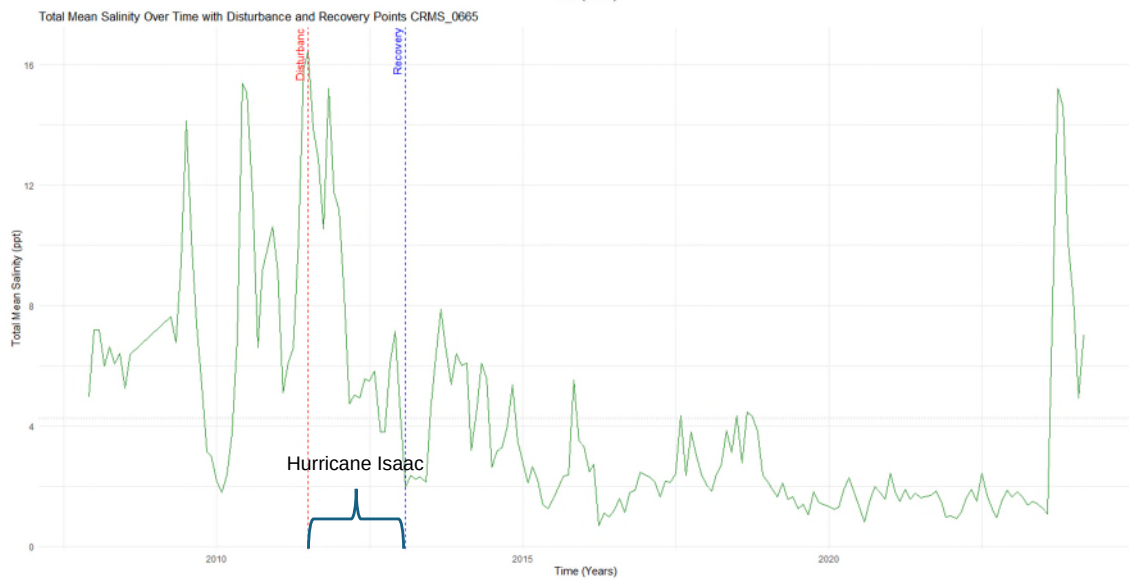
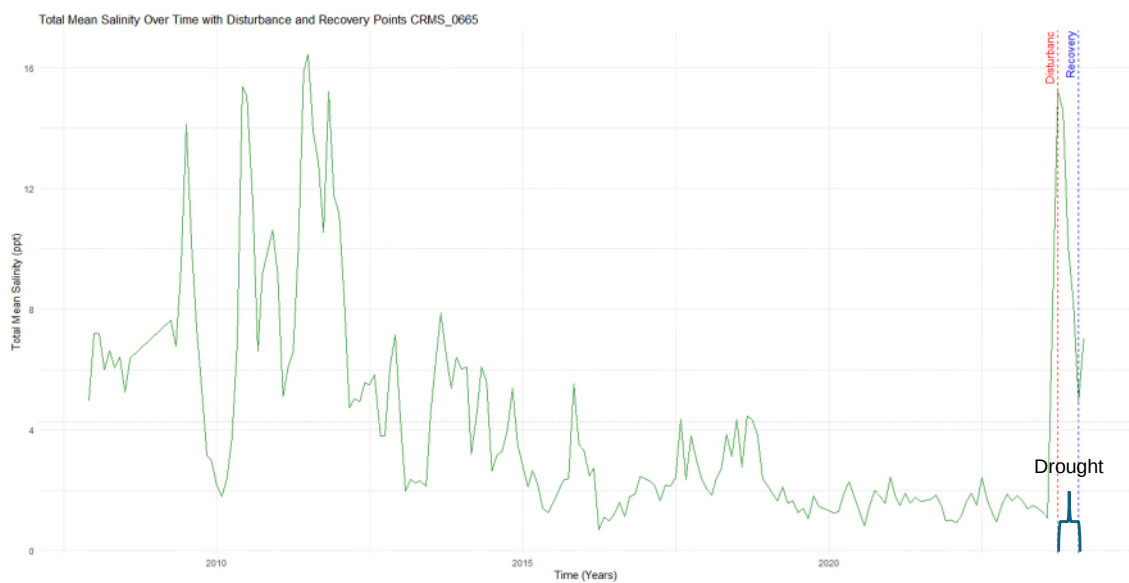


Figure 4-13 Total Mean Salinity over time with disturbance and recovery points for the CRMS_0665 analysed for the three-phases of the perturbations. The disruption of the extreme event (Hurricane Isaac, Drought) is indicative with the blue arrow, as well as the disturbance with red line and the recovery time with the blue line.

4.4.1 Discussion-Analytics of the Louisiana's coastal systems

Many delta marsh regions worldwide have seen a decrease in the amount of sediment available and an increase in salinity due to the construction of dams, impoundments, and levying of the river itself in the watershed of rivers that feed these deltas. Many coastal habitats are experiencing severe ecological issues as a result. Louisiana's coastal region faces a compounded challenge from sea-level rise and subsidence. Subsidence, the gradual sinking of land, exacerbates the effects of rising sea levels, making the region more vulnerable to flooding and wetland loss.

Globally, human activities such as land use changes, eutrophication, river diversion projects, and flood control measures have had a significant impact on estuaries and coastal systems. These activities have an impact on the biomass, diversity, and composition of organisms at all trophic levels through physical, chemical, and biological mechanisms. Land use changes, climatic variability, increased storm intensity and frequency, and future hydromodifications (e.g., sediment diversions, hydrologic restoration projects, construction/abandonment of levees, etc.) are expected to affect freshwater discharge and its associated nutrient loading to surface waters. The Louisiana estuaries around the mouth of the Mississippi-Atchafalaya River system are some of the most thoroughly researched instances of the effects of increased eutrophication on biotic resources. Sea level rise and human activity have combined to cause significant losses of coastal wetlands in the Mississippi River delta.

Large-scale river sediment diversions are being planned by state and federal authorities with the goal of capturing the most sediment possible during spring

flood pulses and directing the resulting sediment subsidy into the coastal basins that are deteriorating. Significant increases in freshwater and nutrient inputs will also result from these extensive river sediment diversions, which may also have an impact on the development of dangerous cyanobacterial blooms and other algal blooms. There are worries that the release of river water with elevated levels of Si, P, and N could cause algal blooms in the receiving basins along the coast. As with any other flood surge, river sediment diversions are likely to disturb the coastal environment; hence, managing the trade-off between the advantages of delaying coastal land loss and possible harm to water quality remains a difficult task. The physical, chemical, and biological elements influencing the formation of primary salinity in shallow coastal systems are reviewed here, together with data on the ecosystem's reaction to both little and major freshwater diversions. Reintegrating coastal systems with neighbouring river systems is a global endeavour aimed at reestablishing the hydrologic connection between riparian wetlands to their original state. One such method to mitigate the high rates of wetland degradation in coastal Louisiana, USA, is the Mississippi River sediment diversions or river reconnections, which contribute freshwater, sediment, and nutrients.

Data from a decadal CRMS station salinity measurements, which show rising salinity, support the Louisiana marsh results. This study shows that due to variations in vegetation, sediment supply, and external weather conditions like hurricane impacts, river reconnection can either increase or, in the case of the Mississippi River, have no statistical influence on the land change in these systems.

One and two-dimensional numerical models were used by the U.S. Army Corps of Engineers to create a temporary underwater sill that would prevent saline incursion upstream. After the sill was built, the freshwater resources in the New Orleans region were successfully safeguarded, and post-drought studies revealed that the models had correctly predicted how the salt wedge and the sill would behave. Few research has clarified the impact of periodic salinity incursions on primary succession in active deltaic wetlands, despite the fact that

several studies have established the physical dynamics of salt-water migration into riverine systems. Since a record Mississippi River flood in 1973, the neighbouring Wax Lake and Atchafalaya Deltas have emerged, creating a unique area of primary succession and land development amid Louisiana's declining wetland landscape.

Regarding Transect 1, the more resilient is the CRMS0662 station and the less resilient is the CRMS2166 station according to the realisations of the variance of the time series and the recovery time (days) after perturbation events (Figure 4-4). Analysing Transect 2 I concluded that the more resilient is CRMS6042 station and the less resilient is CRMS2568 station according to the graphs and the recovery times presented at Table 4-3. The more resilient station from Transect 3. is CRMS0382 station and less resilient CRMS0394 station according to the realisations of variance of the time series and the recovery time (days) after the perturbation events, and for Transect 4 the more resilient is CRMS3565 station and less resilient CRMS4218 station. Concerning the Transect Lines 1, 2, and 3, the Stations sorted from nearest to longest distance from the Louisiana's coastline and the corresponding correlation between salinity and the mean raw water level (ft) of the CRMS stations represented at Figure 4-8. Although, regarding the Transect Line 4, the stations were sorted from nearest to longest distance from the diversion of the Mississippi River, and the corresponding correlation between salinity and the mean raw water level (ft) of the CRMS stations is represented at Figure 4-9.

Comparing the areas, we conclude that the most resilient subregion is located in the second transect, with station CRMS6042 as a more resilient station and only 163 days of recovery time of full functionality, and as a total of the whole transect with 448 days of recovery time against 1224 days of recovery time of the 4 transect, which seems to be the less resilient, with station CRMS3565 being the most resilient and CRMS4218 the less resilient with a total of 1224 days of recovery time to restore functionality to normal levels in response to ecological disturbances.

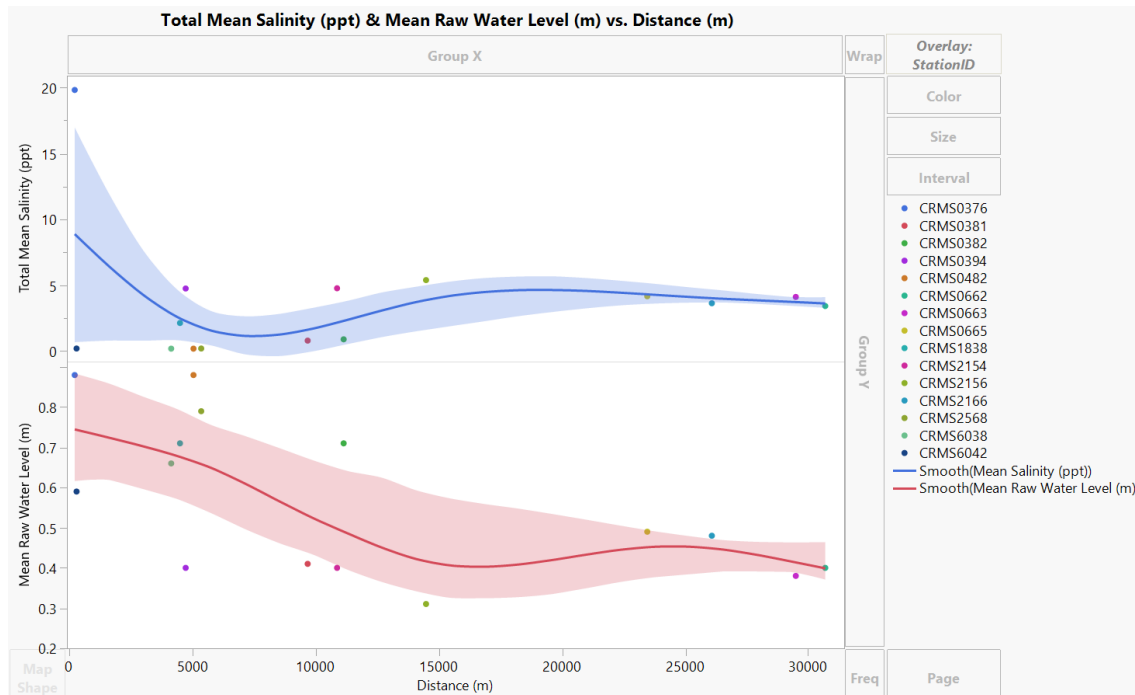


Figure 4-14 Station's Graph Visualization of Transect Lines 1,2,3 measuring distance from Gulf of Mexico (Ocean) and the corresponding correlation between salinity and the mean raw water level (ft) of the CRMS station.

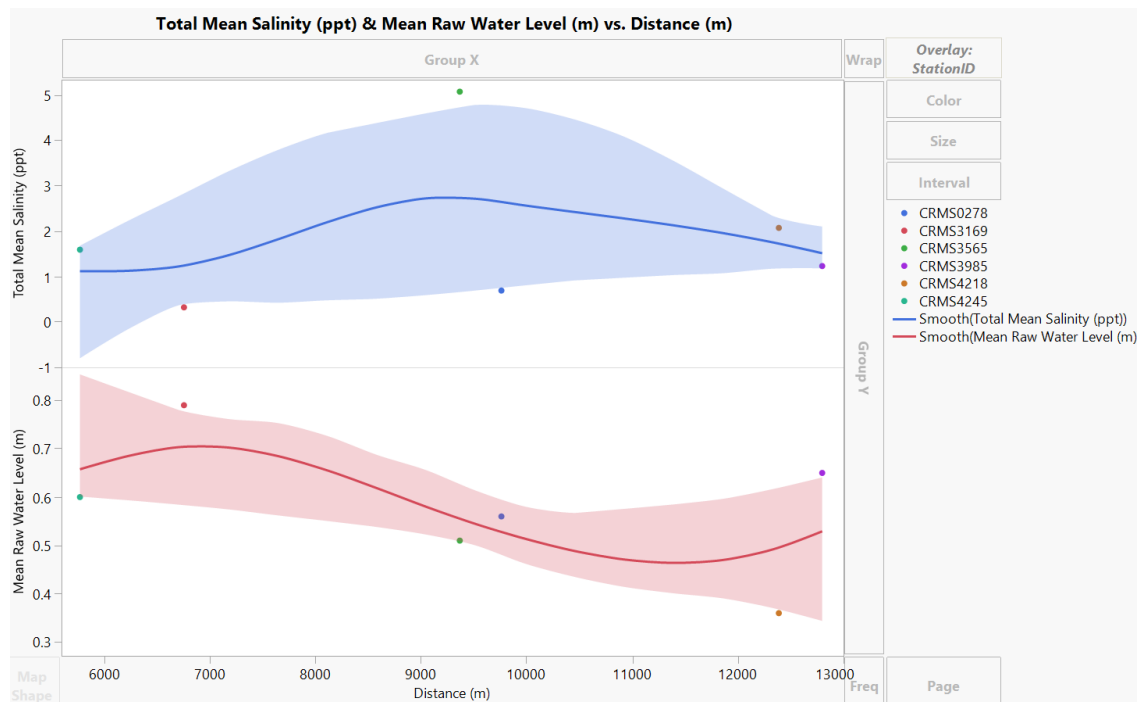


Figure 4-15 Station's Graph Visualization of Transect Line 4 measuring distance from the diversion of Mississippi river and the corresponding correlation between salinity and the mean raw water level (ft) of the CRMS stations.

The findings indicate that the northern region of the study area, which includes the parishes of South Baton Rouge, Southwest Baton Rouge, and Southeast Lafayette, as well as those south of Lake Pontchartrain, is where block groups with higher resilience were primarily located. Most of the lower-resilience CRMS stations were located along the coastline and at lower elevations, especially within transect groups in the south (Cosens et al., 2014; Walker & Salt, 2012).

Multiple component capabilities were shown to be highly correlated with community resilience, according to a regression analysis between the resilience scores and the indicators derived from the discriminant analysis. The results may be used to create adaptation plans that strengthen the coastal region's long-term sustainability, improve resilience, and minimise vulnerability. Pre-disaster planning, post-disaster recovery, and the creation of mitigation measures all depend on locating resilient areas to hurricanes and comprehending the

underlying signs. The requirement for an integrated, interdisciplinary approach in the design and implementation of adaptive and mitigating ecological management for coastal zones is becoming more widely acknowledged. The identification of essential indicators and the ways in which different indicators (i.e., social, economic, and environmental) are integrated to build resilience capacity constitute an important application of resilience assessment. One of the earliest empirically based methods for measuring and validating ecological resilience is the wavelet analysis model. In order to capture significant discrepancy within a county, this work expands the application of the statistical model from coarse-scale county level to fine-scale block group level. This study demonstrates how this approach could be applied as a tool to extract indicators to understand and eventually increase community resilience, even though the study's outcomes may be context, scale, and place-specific. It is feasible to identify certain common indicators that may be used to evaluate a variety of locations and regions in order to facilitate comparisons across various coastal regions in the world with further evaluation conducted at other research areas or using various time periods (Bouska et al., 2019).

4.5 Conclusions-Solutions on reducing land loss in agro-ecosystem coastal regions.

The recovery of coastal deltaic in order to battle and slow down some of the highest rates of coastal land loss in the world, as well as to have the added benefit of lowering some of the nutrients that are currently reaching the coastal ocean, Louisiana is dependent upon re-establishing the river links to the coastal bays and wetlands. We suggest that dividing up this sediment budget between separate projects will be necessary to construct a coordinated system of diversions and other restoration techniques to prevent land-loss. It is evident that the only reliable method for projecting the cumulative impacts of several diversions and other restoration initiatives, like dredge-fed pipelines, on the river

channel for sediment regime, flood control, and navigation is through numerical models. The only method to adequately assess diversion structures in order to optimise their sediment capture and reduce any adverse effects is through numerical models. This article examines the current state of these models and how they are used to study sediment transport and hydrodynamics in the lower Mississippi River channel. Additionally, because the Lower Mississippi River's sediment budget has a significant influence over any future management plans that call for significant diversions, it is recommended to quantitatively analyse the sediment budget in this area as a potential site for construction of a diversion not only in South Louisiana but also in other coastlines worldwide (Mead et al., 2010).

The best course of action for reducing the loss of coastal wetland would be to guarantee that salt marshes receive a sufficient amount of mineral sediment. In areas where increased salinity and sulphide create stress on the community, increasing the freshwater supply (such as through Mississippi River freshwater diversions) will prevent wetland loss when this is not possible. When this occurs, the soil bulk density becomes too low to support the growth of saline marsh plant species (Nyman et al., 1990). The possibility of a record-breaking prior movement of the saltwater wedge from the Gulf of Mexico due to the Mississippi River's record low flow in 1988 threatened the city of New Orleans's water supply as well as the communities nearby.

The extremes of allogenic (riverine and tidal flooding, sedimentation, storm disturbance) and autogenic (herbivory, plant competition) factors affect the vegetation in these deltas. Our investigation focused on whether recurrent saline intrusions were a contributing factor to the region's resilience disruption, given the swift decrease of the dominant vegetation. Our study's goals were to ascertain whether salinity varied between these deltas, explain the mechanisms governing salinity incursions, and identify the degree of salt exposure that negatively impacted the estuary's resilience and stability based on data from CRMS stations near Louisiana Bay. Salinity pulses up to 7.0‰ were typical in the Atchafalaya Delta, whereas elevated salinities were uncommon in the Wax Lake Delta, according to continuous observations of salinity and water level at 26 sites.

Strong ($>10 \text{ m s}^{-1}$) easterly and southerly winds prior to cold front passages pushed water level set-up, which was associated to salinity incursions in the Atchafalaya Delta. Longer-lasting salinity incursions were caused by far-off tropical cyclones moving across the Gulf of Mexico as opposed to cold fronts (CPRA, 2017).

Chapter 5

5 General Discussion

This study focuses on quantitative research and data statistical analysis in ecological systems, specifically examining ecosystem resilience. Ecosystem resilience measures an ecosystem's ability to withstand and recover from shocks, indicating stability. Critical slowing down (CSD) is a phenomenon where a system recovers slowly from short-term shocks, becoming more unstable. Regional studies have limited understanding of ecosystem resilience due to its reliance on mean climatic state, limited application to rainforests, and lack of corresponding attributes of resilience dynamics. The main objective is to determine general analytical approaches to establish ecosystem resilience as a key target for sustainable development. The study aims to compare mathematical approaches to determining resilience and exploring its emergent behaviour at different ecosystem scales (STAs represent the local scale, the different grassland types the regional across the UK, and finally the national scale which is represented by the various Transect Lines along the Louisiana's coastal area).

Monitoring resilience in terms of scale is crucial for understanding the dynamics of coastal wetland ecosystems and grasslands, as different scales—both spatial and temporal—reveal unique insights. The local scale focuses on specific sites, allowing for detailed observations of processes like vegetation recovery or hydrological changes. The regional scale combines data from multiple sites to identify broader patterns, such as habitat connectivity or regional stressors like urbanization and agriculture. The global scale uses satellite imagery and global datasets to compare trends across continents, providing a bird's-eye view of wetland health and resilience worldwide. Combining these scales—spatially and temporally—creates a comprehensive picture of resilience, helping design effective management and conservation strategies. There is growing interest in

understanding the resilience of ecosystems because of the potential of abrupt and possibly irreversible shifts between alternative ecosystem states. Tipping points are observed in systems with strong positive feedback, providing early warning signals of potential instability. These points can be detected through metrics like critical slowing down (CSD), such as increased recovery time, variance, and autocorrelation. These indicators have been tested in laboratory experiments and field settings, ignoring trait changes.

The pressure on the natural world is increasing. However, understanding a system's activity requires an understanding of its constituent elements and their interplay. To better protect and manage ecosystems, we need to understand their resilience to single and multiple perturbations. By integrating eco-evolutionary knowledge—understanding how ecological and evolutionary processes interact over time—with resilience concepts at the ecosystem level, we can develop a more dynamic and adaptable framework for ecosystem management. This approach provides insights into how species and systems respond to disturbances, adapt to changes, and maintain functionality under pressure. Examples of resilience measurements, particularly those involving tipping points and critical slowing down (CSD) behaviour, are relatively scarce and often limited to specific ecosystems. Studies typically focus on systems like lakes, forests, or coral reefs, where resilience can be observed through changes in variables like biodiversity, biomass, or recovery rates after disturbances.

For instance, research has explored resilience in lake ecosystems by monitoring phosphorus levels and algal blooms, which can indicate tipping points. Similarly, forest ecosystems have been studied for their ability to recover from wildfires or deforestation, often using metrics like vegetation regrowth or soil stability. The challenge lies in developing standardized methods to measure resilience across diverse ecosystems. Tools like wavelet analysis, information-theoretic measures, and dynamic modelling are increasingly being used to address this gap.

A comprehensive understanding of various levels is essential for effectively enhancing resilience against current and future environmental threats. The

concept of ecological resilience has gained prominence since Holling's (1973) review; however, effective methods for assessing this vital attribute of ecological systems have been inadequately developed. Recent research on general indicators of ecological resilience has opened up numerous new avenues for exploration and development. Factors such as biodiversity and habitat variability have been recognized as significant influences on ecosystem resilience. Nonetheless, the existing research on these factors has not adhered to a systematic review approach, leading to considerable disagreement regarding the identified influences.

Ecosystem resilience represents a multidimensional concept, as it mirrors the different frameworks of various scientific disciplines. Establishing ecosystem resilience in terms of scale is crucial for achieving sustainable development goals with general analytical approaches that can be applied across different ecosystems which was the primary objective of this thesis. Identifying critical thresholds or tipping points beyond which ecosystems might shift into a degraded state helps prioritize conservation or restoration efforts to prevent irreversible changes.

Concerning the main aim, I was able to determine that it is possible to use general analytical approaches to establish the ecosystem resilience of any given ecosystem. In the analysis presented in Chapter 2, the use of the continuous wavelet transform (CWT) proved instrumental in identifying the periodicity of cyclical activities within the data. Furthermore, CWT facilitated the assessment of variations in autocorrelation and variance, serving as key indicators of changes in systemic dynamics (CSD). The change detection methods were used to find significant changes in variations and correlations across the time series. By employing these techniques, I was able to spot substantial shifts in model-observed wavelet correlation and model residual wavelet variance and thereby identify where these systems exhibit Critical Slow Down (CSD). Leveraging historical data to identify Storm Water Treatment Areas (STAs) vulnerable to perturbation by recognizing patterns and vulnerabilities, decision-makers can develop proactive measures to enhance resilience and mitigate potential impacts.

A historical analysis often serves as the foundation for scenario planning or predictive modelling. While it may not capture future uncertainties directly, it provides a critical baseline for understanding trends and system behaviours. The study also presents one of the few studies in which CSD is observed in practice rather than modelled in theory.

Accounting for variations in climate forcing plays a pivotal role in detecting early warning signals (EWS) for ecosystem tipping points. These variations often highlight nonlinear responses within ecosystems, making them more vulnerable to being nudged toward degraded states. Utilizing satellite imagery and Geographic Information Systems (GIS) to monitor land use changes, vegetation health, and habitat fragmentation over large scales as tools help assess spatial patterns and trends that affect resilience. These challenges have partly contributed to the deficiency of examples detecting critical slowing down in real natural ecosystems. The effectiveness of using an increased *lag1* temporal autocorrelation within a moving window as an EWS to abrupt changes and a rise in temporal autocorrelation was demonstrated in this study using remote sensed images (Chapter 3). This study develops NDVI time series satellite data generated from daily MODIS-TERRA datasets. A Bayesian Dynamic Linear Model (DLM) is proposed using Kalman filtering and relevant climate data in order to estimate autocorrelation. Exploring resilience in ecosystems like California's forests and UK grasslands offers valuable insights into how these habitats adapt to or recover from stressors such as climate change, extreme weather events, and human activity. The representativeness of the identified resilience signal based on autocorrelation of NDVI values, can be impaired by missing data on cloudy days. Many remote sensing applications (Liang et al., 2012) which focus on land surface properties, cloud cover or poor atmospheric conditions can have detrimental effects on the results and the uncertainties inherent in NDVI time-series data such as those due to measurement error, varying atmospheric composition over time and also mixed signals from understory species usually depress NDVI values. I applied an algorithm developed by Stojanovic, M., (2021) to mitigate for this and to produce a high-quality NDVI time series. I observed that

based on seasonal variation inherent in the time series, the Best Index Slope Extraction (BISE) algorithm is developed to produce a threshold, by applying a Fourier transform to remove high frequency variation from the dataset. The magnitude of this threshold, which is constant in time, provided a reference for defining the abnormal range of the EWS and detected valid values accordingly to seasonal variation coalescent in the time series and collated with other cloud filtering methods. This indicated that high autocorrelation is a typical signature of critical slowing down, but it does not guarantee the occurrence of critical slowing down. A novel statistical analysis implemented and when the DLM was addressed to eight different grassland sites across the UK (Aberdeen, Dumfries, Yorkshire, Leicester, Woburn, Somerset, Berkshire, Dorset) periods of increased autocorrelation associated with periods of drought were discovered along with a long-term trend of increased autocorrelation representing an advantage for processing large scale of data. I suggest that this new approach holds great potential for discovering early warning signals on monitoring resilience linked with the ecosystem service degradation.

To date, research efforts have predominantly focused on wetland restoration and the comprehensive understanding of the geographical locations and ecological functions of wetland ecosystems. Nonetheless, existing functional wetlands face substantial pressures and disturbances. Notably, mangrove degradation results from land conversion for aquaculture and agriculture, as well as coastal development and pollution. Similarly, peatland forest deforestation is driven by land use pressures, drainage, and fire.

The Continuous River Monitoring Stations (CRMS) were analyzed using Wavelet Analysis to assess their resilience, employing the "WaveletComp" R package. This program utilizes a small waveform known as a wavelet to evaluate the intensity of various periodicity lengths within continuous data, specifically time-series data in this context. The outcome is a power diagram that illustrates, in red, the regions of the dataset that exhibit the most significant changes in variance. Salinity intrusion in coastal areas, such as those in Louisiana, can significantly impact ecosystems along geographical and temporal gradients. This

phenomenon occurs when saltwater from the ocean moves inland, often due to factors like sea-level rise, reduced freshwater flow, and human activities. Key impacts of salinity intrusion on ecosystems encompass several critical areas:

1. **Changes in Vegetation:** The intrusion of saltwater may result in the decline of freshwater plant species, concurrently facilitating the proliferation of salt-tolerant species. This transition can significantly alter both the structure and the functional dynamics of coastal wetland ecosystems.
2. **Soil and Water Chemistry:** An increase in salinity can modify the chemical composition of both soil and water, impacting nutrient availability and potentially leading to adverse conditions such as sulfidation and alkalinization.
3. **Biodiversity Loss:** Many freshwater species, including various fish and invertebrates, may struggle to survive under elevated salinity conditions, contributing to a notable loss of biodiversity.
4. **Agricultural Productivity:** Salinity intrusion poses a threat to the productivity of agricultural lands by diminishing soil fertility and increasing susceptibility to erosion. In the context of Louisiana, these ecological changes hold particular significance due to the region's dependence on both its natural ecosystems and agricultural practices. A comprehensive understanding and management of these impacts are essential for enhancing resilience in coastal communities (Tully et al., 2019).

Louisiana's Mississippi Delta's coastal regions due primarily to sea level rise brought on by climate change, freshwater systems in Florida are becoming more and more prone to saline intrusion, which is threatening the productivity of agriculture. A coastal area in Louisiana was chosen as a study area so to determine the influence of salinity intrusion on ecosystems along geographical and temporal salinity gradients. Four transects, of which fifteen stations across three Transects along the coastline and another six stations located closer to the Mississippi river, located further inland. I analysed the resilience of various water supply systems in Louisiana, focusing on Transect 1, Transect 2, Transect 3, and

Transect 4. The results showed that the most resilient subregion was found in the second transect, with station CRMS6042 having the most resilience and only 163 days of full functionality recovery time. The total recovery time for the transect was 448 days, while the less resilient transect had 1224 days. The northern region of the study area, including the parishes of South Baton Rouge, Southwest Baton Rouge, and Southeast Lafayette, as well as those south of Lake Pontchartrain, was where block groups with higher resilience were primarily located. Most lower-resilience CRMS stations were located along the coastline and at lower elevations, especially within transect groups in the south. The study also found that the northern region of the study area, including the parishes of South Baton Rouge, Southwest Baton Rouge, and Southeast Lafayette, was where block groups with higher resilience were primarily located.

The study reveals that community resilience is highly correlated with multiple component capabilities, which can be used to create adaptation plans that strengthen the coastal region's long-term sustainability, improve resilience, and minimize vulnerability. The identification of essential indicators and their integration into resilience assessment is crucial for enhancing community resilience. The wavelet analysis, one of the earliest empirically based methods for measuring ecological resilience, can be applied to extract indicators to understand and increase community resilience. The recovery of coastal deltaic areas, such as Louisiana, relies on re-establishing river links to coastal bays and wetlands. To prevent land loss and reduce nutrient levels, dividing the sediment budget between separate projects is necessary (Farzamian et al., 2024). Numerical models are the only reliable method for projecting the cumulative impacts of diversions and restoration initiatives on the river channel for sediment regime, flood control, and navigation. The study examines the current state of numerical models and their use to study sediment transport and hydrodynamics in the lower Mississippi River channel. The sediment budget in this area is crucial for future management plans that call for significant diversions, and it is recommended to quantitatively analyse the sediment budget in this area as a

potential site for construction of a diversion in South Louisiana (Bailey et al., 2014)

Observing my first aim, to compare different mathematical approaches determining resilience, I was able to determine, the best performing index to develop the STA's model, which in this case was a tiny waveform known as a wavelet to calculate the strength of different periodicity length along any type of continuous data, often time-series data in this case. The output is a power diagram describes the variance of different periodic components across the time series developed using the 5 STA's data reflecting the main locations across Everglades in Florida, US. The wavelet analysis involves passing a time series to a band of low- and high-pass filters whereby low-pass filters condense the main features from the data and high-pass filters condense the background information. The wavelet transform was performed using the R package wavelets. The DWT (Discrete Wavelet Transform) has some drawbacks, such as not computing the sub-series length identical to the original series length owing to boundary effects. The wavelet transform and an in-built command in R were used to initiate periodic extension, which ensures that the sub-series length is the same as the initial processing of the series, and there is no information loss at any point. Wavelets are interesting computational tools with an extensive variety of uses, such as data compression, image analysis, and signal processing. I presented an overview of how dynamical systems modelling is applied to ecology models where differential equations $\frac{dx}{dt} = F(x, \mu)$ characterise the rates of change of the state variables ($x \in R^n$) as functions of the parameters ($\mu \in R^d$), and state variables are a great starting point. State variables work effectively for quantities like population densities that fluctuate quite quickly due to continuous feedback. Although parameters do not change dynamically, they have an impact on the behaviour of the state variable and are frequently suitable for slowly changing quantities like environmental conditions. The modeller selects state variables and parameters to fit the issues in mutually beneficial ways, obviously neglecting numerous quantities; therefore, it seems reasonable that the relative timetables of variables will be highly context-specific (Barreiro et al., 2024).

5.1 Advantages and disadvantages of using wavelets in STA's case study.

The advantages and disadvantages of use wavelets to measure resilience will be discussed here. Wavelets provide both frequency and temporal localisation, unlike the Fourier transform, which only provides frequency component information. They can therefore capture fleeting features or sudden changes in a signal more effectively. Since a typical feature of resilience is the ability to respond to abrupt shocks or disturbances, this is significant for resilience analysis.

Wavelets make it possible to analyse a signal at different sizes, or resolutions, a process known as multiresolution analysis. We can focus on specific features or broad patterns by dividing a signal into distinct frequency bands. During resilience evaluations, this flexibility helps us comprehend how a system acts at different time and location scales (Dakos et al., 2012).

5.1.1 Benefits and drawbacks of using a Bayesian DLM method in measuring resilience of grassland's case study.

When studying and analysing time series data, a particular kind of statistical model known as DLMs is used. When processing observations with different accuracies, non-uniform sampling, missing values, and non-stationary processes, they are often especially helpful. To put it simply, they allow us to capture the dynamic behaviour of a system across time. Linear Dynamics Model Advantages:

Flexibility: DLMs can adapt to their surroundings. The fact that real-world data usually exhibits patterns or seasonality makes its handling of non-stationarity crucial.

Missing Data Handling: DLMS' ability to gracefully tolerate missing observations makes them reliable for real-world applications. **Accurate Prognosis:** By analysing historical data and its dynamics, DLMS generate accurate projections for next time periods.

State-Space Representation: To differentiate between the visible data and the underlying system state (hidden variables), DLMS use a state-space framework. This divide makes filtering and modelling more effective.

Bayesian Approach: Many DLMS employ Bayesian inference, which allows us to revise our opinions in light of new information and prior understanding. The disadvantages of dynamic linear models:

Complexity: DLMS can become challenging, especially when dealing with high-dimensional systems or nonlinear dynamics.

Estimating model parameters can be computationally demanding, particularly when dealing with big datasets. DLMS are predicated on specific assumptions, much like any other model. Their performance might suffer if specific assumptions-like Gaussian noise and linearity-are broken.

Interpretability: Because of their intricacy, DLMS' underlying dynamics can oftentimes be challenging to comprehend.

Initial conditions: DLMS must specify the initial conditions of the concealed states. Choosing the wrong initial value could have an impact on the result.

Selecting the proper DLM we need to take into account the particular issue: Is it an anomaly identification, a long-term trend analysis, or a short-term prediction? Analyse trade-offs between interpretability and complexity and simplicity and accuracy. Also to recognise the context: What is the behaviour of the system? Are there nonlinearities, or is it genuinely linear? In conclusion, DLMS are effective tools for comprehending dynamic systems, but they have trade-offs just like any other instrument (Laine, 2020).

5.1.2 Autocorrelation, as a statistical measure of the relationship between observations over time, having both positive and negative points in resilience assessment.

One helpful method for identifying temporal trends in data is autocorrelation. Understanding how past values impact existing ones can help identify cyclical or recurrent patterns when assessing resilience. Resilience evaluations, for instance, might be influenced by seasonal variations or recovery cycles in natural systems. We can evaluate how long shocks or disturbances last by using autocorrelation. To be resilient means to recover from challenging events and determining whether previous shocks have an effect on future results is one way to assess system stability.

Autocorrelation measures the degree to which the current state of a system is influenced by its previous state. Autocorrelation, as a statistical measure of the relationship between observations over time, has both positive and negative points in resilience assessment, particularly in case studies like Louisiana's. Longer memory is indicated by high autocorrelation, and this can be important for evaluating long-term resilience. The autocorrelation's drawbacks in assessing resilience are:

- The underlying premise of autocorrelation is the independence of errors (residuals) over time. However, dependencies are frequently present in real-world systems because of feedback loops or unobserved variables. Estimates that are affected may result from breaking this basic assumption.

- Causality isn't always implied by high autocorrelation. Occasionally, apparent patterns are the result of chance or outside influences. Policy decisions can be influenced when erroneously interpreting spurious associations as genuine in resilience evaluation.

-The frequency at which data is collected has an impact on the autocorrelation results. While low-frequency data may obscure underlying patterns, high-frequency data may show more autocorrelation (Grekousis, 2020).

Ecosystems are dynamic and complex, with responses to disturbances varying in duration and size. Assessing resilience is challenging due to the underlying mechanisms remaining unidentified. To minimize this, four characteristics of ecosystems and their emerging characteristics can be used as models for resilience. Many dynamical systems, such as animals, lakes, financial markets, or ocean circulation patterns, have tipping points where important transitions to opposing states can occur. Algorithms to detect the impending arrival of critical transitions are necessary, as these events can happen without warning and are challenging to handle. Recent theory, known as EWS, can be employed to identify when a system is about to undertake a crucial shift.

A new integrated technique combining wavelet and correlation analysis could potentially monitor CSD measurements in these systems globally. Resilience theory was originally structured around the existence of several states and the equilibria dynamics within them. Data-assimilation techniques, such as Fourier analysis in time series, have huge potential for large-dimensional applications. Remotely sensed vegetation indices can be used to identify indicators for important transitions in grassland ecosystems, demonstrating the value of these metrics for assessing ecosystem conditions and improving indicators' ability to generate early warning signals of impending changes.

The study of sediment transport and hydrodynamics in the lower Mississippi River channel, focusing on the potential construction of a diversion in South Louisiana. The sediment budget in this area is crucial for future management plans that require significant diversions. The study uses data from CRMS stations close to Louisiana Bay to determine the salinity variations between deltas and the mechanisms controlling salinity incursions. Wetlands are self-adjusting systems with adaptive vegetation of aquatic plants, characteristic of the unique hydric soil. Constructed wetlands play a crucial role in functions such as water purification,

water storage, carbon processing, and recycling of micro-macro nutrients. The removal mechanisms within these wetlands can act uniquely, sequentially, or simultaneously, enhancing sustainability in wastewater management (Kadlec, 2008; Feder et al., 2024).

Recovery after extreme events (i.e. hurricanes, droughts, wildfires, earthquakes, human-induced disturbances like deforestation, pollution etc) encourages new development activities and allows reconstruction through the conversion of naturally occurring wetlands to other land uses. This study examines into the extent to which coastal habitats efforts to recover from hurricanes have undermined their capacity to mitigate the effects of upcoming storms.

Enhancing ecological resilience involves a combination of strategies aimed at strengthening ecosystems' ability to withstand and recover from disturbances. Key approaches include increasing biodiversity, increasing connectivity, sustainable land management, protecting and restoring natural habitats, adaptive management, engaging stakeholders, and reducing pollution and overexploitation. By integrating these strategies, we can build more resilient ecosystems capable of withstanding and recovering from extreme events and long-term environmental changes. Higher diversity often enhances resilience because it provides a wider range of responses to disturbances. The size of an ecosystem can influence its resilience, as larger ecosystems can support more species and have more resources to buffer against disturbances (Urban et al., 2016).

Resilience is essential for intensely managed ecosystems, such as agricultural lands, urban green spaces, and managed forests, which often face significant pressures and disturbances. Long-term ecological monitoring datasets are invaluable for observing and understanding resilience in ecosystems, providing insights into how ecosystems respond to various disturbances over time. Effective management ensures that vital ecosystem services are continued to be provided, benefiting both the environment and human well-being (Corstanje et al., 2007).

5.1.3 Managing resilience under enhanced ecological benefits.

To observe the resilience of an ecosystem requires time, careful observation, and a clear understanding of the ecosystem's dynamics. Tracking the autocorrelation after a disturbance can indicate how well the ecosystem is bouncing back. Monitoring the flow of water nutrients (like Total Phosphorus (TP)) shows whether the ecosystem processes are returning to normal. The results presented above suggest that resilience will provide the region with the ability to deal with impending dangers and prepare for future consequences that may arise by operating within a framework of adaptation, learning and transformation. The most significant (highest) concentration levels of total phosphorus (TP) occurred for inflow flow-way and water P increased with P input. This study used a new integrated approach, based on wavelet analysis, and might offer possibilities to monitor resilience of such systems globally.

The resilience indicators help identify when action is needed to avoid degradation or promote recovery, and dynamical systems theory to quantify and visualize how deltas respond to disturbances like salinity intrusion, flooding, or sediment loss. By analysing hydrological changes, researchers can estimate how long it takes for a delta to recover from specific disturbances.

Using an AR (1) procedure, we compared the relevance of the spectrum to the black line (anything within is important). As a result, ecosystems nearing a tipping point lose their ability to withstand disturbances and shift towards an alternate state. Our study also confirms that the most significant concentration levels of total phosphorus (TP) occurred for inflow-way and water P increased with P input. The Everglades ecosystem's water quality has changed dramatically during the past 200 years and has declined as a result of human contact, which has upset the ecology. Water quality consists of many aspects such as nutrients utilized by plants for growth, dissolved materials that affect hardness, salinity, pH and toxins that may inhibit or even more poison living processes. Degraded water has created large modifications withinside the Everglades. Water quality concerns in

the freshwater Everglades have focused on two main issues: phosphorus enrichment and elevated mercury in wildlife. Needs for Phosphorus waters within the Everglades Protected Area are required to maintain P concentrations of 10 parts per billion in accordance with the Everglades Forever Act and Florida Administrative Code, to ensure the wellbeing of native flora and fauna species indigenous to the Everglades ecosystem (Florida Department of Environmental Protection, 2004). A dissolved oxygen content of at least 5.0 mg/L must be maintained in all fresh waterways, according to Florida Administrative Code. Dissolved oxygen levels still need to be kept at this level despite significant changes brought on by periphyton and macrophyte populations engaging in photosynthesis and respiration within the Everglades (Florida Department of Environmental Protection, 2003). Prior to the construction of STA's, phosphorus levels in Everglades-bound streams reached 170 parts per billion (ppb) and are now as low as 12 parts per billion. Although several STA's have shown positive results, more effort needs to be done to lower total P concentrations to meet the 10 parts per billion threshold (SFWMD, 2013). The kind of vegetation, inflow water quality, hydraulic loads, as well as the strength, duration, and timing of flow events, all have a significant role in how effectively these places work. STA's are intended to stop stormwater discharge—a point source for nutrient enrichment—before it reaches the Everglades wetlands. In addition to filtering water, STA's provide essential habitat for wildlife species, act as a storage basin to assure water availability during dry spells, and enable scientific research and experimentation (SFWMD, 2013). Since the beginning of STA's, their effectiveness has been tracked. Excess P and nitrogen-contaminated water is directed into STAs where it comes into contact with plots of emergent aquatic vegetation and submerged aquatic vegetation (SAV) (Juston & DeBusk, 2015).

The STAs' efficiency at removing P is also influenced by the soil type and previous land use. STA's based on periphyton, that includes algae and bacteria occurring on or in emergent and submerged plants, have been introduced in South Florida to assess their efficacy in lowering P concentrations. Periphyton research in labs has shown that it can lower total P concentration levels to the

necessary 10 parts per billion by traversing just 100 feet (USACE, 2003). The first periphyton-based STA's construction started in 2004, and it became operational in 2007. Over 190,000 tons of legacy P are currently stored in the soil of Lake Okeechobee as a result of agricultural activities in the area. Between the Lake Okeechobee basin's contaminants and the Everglades Protected Area, stormwater treatment areas act as a filter. As the legacy phosphorous is gradually released into the water column and flows south into the STA's, the impact of the excess of stored P on water quality may last for years to come. South Florida has averaged 11 tornadoes per year since 1996, with a total of 154 storms of EF-1 or EF- 2 severity on the Enhanced Fujita Scale (winds more than 85 mph) occurring since 1950. Tornadoes in South Florida occur as a result of a range of weather systems, including powerful winter/spring cold fronts, onshore waterspouts, and cyclones contained in the outer rainfall bands of tropical storms and hurricanes. In 2018, South Florida was hit by two big storms. In 2005's Hurricanes Francis & Jeanne wreaked havoc on STA-3/4, but little damage was seen in the wetlands (Pietro et al.,2006). SAV in Cell 2B was somewhat damaged by Hurricane Wilma in WY2006, whereas the emergent vegetation was moderately damaged. Despite the beginning of water conservation activities in 2011, the conditions of the regional drought were so severe that the SAV-dominated treatment Cells 1B, 2B, and 3B dried up and caused damage to the SAV community (Pietro et al., 2007).

STA-1E is one amongst five areas that SFWMD owns and also the closest to urban areas. Levees and canals ring the perimeter of the treatment areas which are divided into several cells, and several have open water with submerged aquatic vegetation, and others have very dense cattail growth. The variability provides for varying degrees of water quality treatment to maximize the clean-up. STA-1E is essentially 6,600 acres of mostly water surrounded by a series of levies and began full operation in 2006, and consists of three flow ways: Eastern, Western and Central. The STA_3/4 with over than 16,480 acres in western Palm Beach County, is the largest constructed wetland within the world. STA-34 consists of three flow ways (flow way 1,2,3) and became operational in 2004. Hurricane Irma (on Sept. 10, 2017) resulted in vegetation damage, included

shredded and flattened cattail, STAs received high inflow volumes, phosphorus concentrations, loads, impacting treatment performance (STA_34).

Our findings support efforts to secure landscape resilience, because reduced resilience potentially leading to changes in functional ecosystem characteristics. Finally, the results indicate an anthropogenic environmental influence concluding that after comparing all the individual regions of STA's the most resilient area is STA-1E with the least critical transitions and the lowest TP (Total Phosphorus) concentrations having the maximum functionality and ensuring the greatest resilience in this specific area. Our analysis suggests that the primary distribution of total phosphorus in the STA's after perturbations through flow-ways are associated with autocorrelation, accumulated or not, and may begin to follow the variance, as indicators of resilience, measuring such traits not just for preventing collapse, but also for improving the success of ecological restoration.

In my second case study I was primarily interested in methods that examine resilience to climate variability using vegetation indices of satellite time series to identify EWS as resilience indicators at local levels, particularly those associated with the decline of grasslands and forest ecosystem dynamics. Limiting the review to such geographic scales allows for far greater comparability and nuance; when indices represent temporal autocorrelation taken from NDVI they determine to have the maximum explanatory power within the Early Warning Signals and ecological resilience assessments often feature characteristics and indicators that differ markedly from those of localized evaluations and reviews of their core features appear more prominently within the academic literature. Accordingly, each listed framework is screened for suitability against the review's primary criteria, specifically: a main focus on the effectiveness of using an increased *lag*1 temporal autocorrelation within a moving window as an EWS to abrupt changes, climate resilience; an application at the rise in temporal autocorrelation has been demonstrated using remotely sensed imagery; and the ability to generate a quantifiable metric of overall resilience. Compared to the first case study using wavelet analysis methods, here a Bayesian Dynamic Linear Model (DLM) applied in UK grasslands and woodlands uses Kalman filtering and relevant hydroclimatic

data (i.e. rainfall) to determine these changes in autocorrelation, however NDVI values calculated from a normalised transform of the NIR, sometimes can be impaired by missing data due to the amount of cloudy UK days (Racca et al., 2005; Hirota et al., 2011).

"Forewarned is forearmed," without a doubt. Even so, being aware of the possibility of an impending shift might not be enough to prevent it. Most of times, the indicators are only noticed after the fact or when the transitions are already taking place. Studies using simulations have even demonstrated that early warnings might not be sufficient. In certain ecosystems, at a transition, increased variability may happen over a broad range of conditions, whereas in other ecosystems, the range of increased variability may be so small as to be practically meaningless. However, it has been shown that CSD indicators may reliably identify transitions in well-sampled bistable systems. All of these suggest that CSD indicators might have a role in the sustainable management of ecosystems that are on the edge of collapse, but there are still challenges to overcome before they can be used in real-world situations. While CSD signs can alert us to the possibility of "something" significant happening soon, they are unable to provide specific details about what this "something" might be or when it will occur. Therefore, in addition to the warnings, understanding the underlying behaviour of the ecosystem is crucial to placing the signals in the appropriate context. There is no replacement for site-specific expertise and model-compounded experiments in this context. Approaches to establishing resilience in management need to be aware of the possibility that, even in the best-case situation, surprises could strike without notice.

In practice, these resilience assumptions should be considered carefully when interpreting the results of any subjective evaluation. Little is known about how different toolkits measure the ecosystem's resilience. Comparisons have assessed whether one approach generates results that are comparable to that of others. This not only applies to comparisons across subjective and objective categories of statistical toolkits but even among mathematical toolkits that adopt the same general approach. When taking into consideration the wide range of

techniques applied across available toolkits, it is crucial for understanding the implications of employing various characterisations of resilience and sets of indicator lists. In fact, the variety of definitions of resilience found in academic papers enables researchers to defend practically any combination when constructing a toolkit. In my third case study for example I examined the environmental factors that control temperature and salinity dynamics as well as the consequences of a projected large-scale Mississippi river water diversion for land development investigating if the estuary experiences highly complex temporal and spatial variability of salinity examining the phenomenon of rapid wetland loss (Iqbal, 1995; O'Neill, et al., 1986; Hu et al., 2023).

There are significant gaps in our understanding of whether and how context-specific subjective types of measurement vary. The increasing number of measurement experts has contributed significantly to the increased interest in resilience measurement. The main goals of the research are related to the factors that influence ecosystems' resilient behaviour, the significance of spatiotemporal scales, the distinctions between short- and long-term dynamics, the fundamental methodological requirements for precisely defining resilience, the function of indicators and the reference state, and the applicability of resilience as a management concept. The length of the time series is mostly related to the temporal scales (long term to short term observations) in which the case studies are organised.

Originating in field measurements, ecosystem classifications and maps, different wetland types, grasslands or transects have been distinguished and modelled with this landscape resilience analysis. This study may therefore document the normative loading of resilience analyses: the evaluation is a result of the observer's objectives, the selected indicators and the applied thresholds of reversibility. If we define the systems in structurally only (a generalised coastline or a large size wetland-grassland), the study's results show resilience, but if we include functional measures, focused in, they don't set a reliability indicator or targeted area. Another normative point originates in the scale of observation: if we concentrate on the recovery potential of single states, the results might be

satisfactory, however, if we incorporate integrity indicator sets or functional metrics that are area-specific, they don't. The scope of observation gives rise to another normative point: the outcome will be frustrating if we focus on the recovery potential of individual stages rather than the overall retrogressional sequence. Additionally, the chosen time scales naturally influence the recovery potential as well. Another potentially thought-provoking notion is as follows: Degraded and "simple" ecosystems are more resilient than healthy ones (e.g., restoring a simple ecological system might not be difficult, but restoring a complex system will require a lot of work). They also have a much larger buffer capacity than complex systems, which indicate a higher level of ecosystem integrity (DeLaune et al., 2003).

A future line of research will be to investigate possible vulnerable areas assessing ecological resilience and impacts, as a key concept, for Louisiana region during and after drought events, located in different environments. Coming back to the initial questions from the introduction, the results can be summarized as follows: an exclusive resilient behaviour of ecosystems in the investigated long-term data sets was mainly found under the conditions of short-term disturbances, while over longer periods, adaptability comes into play and the efficiency of high-magnitude disturbances is rising: the longer the time series, the more changes could be observed. Consequently, spatio-temporal scales play a major role in resilience analysis. Not only the ecosystem processes are operating in a spatio-temporal hierarchy, but also the disturbances can be characterized by special spatio-temporal characteristics. These scales are interlinked in the ecosystem, which is receiving the inputs, and therefore the many disturbances are interacting here: long-term processes can produce cumulative impairments and indirect effects which are fostering degradations; thus, the vulnerability of the ecosystem can be increased. If in that situation, short events with high potential magnitudes occur, the system has a high probability for non-resilient dynamics at these tipping points (Turner et al., 2021).

Identifying Early Warning Signs of salinity intrusion helps in understanding ecosystem transitions, such as shifts from freshwater marshes to brackish or

saline environments. This knowledge can guide studies on plant and soil responses to salinity thresholds. Insights into salinity thresholds and ecosystem resilience can inform coastal restoration projects, such as sediment diversions and freshwater introductions. Policymakers can use this data to draft adaptive management plans, ensuring sustainable use of resources while mitigating the impacts of sea-level rise and saltwater intrusion.

From a strategic viewpoint, there is a high demand to critically reprove and rethink the definitions of resilience used in the literature and in environmental politics, as meanwhile some modern comprehensions seem to explain the opposite of the original meaning of the term. Although it is nice to see that the word resilience provides a multitude of positive connotations, a strict delineation of the contents and a clear distinction between different classes of dynamics (i.e. resilience vs. adaptability) would be extremely helpful for a consistent environmental analysis and serious policy. Therefore, the communicating concepts should be considered stronger, of course with linkages to resilience, but they should not be hidden under the highly and happily accepted resilience term.

5.1.4 Limitations and next steps of the current study

Ecological resilience measurement has proven challenging, but engineering resilience is linked to well-defined indicators. Because of this, the two concepts have been studied mainly independently of one another. Despite multiple attempts at connecting them together in a logical framework, it is still unclear how much they overlap or enhance one another when it comes to measuring a system's resilience. From this angle, we concentrate on measures that express resilience in accordance with Holling's description, which is grounded in the idea of the stability landscape. I examined the relationships between several ecological and engineering resilience indicators derived from bistable systems and showed that there may be a significant relationship between the two for low

dimensional ecological models. I also examined the methods currently used to quantify resilience from models and data, and I listed the problems that need to be solved in order to move closer to a more accurate measurement of resilience in real-world applications. The issue is that we are often unaware of the stability landscape's form for the majority of systems. Theoretically, we could calculate their shapes. A useful description of the several mathematical depictions of a stability landscape can be found in Christopher W. Pawlowski (2008), (Karunanithi et al., 2008).

The most popular mathematical illustration of stability landscapes is provided by the potential function. The potential function characterises the system's potential energy over a range of parameter values. The slopes of the potential surface are proportional to the system's rates of change, stable and unstable equilibria are represented by minimum and maximum, respectively. Stated differently, a gradient surface that establishes the system's (the ball's) direction and speed of motion across and inside basins of attraction is described by the potential function. However, understanding the real underlying dynamical model that characterises the system under investigation is necessary to determine the potential of a given system. This is where things get even more complicated because a possible function for a given model may not always exist, even if 'a' model is expected. Consider the well-known predator-prey paradigm of two species developed by Lotka and Volterra, which results in limit cycle behaviour. A model of this kind might potentially represent a stability landscape in which the system both orbits and converges to the stability landscape's valley bottom; this kind of landscape would be equivalent to an impossibility. Finding a suitable purpose for multidimensional systems is usually challenging. Nonetheless, approaches for estimating stability landscapes for systems with high dimensions have been developed (Rodríguez-Sánchez et al., 2020).

The greatest knowledge comes from using a variety of techniques, from quantitative modelling and regulated experiments to long-term observations, field modification, and the interpretation of natural patterns. Universal features of dynamical systems underlie all of them. It is innovative, however, to think that

these universal rules may be utilized to predict important changes. Resilience may be measured using a set of generic indicators that can be applied to a wide range of data sets. If we are to grasp the impact of fast global changes on the stability features of the network of complicated natural systems as to which mankind ultimately relies, we need fundamental advancements in our understanding.

The case study sites share similarities in numerous indicators and metrics, which contribute to establishing a baseline of the current landscape topology, according to the findings. When contrasting various development models with this baseline, the STA's wavelet analysis model resembles traditional landscape structure indicators the best, supporting resilience. Sea levels have risen, and flooding has been exacerbated by global warming, which has followed the path set by human activity and raised average global temperatures, causing the world's oceans to expand. The majority of natural disasters that occur nowadays include water, which makes planning and constructing for coastal defense extremely difficult. In order to withstand extreme weather events and flood risk, this thesis is designed to identify design principles through an understanding of resilience and climate change adaptation concepts.

The resilience theory's principles will be further implemented in a case study to test and investigate strategies that emphasize evaluating ecological resilience and impacts as a key concept for the Louisiana region both during and after drought occurrences. The design principles will serve as an inspirational handbook for architects, designers, planners, and other stakeholders while diving into the most basic design procedures concerning coastal landscapes and the water-related issues they present. The interaction between people and water, global projects, and established strategies for addressing flood risk and sea level rise provide the foundation for and sources of inspiration for the design principles. The integrate principle aims to improve adaptation to living with water by viewing the coastal landscape as an opportunity rather than a limitation. The goal of protecting is to manage water and shield specific interests while maintaining water out of the area in order to preserve life there. Lastly, slightly different seeks

to distance the water by a temporary or permanent relocation; it may also imply imposing limitations on where and how it can be exploited (White et al., 2019; D'Angelo et al., 1999).

Ecological memory, including species networks and interactions with the environment, is crucial for ecosystem resilience. It includes structural and biological legacies, as well as immigration-influencing elements. Human activities have altered ecosystem resilience, leading to reduced landscapes and species composition. Diversity, including species, habitats, and genetic traits, is essential for adaptability, recovery, and resistance. Data on biological and environmental factors can help investigate ecosystem conditions (He et al., 2023).

More precisely this work integrates theoretical tools and agent-based modelling in the resilience framework to approach ecological systems from structural perspectives. Comparing the three study cases in terms of ecological resilience we conclude that computationally the most stable resilience system is the STA's because they operate independently and individually in a potentially fragile area that is seasonally plagued by severe weather phenomena due to the topography, but also that protects the biodiversity there and quite years.

Chapter 6

6 General Conclusions

There is increasing concern about ecosystems' ability to recover from sudden and irreversible shifts. Tipping points occur when strong feedback loops create new stable states, but they are hard to detect. Early warning indicators, like longer recovery times and greater variability, can signal the risk of these shifts. This study examines constructed wetlands in the Everglades Stormwater Treatment Areas (STAs), which have shown sudden changes in plant communities. By using wavelet analysis on long-term data about water flow, quality, and nutrients, we identified which STAs are less resilient to disturbances and detected signs of critical slowing down (CSD). This research highlights vulnerable areas and offers real-world evidence of CSD (Objective 1).

Using a Bayesian dynamic linear model (DLM) to analyse autocorrelation in the Normalized Difference Vegetation Index (NDVI) time series and handling significant data noise from cloudy days, we developed an algorithm that produces a high-quality NDVI time series by filtering out invalid values and accounting for seasonal variations. Our DLM findings revealed increased autocorrelation during droughts and a rising trend over time (Objective 2). Salinity intrusion poses a significant threat to Louisiana's coastal wetlands, impacting their ecosystems and the communities that rely on them. Salinity intrusion can lead to the loss of freshwater vegetation, which is replaced by salt-tolerant species (Jackson et al., 2009). Increased salinity can reduce the productivity of wetland plants, leading to habitat degradation (www.lacoast.gov).

Identifying early warning signs is crucial for effective conservation and restoration efforts. Remote sensing data, like trends in vegetation indices (e.g., NDVI), can indicate shifts in ecosystem health. There are some conservation and restoration strategies such as Implementing freshwater diversions to counteract salinity

intrusion, Using remote sensing and other technologies to prioritize areas for restoration and monitoring vegetation indexes to detect early changes (Objective 3), (Steyer et al., 2007; Martinez et al., 2024).

This thesis explores the impact of land use on ecological resilience in highly managed ecosystems. Environmental indicators were developed to assess resilience measures using long-term time series data. A multivariate framework was applied to evaluate the resilience of three ecological networks at local regional, and global-national scales, revealing that one network demonstrated greater resilience based on certain variables. However, all networks remain highly vulnerable to targeted threats. We determined the relationships between different ecological resilience metrics and wavelet analysis, highlighting challenges in improving the quantification of resilience in practice. The wavelet analysis can help balance sustainability and growth in coastal zones and aid in developing ecological corridors. Also, four transects of a floodplain-river ecosystem were examined, revealing distinct variations in overall resilience. The indicators can be applied to other significant estuarine ecosystems, addressing whether conflict, ecological management, and collaborative learning enhance ecological resilience. The study also examined the relationships between different ecological resilience metrics and wavelet analysis, highlighting challenges in improving the quantification of resilience in practice. Wavelet analysis can help balance sustainability and growth in coastal zones and aid in developing ecological corridors.

6.1 Recommendations for further work

To advance the understanding and management of salinity intrusion in Louisiana's coastal wetlands, is not only to develop and deploy advanced sensors to monitor salinity levels, vegetation changes, and soil health in real-time, but also to use remote sensing technologies to track large-scale changes in wetland

ecosystems (He et al., 2024). It is necessary to create predictive models to simulate the impacts of various salinity intrusion scenarios, including sea-level rise and freshwater diversion projects. By integrating climate change projections into these models, we can assess long-term impacts. Some of the restoration techniques are to conduct experiments with innovative restoration methods, such as sediment diversions and planting salt-tolerant vegetation and to evaluate the effectiveness of these techniques in different wetland types. Beneficial could be to collaborate with local communities to incorporate traditional knowledge into conservation strategies and raise awareness about the importance of wetlands and the threats posed by salinity intrusion. Studying the interactions between salinity intrusion, nutrient cycling, and microbial communities is one method for more interdisciplinary research, and the next step is to investigate the socio-economic impacts of wetland loss and develop strategies to mitigate them. Essential is the policy management by advocating for policies that prioritize wetland conservation and restoration. Generally developing adaptive management plans that can respond to changing environmental conditions.

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Appendices

Appendix A Ethical approval letter



25 March 2021

Dear Sgt Toumasis ,

Reference: CURES/12932/2021

Title: "Securing Lawtonian Landscape Resilience"

Thank you for your application to the Cranfield University Research Ethics System (CURES).

We are pleased to inform you your CURES application, reference CURES/12932/2021 has been reviewed. You may now proceed with the research activities you have sought approval for.

If you have any queries, please contact CURES Support.

We wish you every success with your project.

Regards,

CURES Team

Appendix B Supplementary data-materials of the STA's analysis

B.1 Appendix section with list of figures created with R software of all the Stormwater Treatment Areas in Everglades of South Florida according to our Time Series Data.

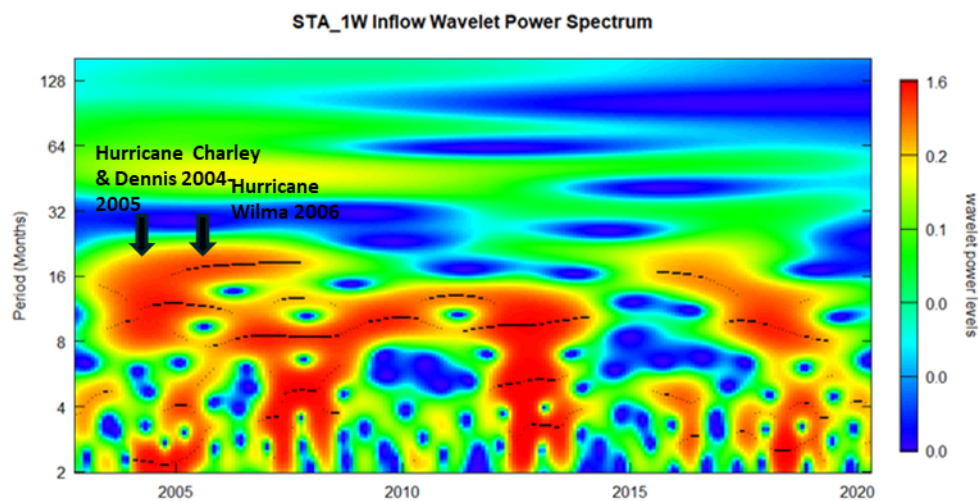


Figure B-1 The Wavelet Power Spectrum of STA_1W inflow as a function of frequency. The figure shows the realizations of variance of the time series, and as the spectrum gets hotter (red areas) more is the volatility and less in blue areas. The white arrows indicate the extreme events occurred in STA_1W for which the segments trend statistic is higher than the trend statistic prior to the event.

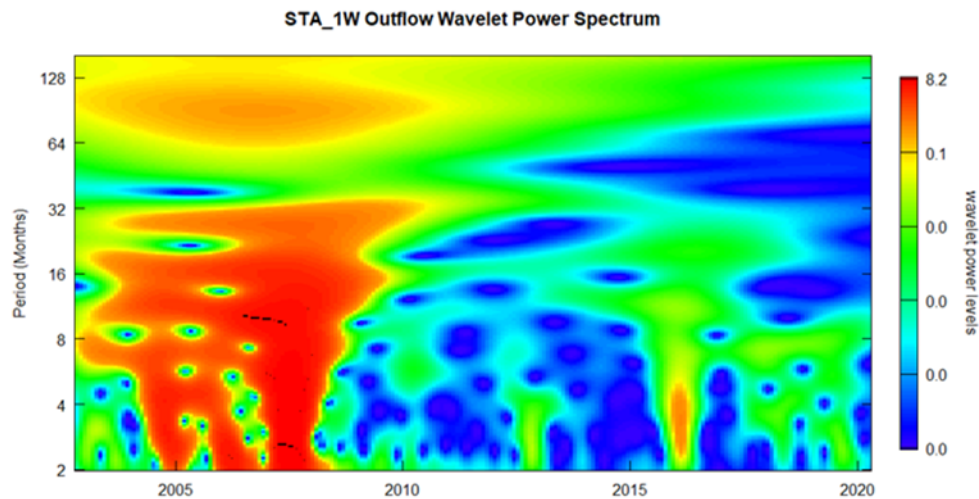


Figure B-2 The Wavelet Power Spectrum of STA_1W outflow as a function of frequency.

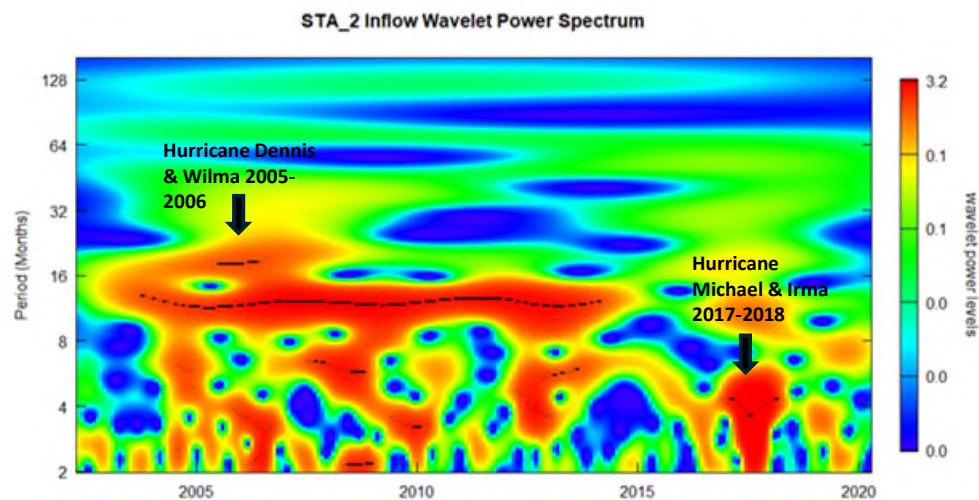


Figure B-3 The Wavelet Power Spectrum of STA_2 inflow as a function of frequency. The figure shows the realizations of variance of the time series, and as the spectrum gets hotter (red areas) more is the volatility and less in blue areas. The white arrows indicate the extreme events occurred in

STA_2 for which the segments trend statistic is higher than the trend statistic prior to the event.

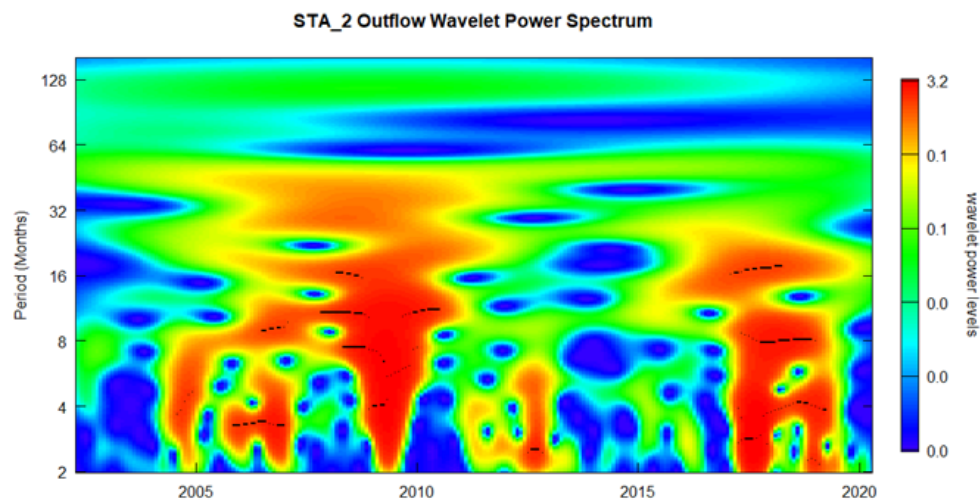


Figure B-4 The Wavelet Power Spectrum of STA_2 outflow as a function of frequency.

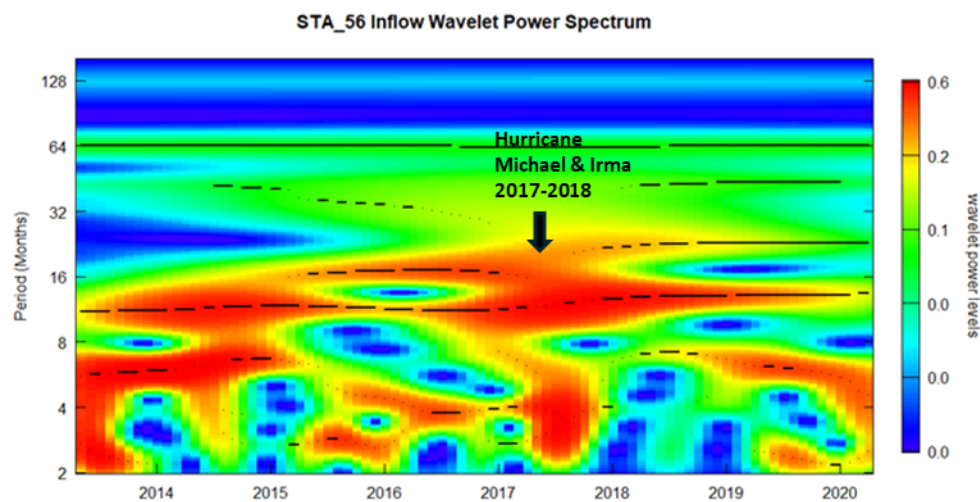


Figure B-5 The Wavelet Power Spectrum of STA_56 inflow as a function of frequency. The figure shows the realizations of variance of the time series, and as the spectrum gets hotter (red areas) more is the volatility and less in blue areas. The white arrows indicate the extreme events occurred in

STA_56 for which the segments trend statistic is higher than the trend statistic prior to the event.

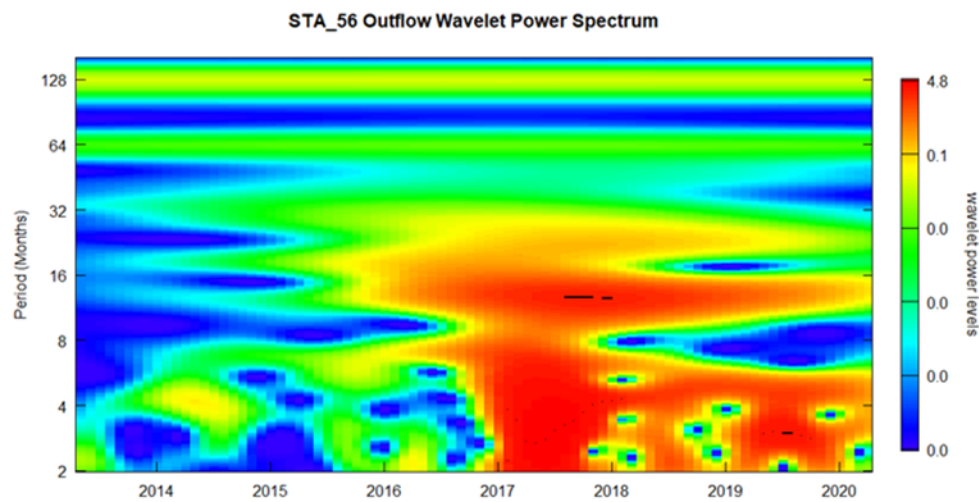


Figure B-6 The Wavelet Power Spectrum of STA_56 outflow as a function of frequency.

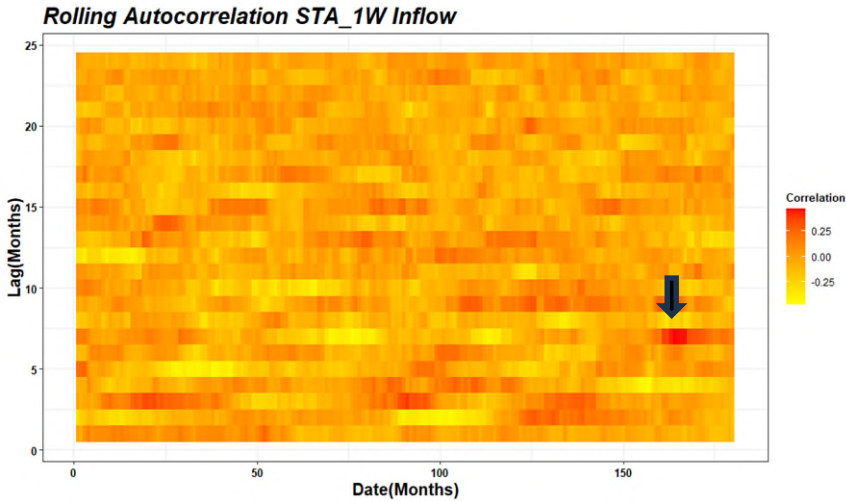


Figure B-7 Rolling Autocorrelation plot of STA_1W inflow as a function of Dates.

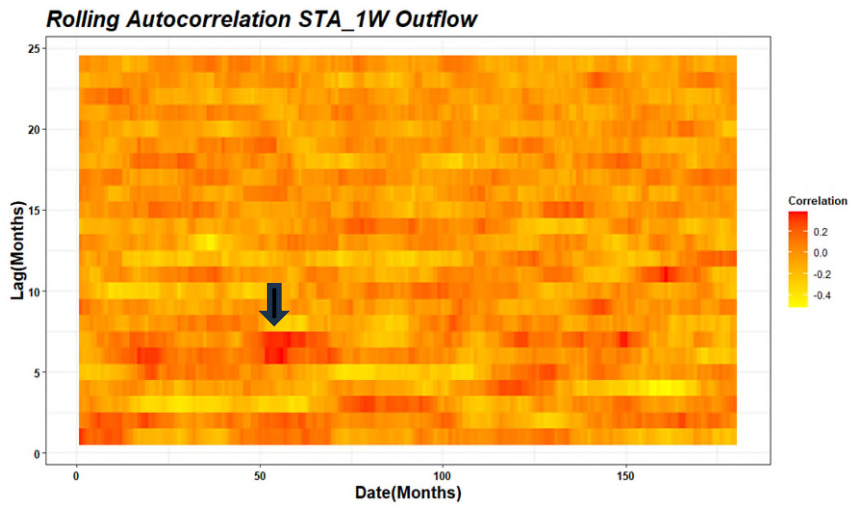


Figure B-8 Rolling Autocorrelation plot of STA_1W outflow as a function of Dates.

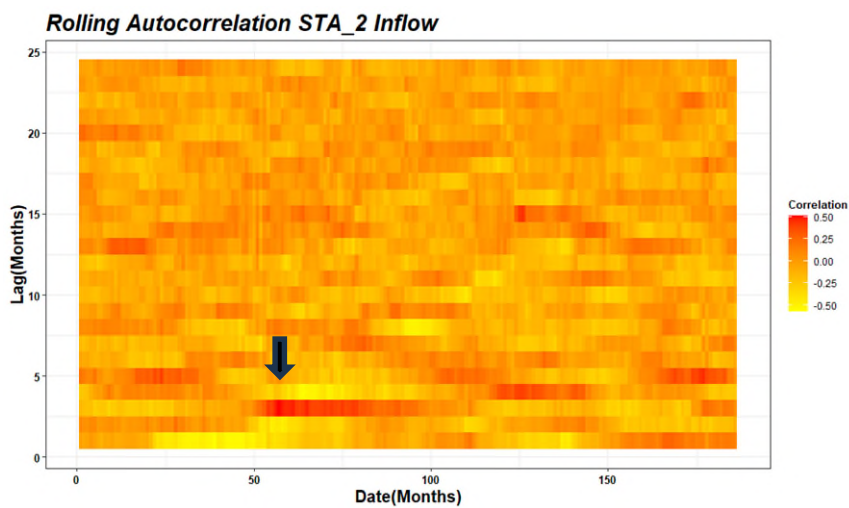


Figure B-9 Rolling Autocorrelation plot of STA_2 inflow as a function of Dates.

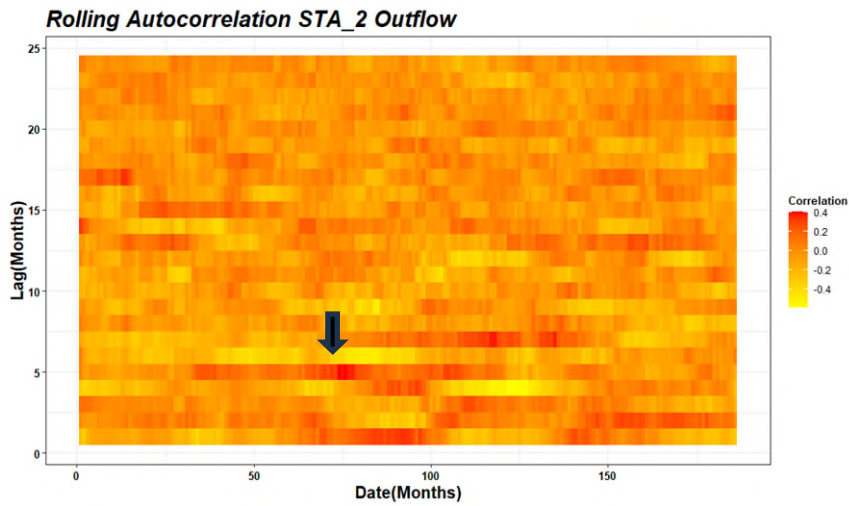


Figure B-10 Rolling Autocorrelation plot of STA_2 outflow as a function of Dates.

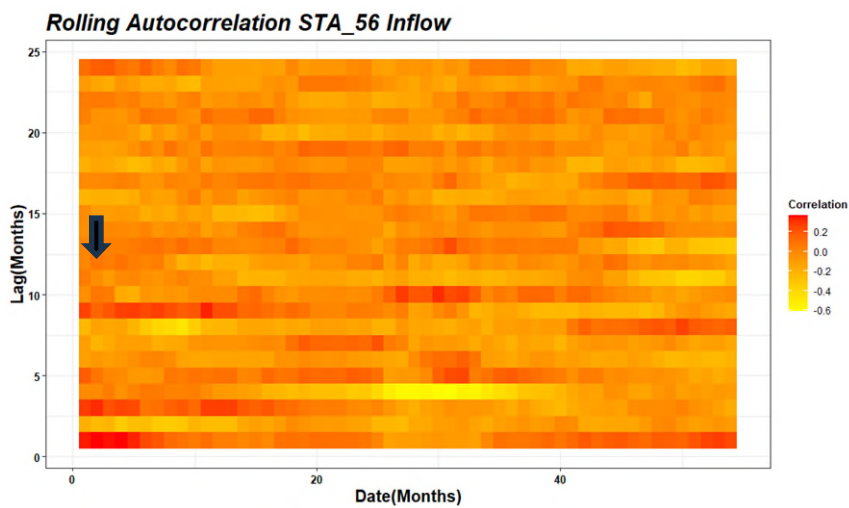


Figure B-11 Rolling Autocorrelation plot of STA_56 inflow as a function of Dates.

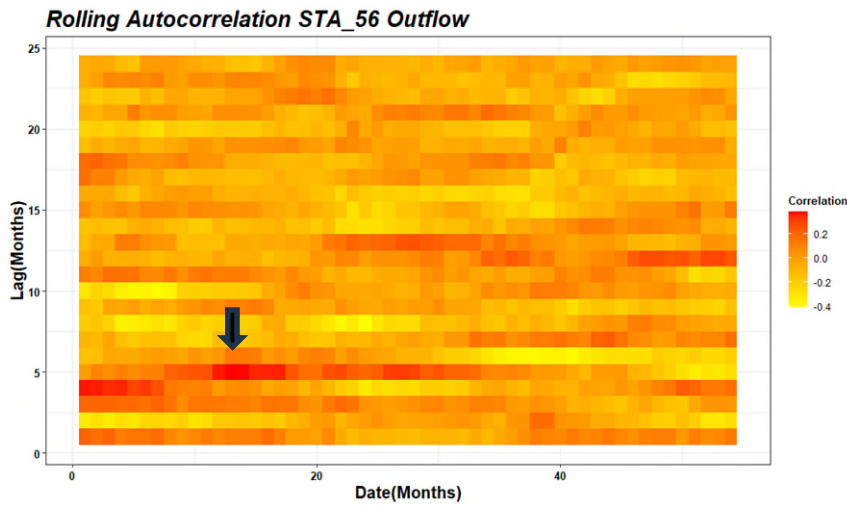


Figure B-12 Rolling Autocorrelation plot of STA_56 outflow as a function of Dates.

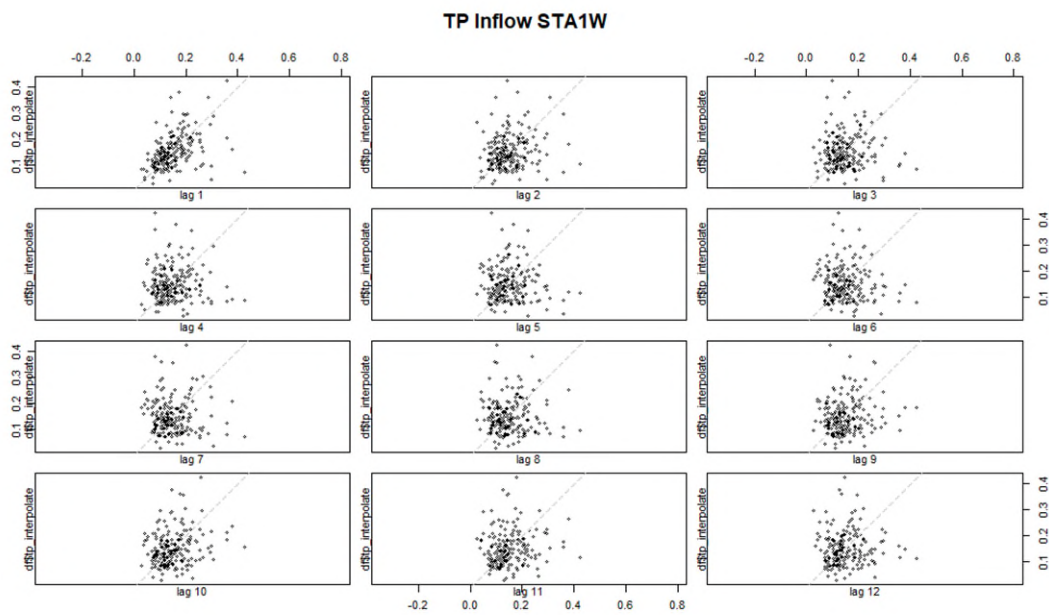


Figure B-13 ACF plots at different lags of STA_1W inflow.

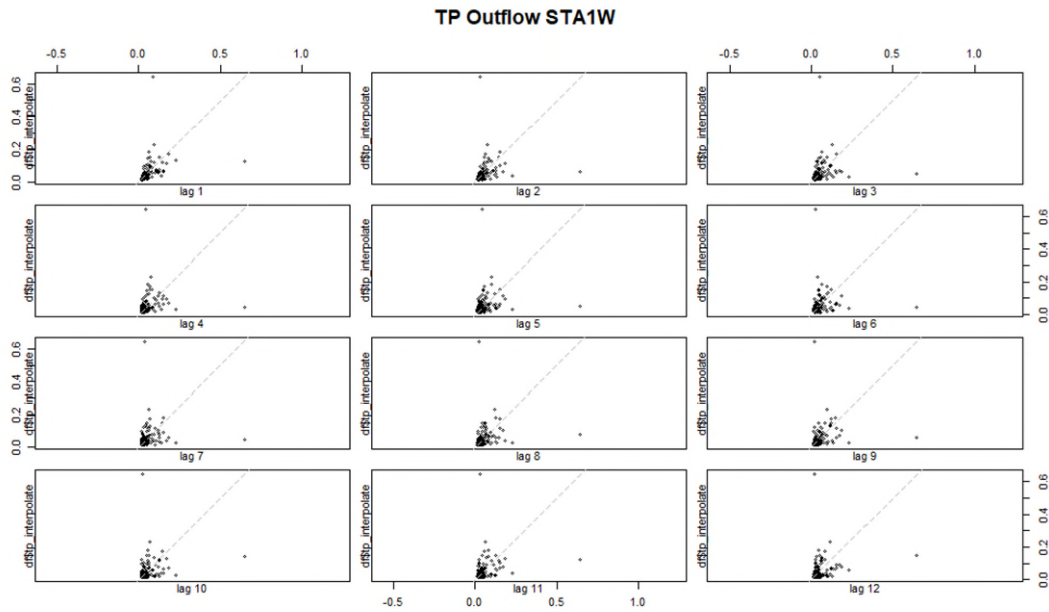


Figure B-14 ACF plots at different lags of STA_1W outflow. Statistical properties of our indicators of loss of resilience illustrated on results. The more distributed points in autocorrelation figures indicate at lag1 lower autocorrelation with rising resilience and focused points indicate loss of resilience based on each segment of lags in the system.

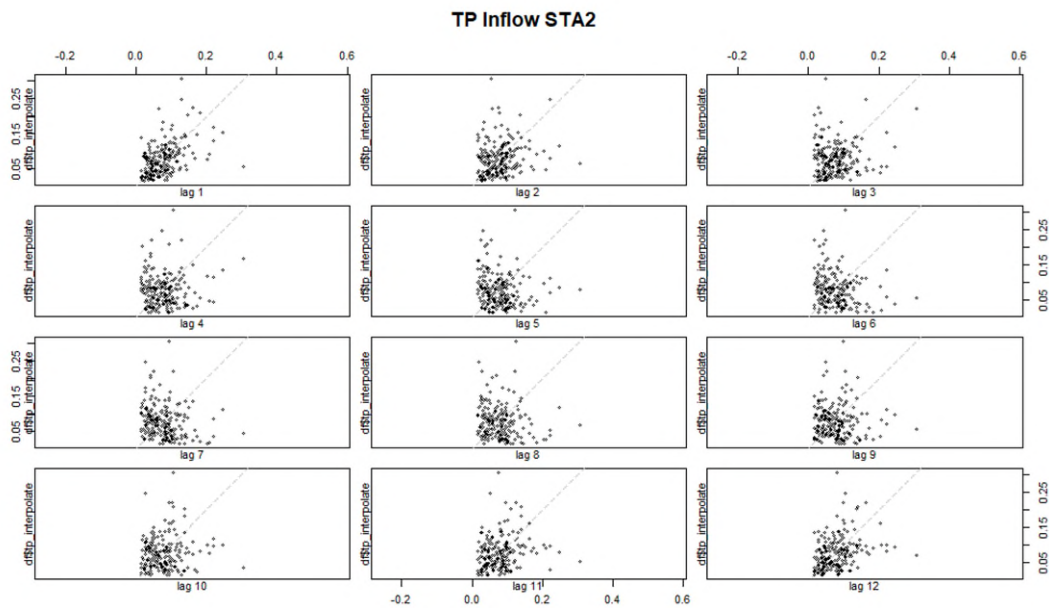


Figure B-15 ACF plots at different lags of STA_2 inflow

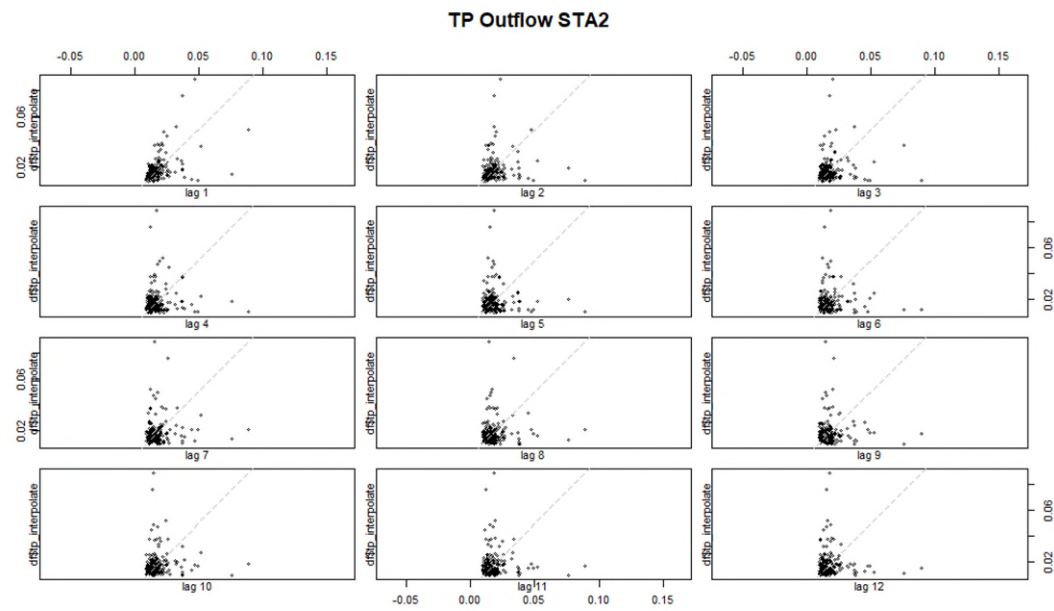


Figure B-16 ACF plots at different lags of STA_2 outflow. Statistical properties of our indicators of loss of resilience illustrated on results. The more distributed points in autocorrelation figures indicate at lag1 lower autocorrelation with rising resilience and focused points indicate loss of resilience based on each segment of lags in the system.

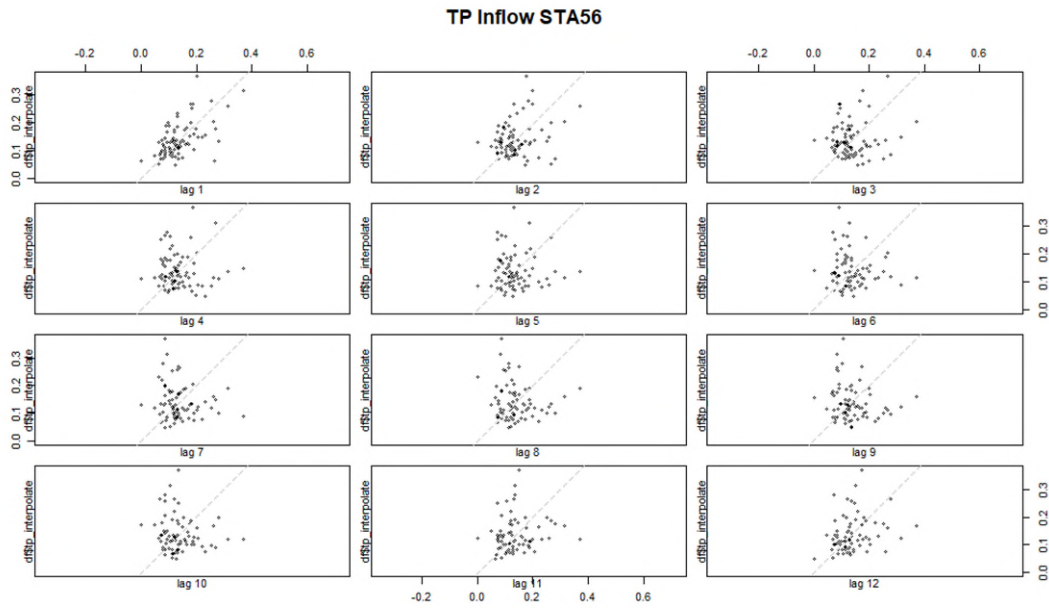


Figure B-17 ACF plots at different lags of STA_56 inflow

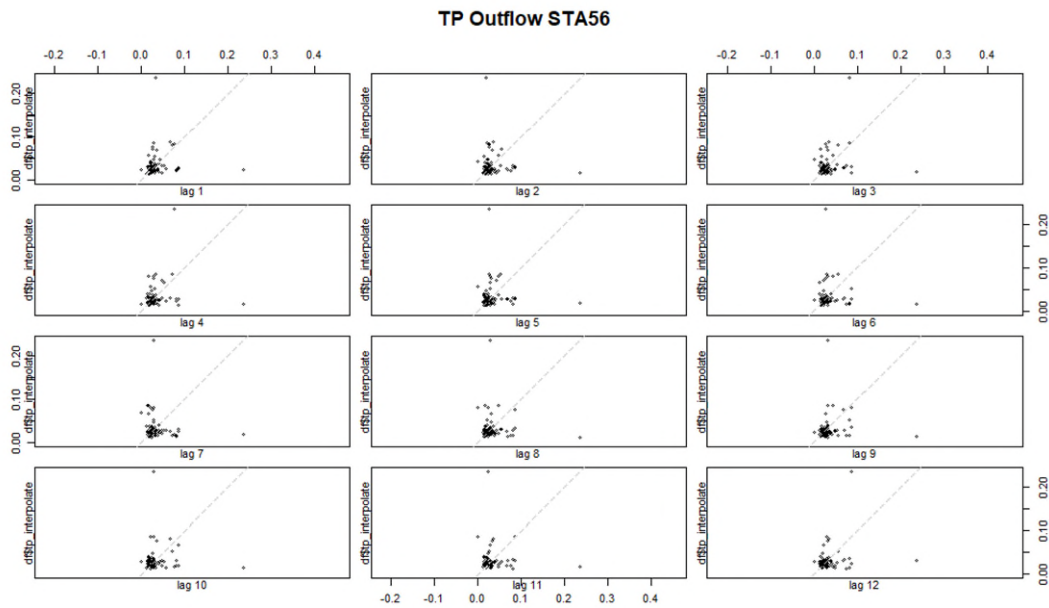


Figure B-18 ACF plots at different lags of STA_56 outflow. Statistical properties of our indicators of loss of resilience illustrated on results. The more distributed points in autocorrelation figures indicate at lag1 lower autocorrelation with rising resilience and focused points indicate loss of resilience based on each segment of lags in the system.

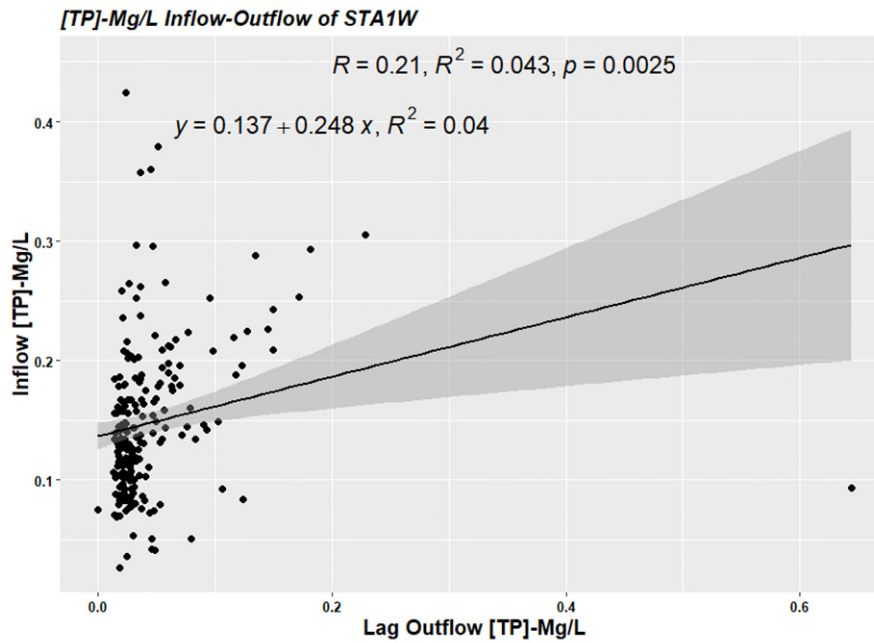


Figure B-19 Total phosphorus concentration (Mg/L) by response of resilience.

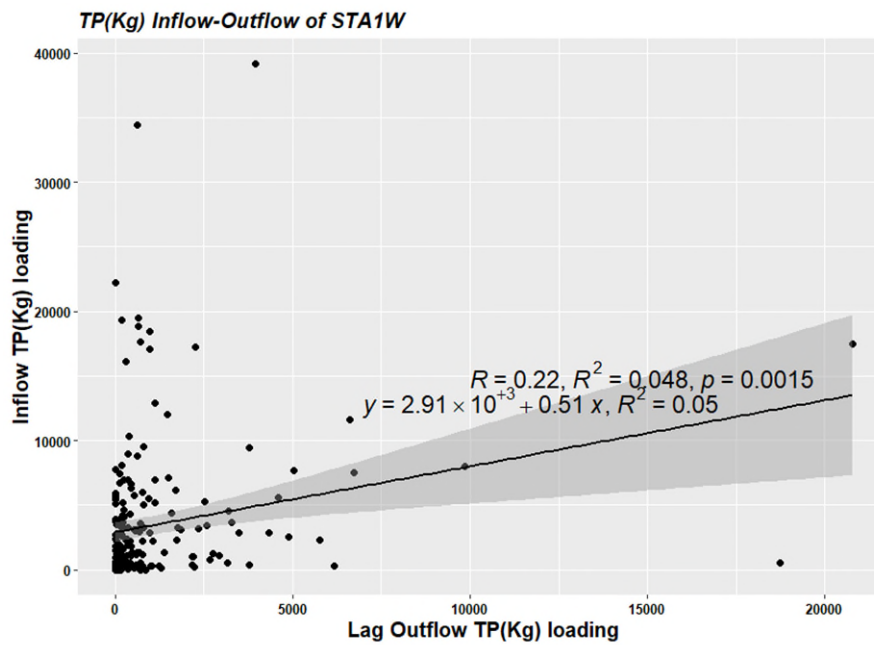


Figure B-20 Total phosphorus loading (Kg) by response of resilience.

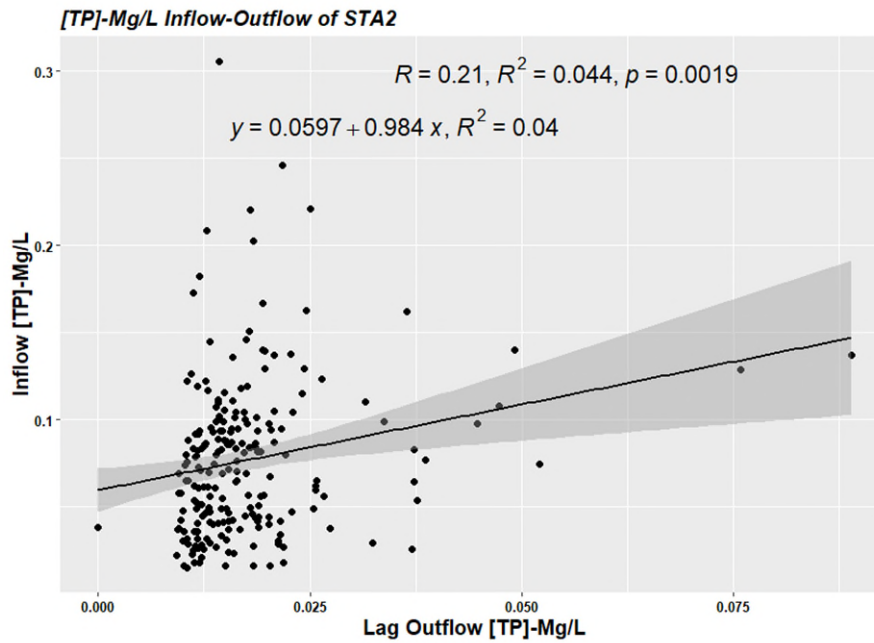


Figure B-21 Total phosphorus concentration (Mg/L) by response of resilience.

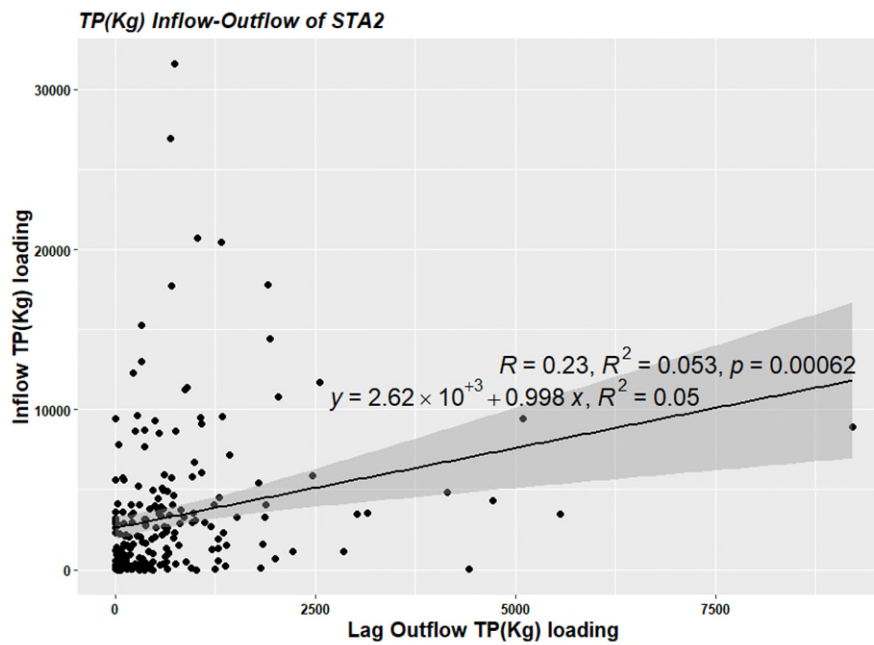


Figure B-22 Total phosphorus loading (Kg) by response of resilience.

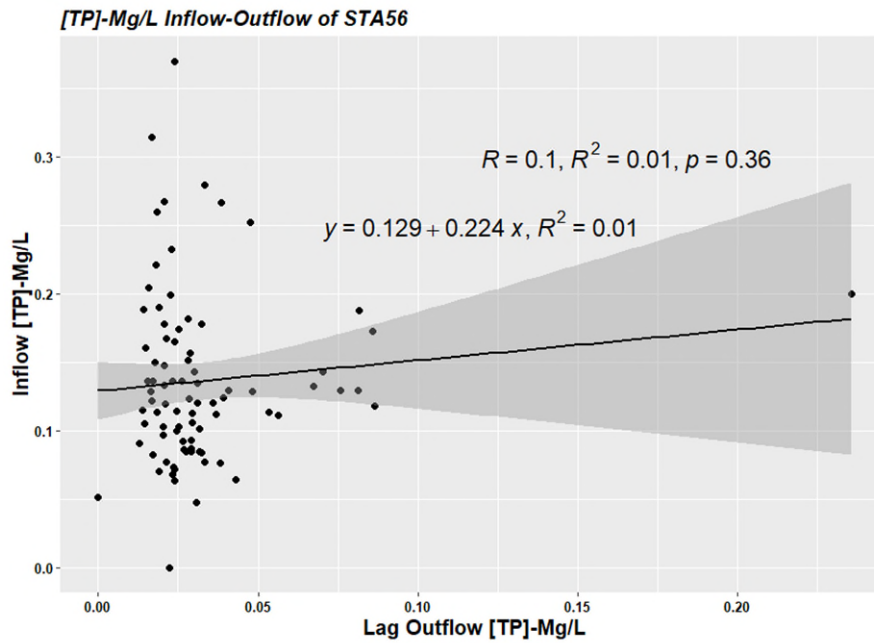


Figure B-23 Total phosphorus concentration (Mg/L) by response of resilience.

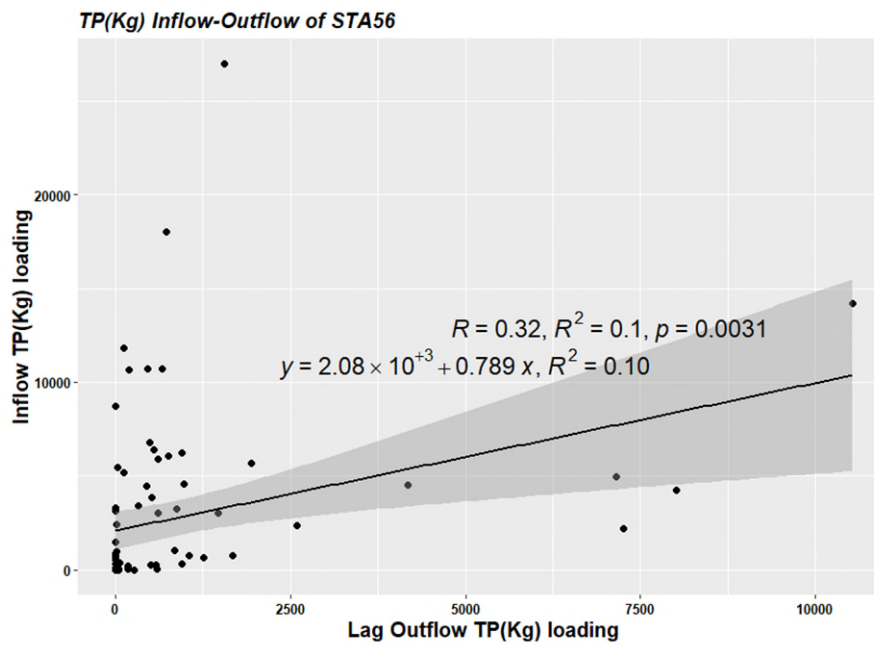


Fig. 12b Total phosphorus loading (Kg) by response of resilience.

Appendix C The DLM applied to the other UK grassland sites.

C.1 This appendix contains the filtered daily NDVI time series, and autocorrelation, plotted as in Figure 3 for the remaining fields identified in Figure 2. The daily time series is plotted. The number on each figure corresponds to the field number in Figure 2. Note that the scale of the x-axis changes, depending on the year of establishment of each field.

List of figures created with QGIS, Google maps and Python of all the UK grassland sites according to our data in order to produce high-quality NDVI time series for the DLM. The DLM was applied to 8 different grassland sites across the UK (Aberdeen, Dumfries, Yorkshire, Leicester, Woburn, Somerset, Berkshire, Dorset).

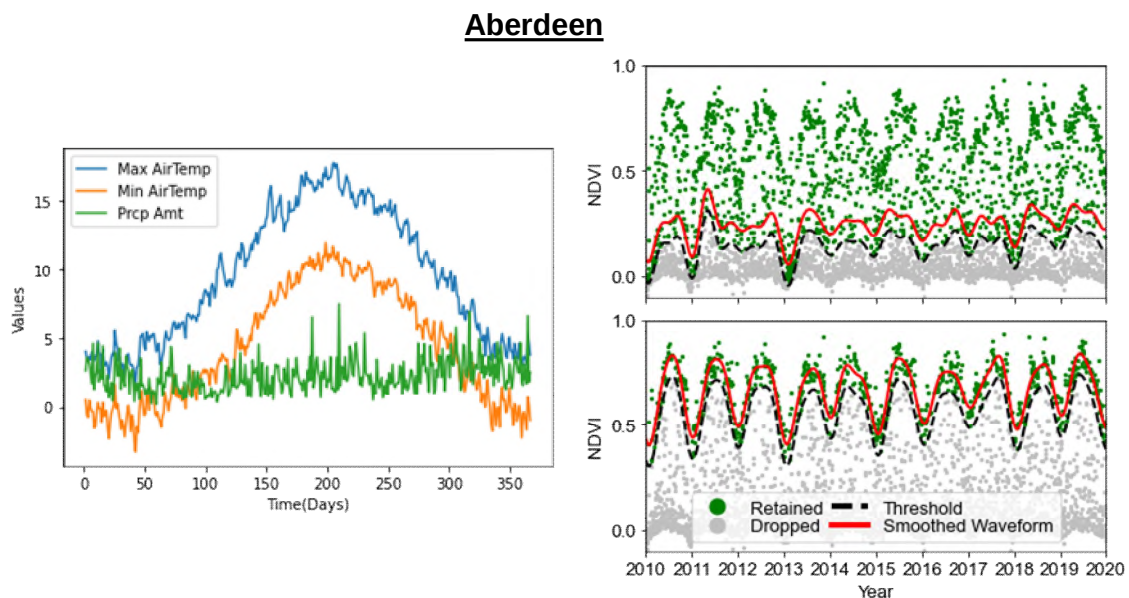


Figure C-1 The max-min temperature average (yearly) and the average precipitation amount of the Aberdeen Site. The right Figures represent a) First and b) Final iterations of the cloud filtering algorithm (for Field). The smoothed

waveform (red line) is the result of removing high frequency variation, the threshold is 0.1 units below it.

Dumfries

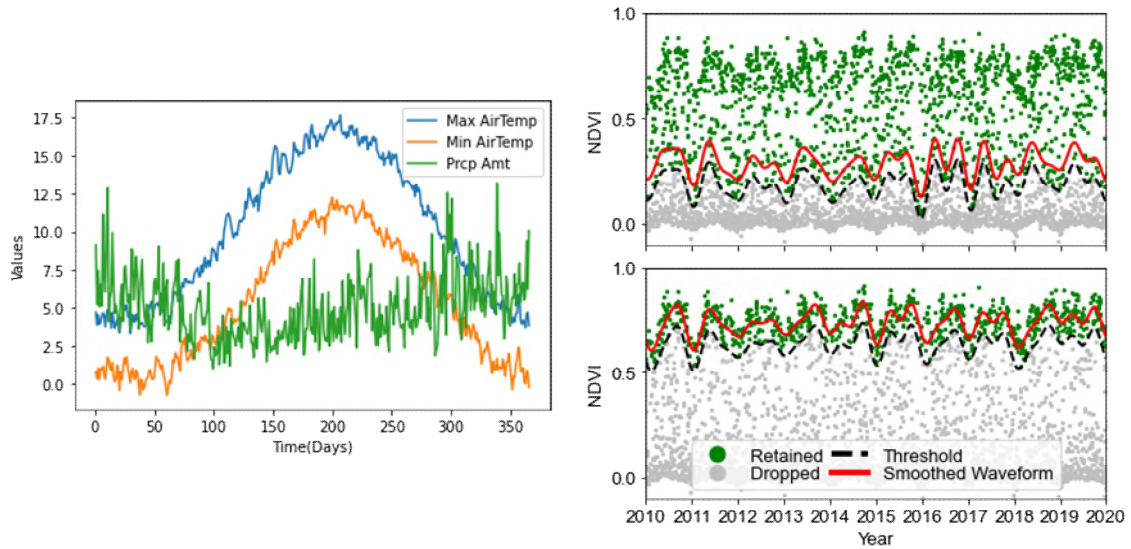


Figure C-2 The max-min temperature average (yearly) and the average precipitation amount of the Dumfries Site. The right Figures represent a) First and b) Final iterations of the cloud filtering algorithm (for Field). The smoothed waveform (red line) is the result of removing high frequency variation, the threshold is 0.1 units below it.

Yorkshire

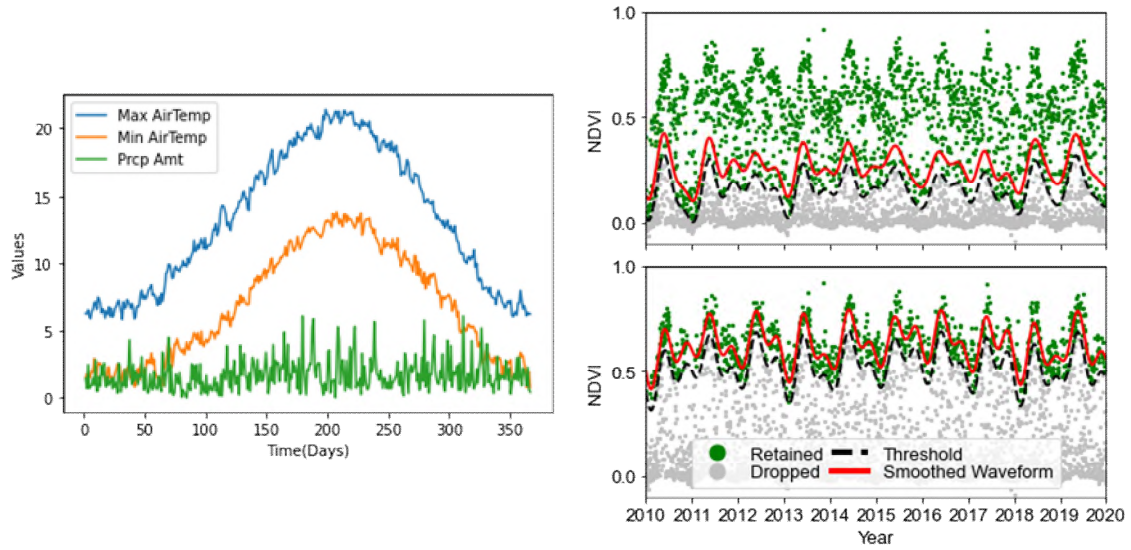


Figure C-3 The max-min temperature average (yearly) and the average precipitation amount of the Yorkshire Site. The right Figures represent a) First and b) Final iterations of the cloud filtering algorithm (for Field). The smoothed waveform (red line) is the result of removing high frequency variation, the threshold is 0.1 units below it.

Leicester

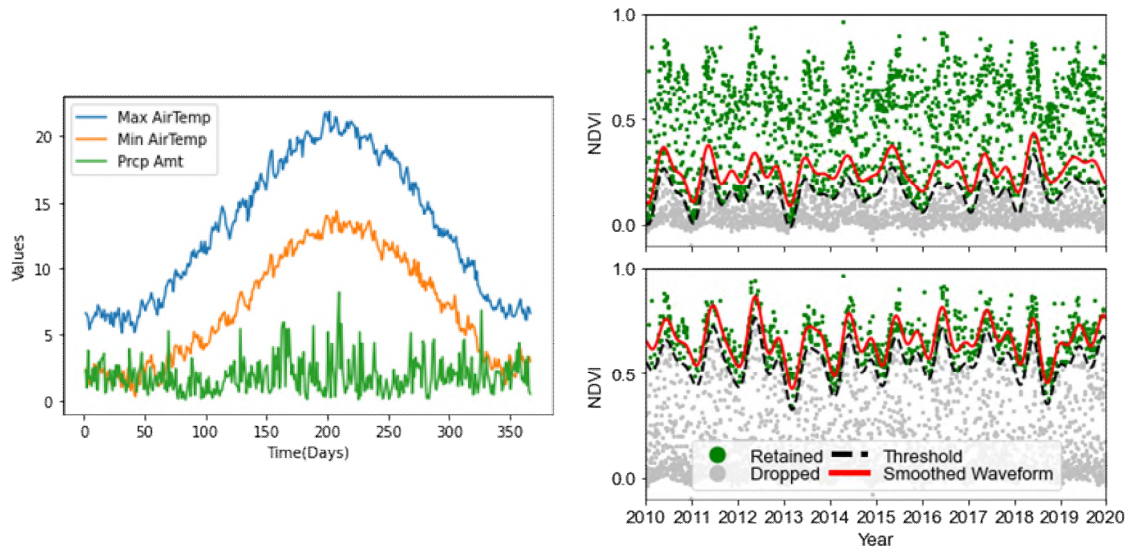


Figure C-4 The max-min temperature average (yearly) and the average precipitation amount of the Leicester Site. The right Figures represent a) First and b) Final iterations of the cloud filtering algorithm (for Field). The smoothed waveform (red line) is the result of removing high frequency variation, the threshold is 0.1 units below it.

Woburn

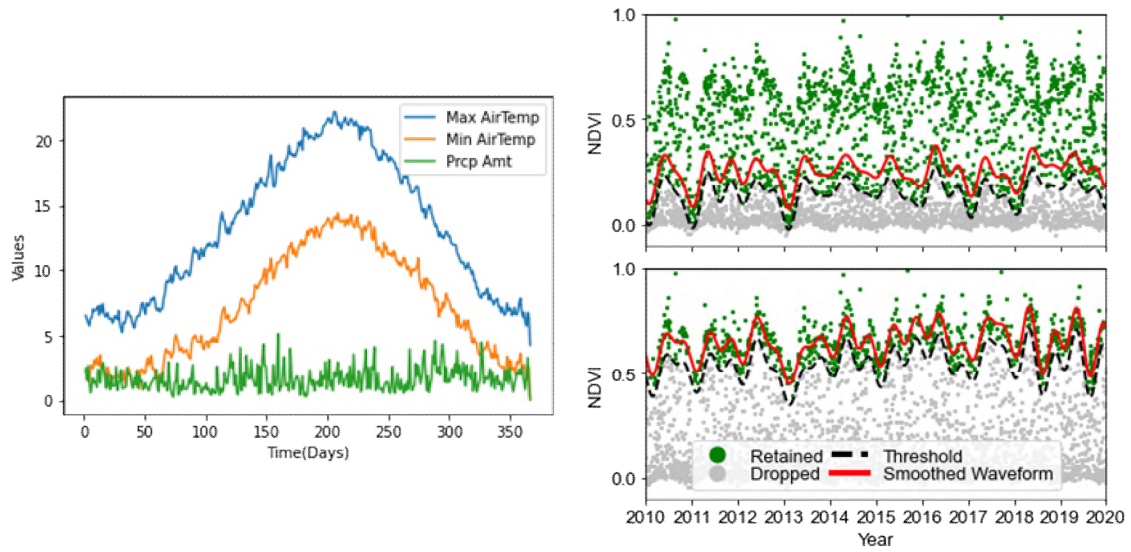


Figure C-5 The max-min temperature average (yearly) and the average precipitation amount of the Woburn Site. The right Figures represent a) First and b) Final iterations of the cloud filtering algorithm (for Field). The smoothed waveform (red line) is the result of removing high frequency variation, the threshold is 0.1 units below it.

Somerset

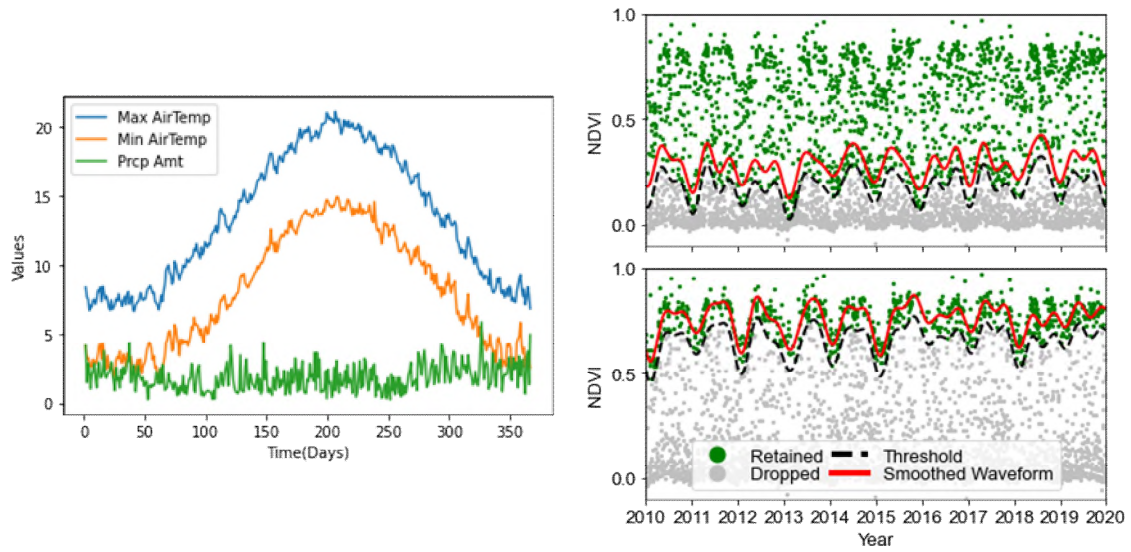


Figure C-6 The max-min temperature average (yearly) and the average precipitation amount of the Somerset Site. The right Figures represent a) First and b) Final iterations of the cloud filtering algorithm (for Field). The smoothed waveform (red line) is the result of removing high frequency variation, the threshold is 0.1 units below it.

Berkshire

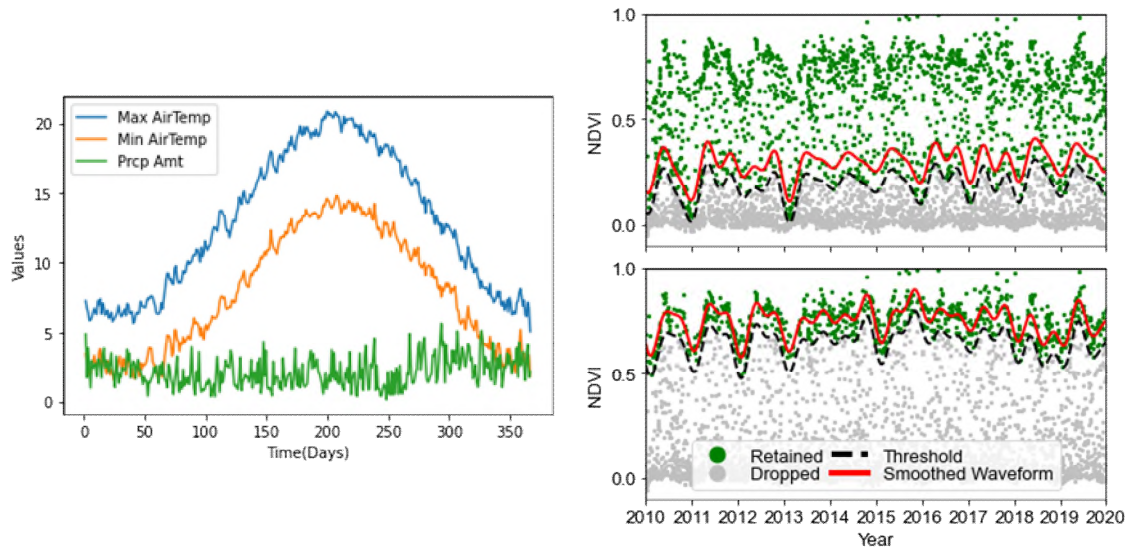


Figure C-7 The max-min temperature average (yearly) and the average precipitation amount of the Berkshire Site. The right Figures represent a) First and b) Final iterations of the cloud filtering algorithm (for Field). The smoothed waveform (red line) is the result of removing high frequency variation, the threshold is 0.1 units below it.

Dorset

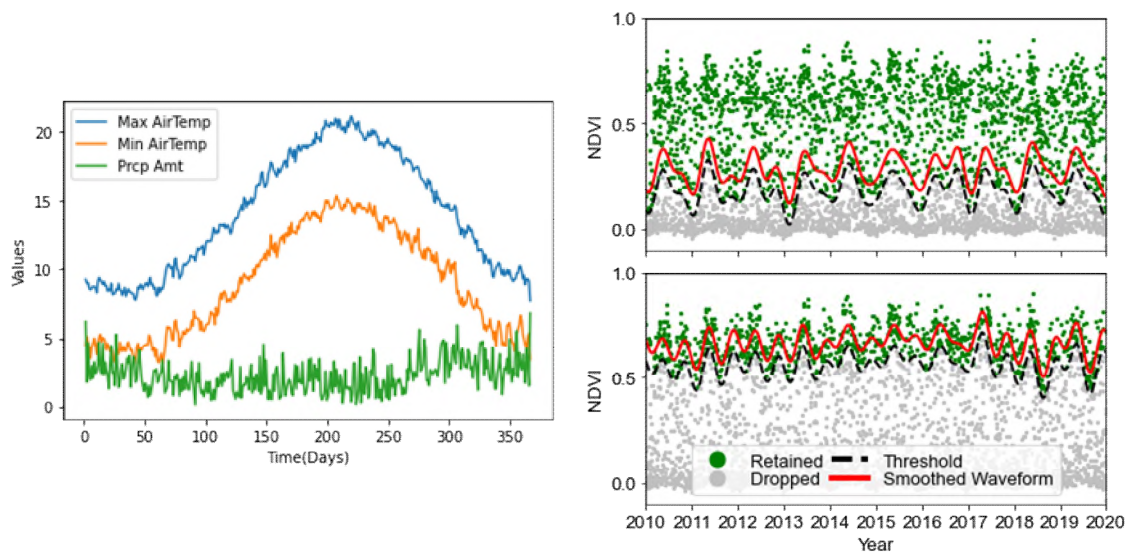


Figure C-8 The max-min temperature average (yearly) and the average precipitation amount of the Dorset Site. The right Figures represent a) First and b) Final iterations of the cloud filtering algorithm (for Field). The smoothed waveform (red line) is the result of removing high frequency variation, the threshold is 0.1 units below it.

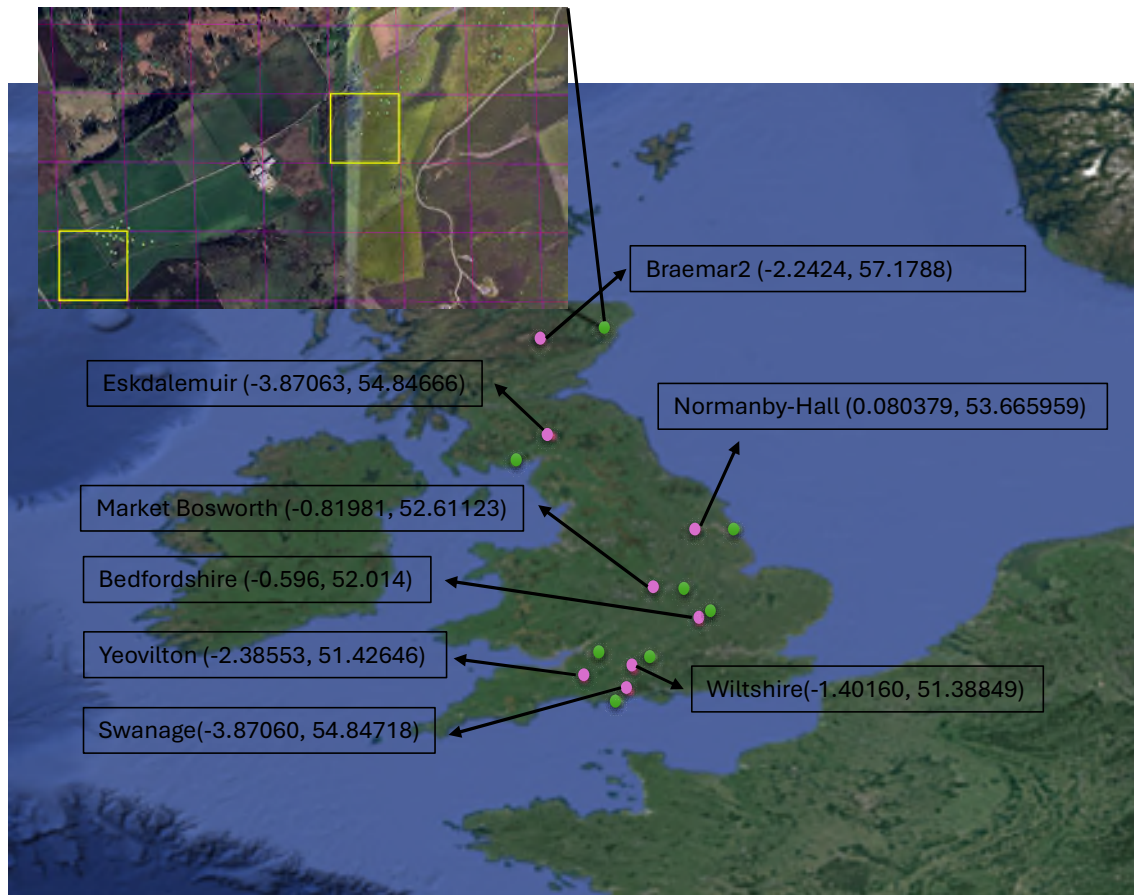


Figure C-9 The study sites and distribution of weather stations, (e.g. Braemar-2 weather station is located at the pink circle).

Appendix D Managing landscape resilience at CRMS stations via R software and QGIS statistical analysis.

D.1 List of figures created with Rstudio and QGIS of all the CRMS stations in Louisiana of South Florida according to our Time Series Data:

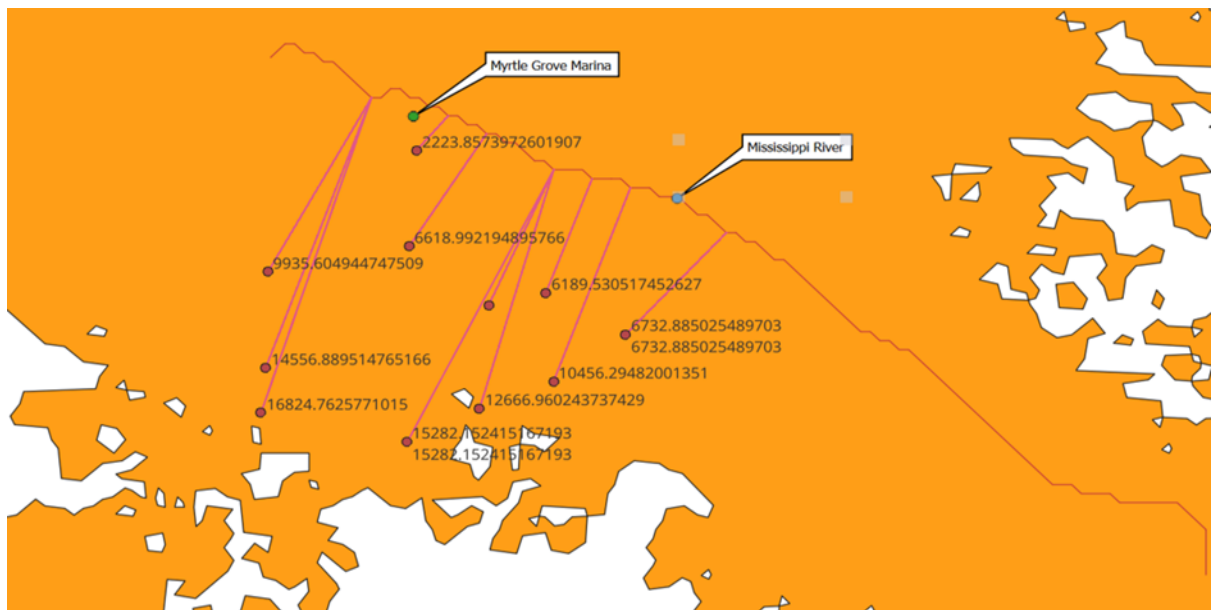


Figure D-1 The analyzed points (locations of the sub-regions) interpolating the distance of the CRMS station's points from the Mississippi river. In the deltaic plain, the coastal basins are separated by current and abandoned river channels.

Table D-1 A hierarchy of forcing mean salinity (ppt), pulsing Euclidean distance (m) from the Mississippi river (Diversion) affecting the resilience formation of CRMS stations, according to mean raw water level (ft).

Station ID	Total Mean Salinity (ppt)	Distance (m)	Longitude	Latitude	Mean Raw Water Level (ft)
CRMS0276	6.02	2223.857397	-89.94501897	29.61936079	0.88
CRMS0263	7.77	6189.530517	-89.88885734	29.55324889	1.64
CRMS3601	7.02	6618.992195	-89.94810901	29.57505163	1.82
CRMS0260	8.58	6732.885025	-89.85422681	29.53410765	1.98
CRMS3617	8.18	7467.357736	-89.91364609	29.54773115	1.63
CRMS0225	5.14	9935.604945	-90.0095165	29.56317423	1.54
CRMS0226	9.14	10456.29482	-89.88550016	29.51238918	2.11
CRMS0224	9.21	12666.96024	-89.91767272	29.49967494	4.6
CRMS0251	6.49	14556.88951	-90.01049609	29.51870615	1.08
CRMS3590	7.69	15282.15242	-89.94905225	29.48427375	2.24
CRMS0232	7.06	16824.76258	-90.01256228	29.49787383	1.74

Table D-2 Stations sorted by the Diversion and perturbation events analysing the periodicity, the end date, and the recovery time (Days).

Diversion	Tropical Storm Gustav (1st Sep 2008)			Hurricane Ian & Nicole (10th Oct-7th Nov 2022)			Tropical Storm Lee (4th Sep 2011)			Hurricane Humberto (13th Sep 2007)			Drought (June 2023)		
	Periodicity (Months)	End Date (Years)	Recovery Time (Days)	Periodicity (Months)	End Date (Years)	Recovery Time (Days)	Periodicity (Months)	End Date (Years)	Recovery Time (Days)	Periodicity (Months)	End Date (Years)	Recovery Time (Days)	Periodicity (Months)	End Date (Years)	Recovery Time (Days)
CRMS_3590	4	2011	261	Tropical Storm Karen (6th Oct 2013)			6	2013	32						
CRMS_0224				9	2014	177							71	2024	31
CRMS_0226							Tropical Storm Ida (10th Nov 2009)			26	2015	56	27	2024	89
CRMS_0232	Hurricane Isaac (29th Aug 2012)						18	2013	138	17	2013	63			
CRMS_0260	13	2016	189				Tropical Storm Gustav & Ike (1st Sep 2008)			Hurricane Ian & Nicole (10th Oct-7th Nov 2022)			20	2024	46
CRMS_0251				9	2016		17	2012	101	49	2024	169	48	2024	104
CRMS_3617	19	2014	150										20	2024	68
CRMS_0263	12	2016	36				Hurricane Ida (29th Aug 2021)			Hurricane Humberto (13th Sep 2007)			17	2024	31
CRMS_0225							17	2024	59	14	2013	117	49	2024	110
CRMS_3601	Tropical Storm Edouard (4th Aug 2008)			Hurricane Isaac (29th Aug 2012)			16	2024	91	11	2013	132	17	2024	7
CRMS_0276	18	2017	119	20	2017	142							47	2023	31

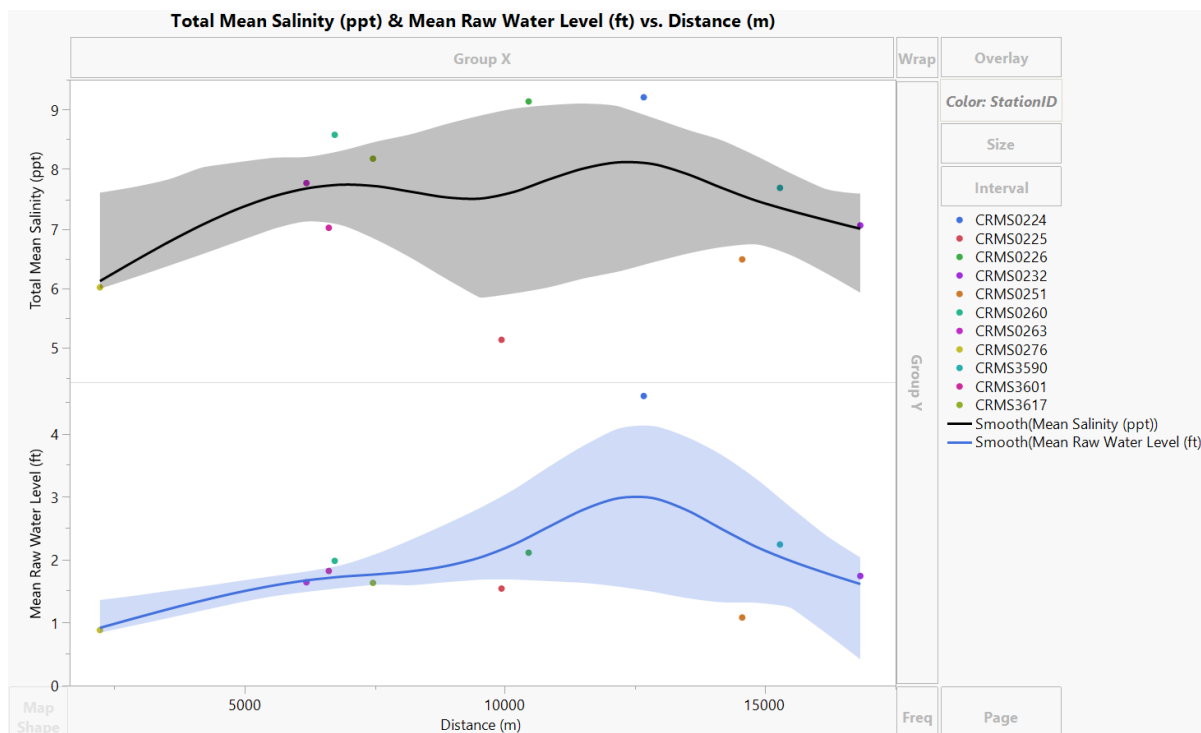
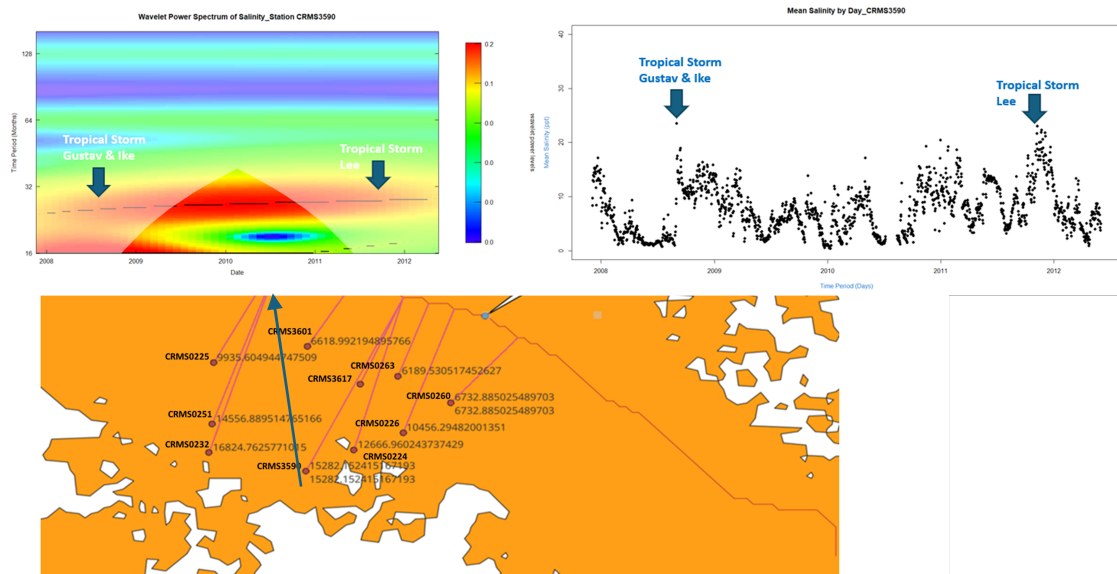
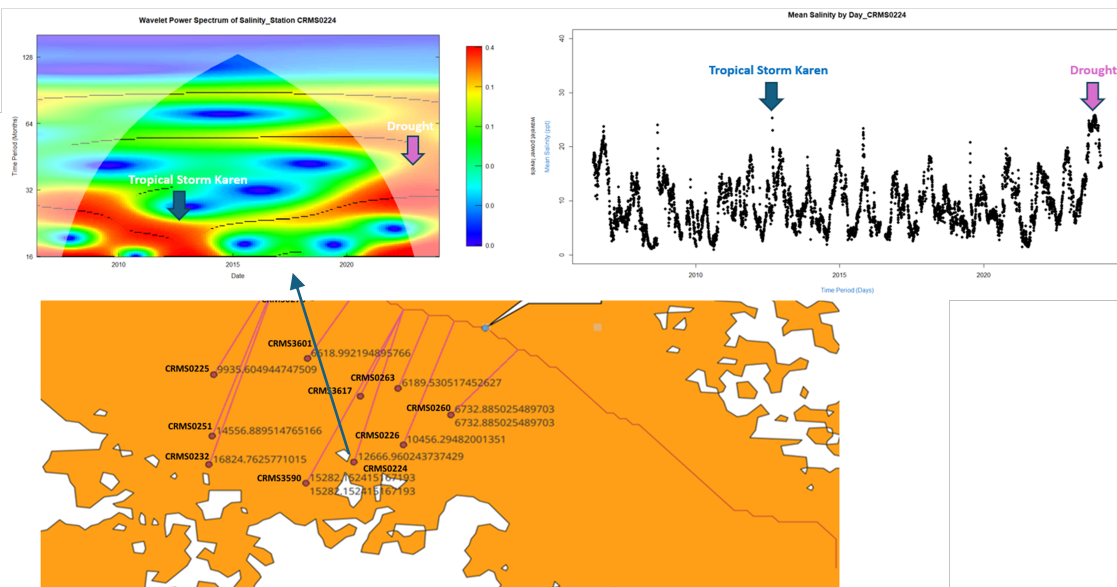
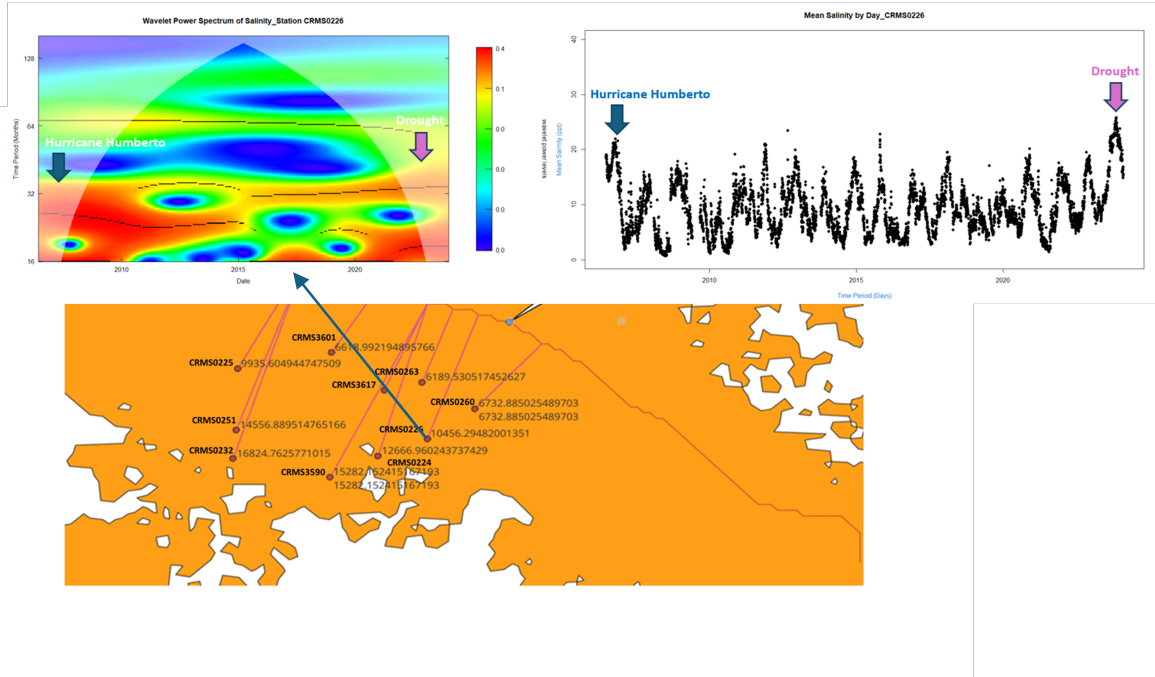
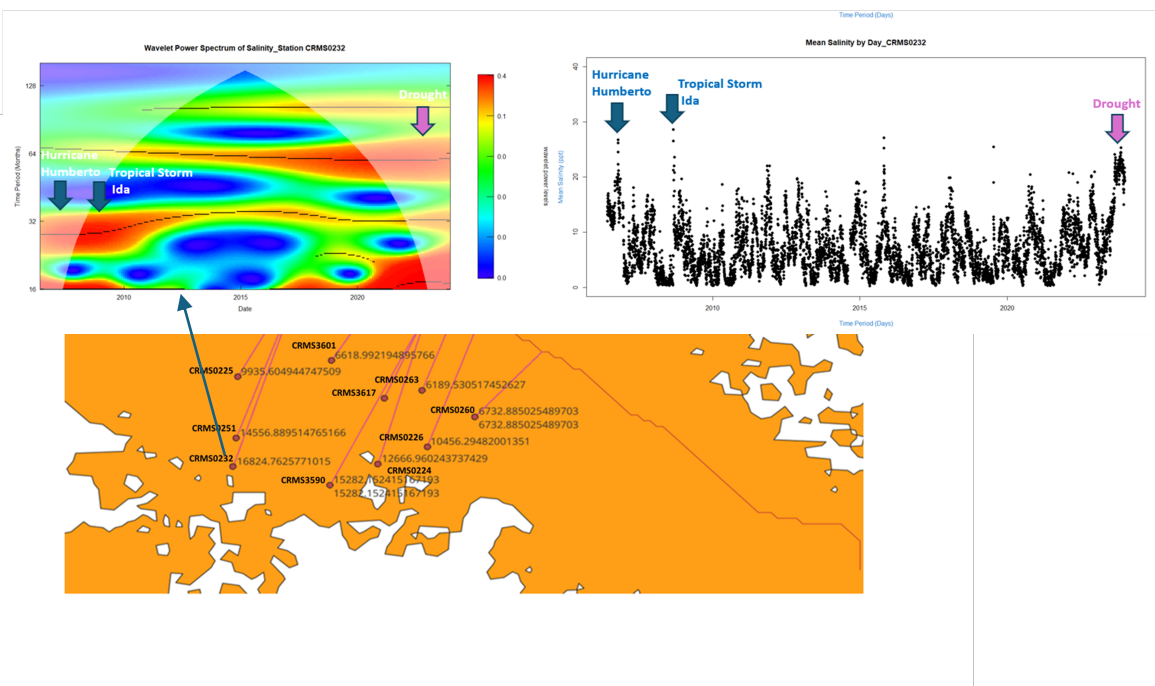


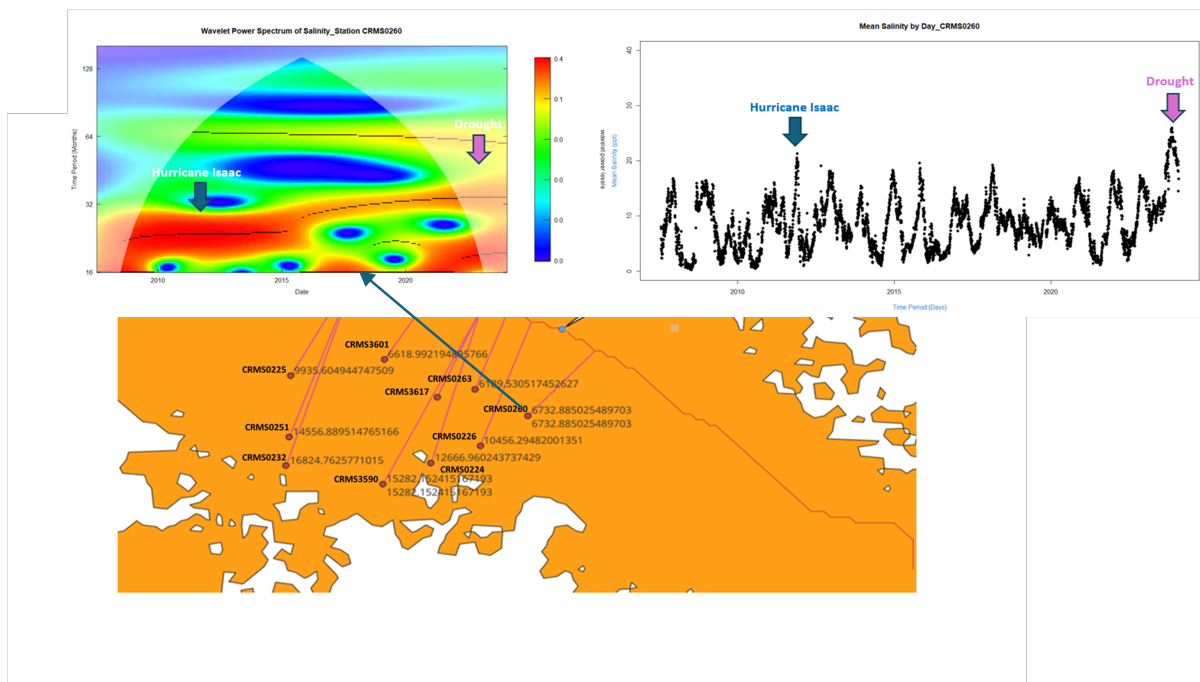
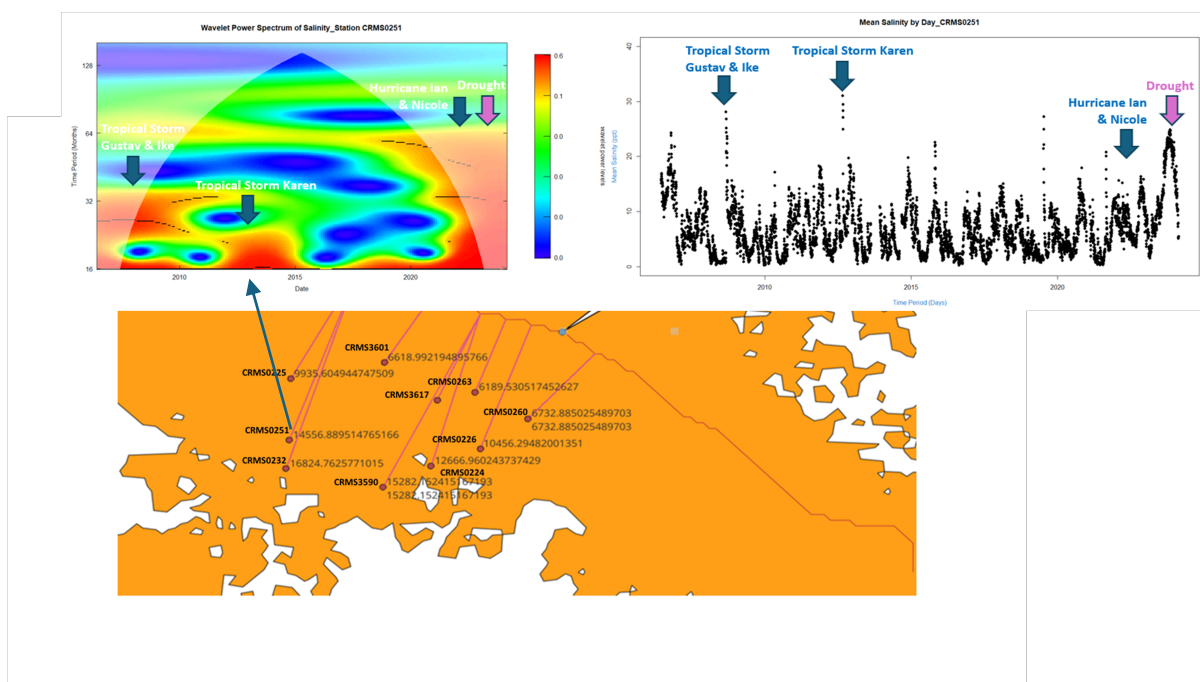
Figure D-2 Stations sorted from nearest to longest distance from the Mississippi River (Diversion). Station's Graph Visualization of scattered located stations of the diversion measuring distance from the Mississippi river and the corresponding correlation between salinity and the mean raw water level (ft) of the CRMS stations.

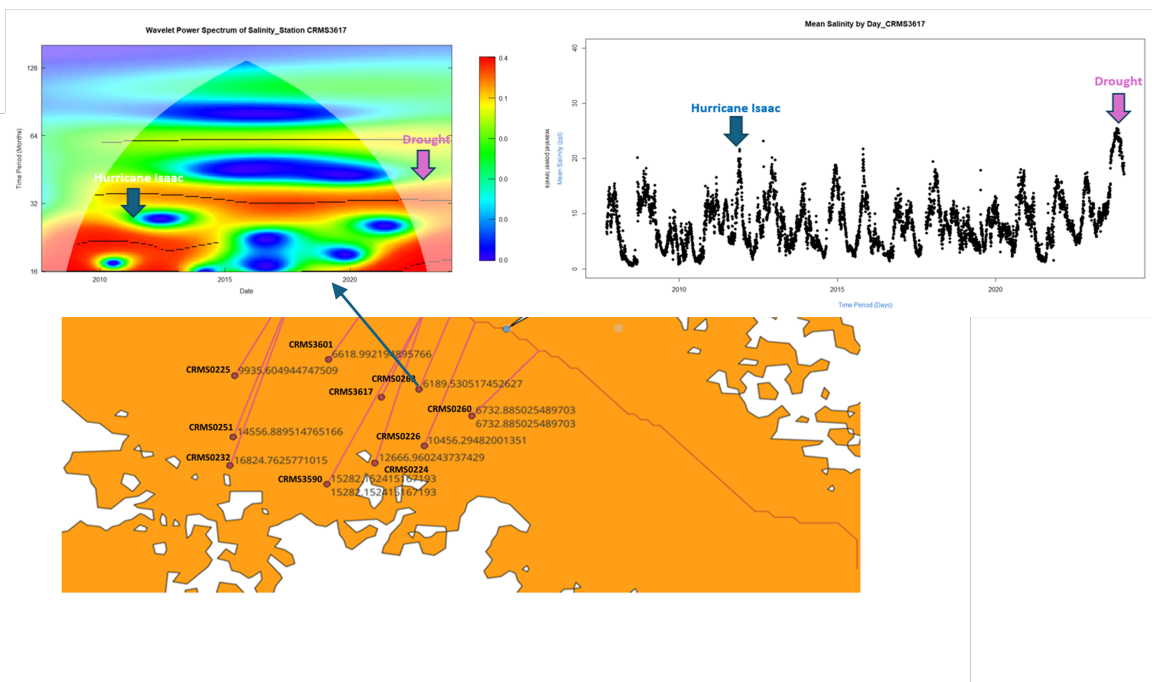
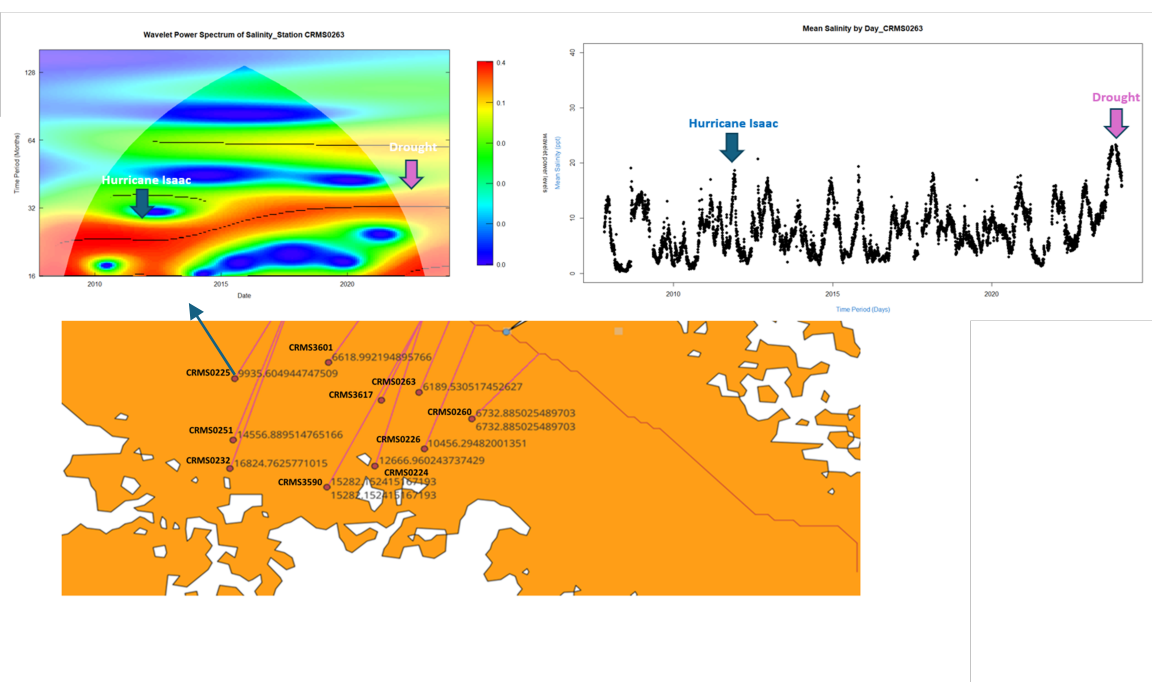
a)

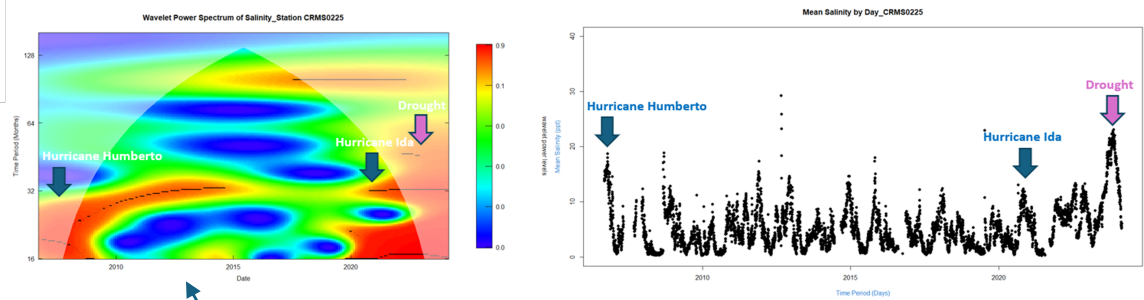
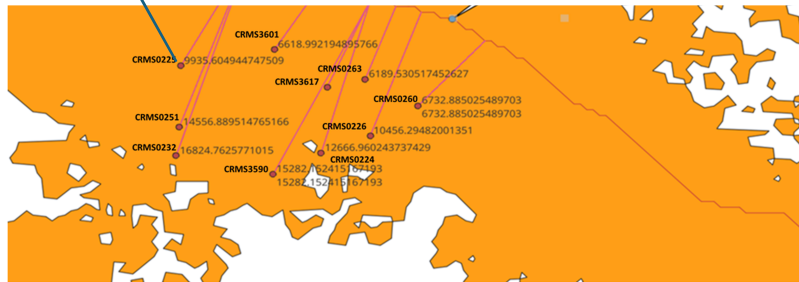
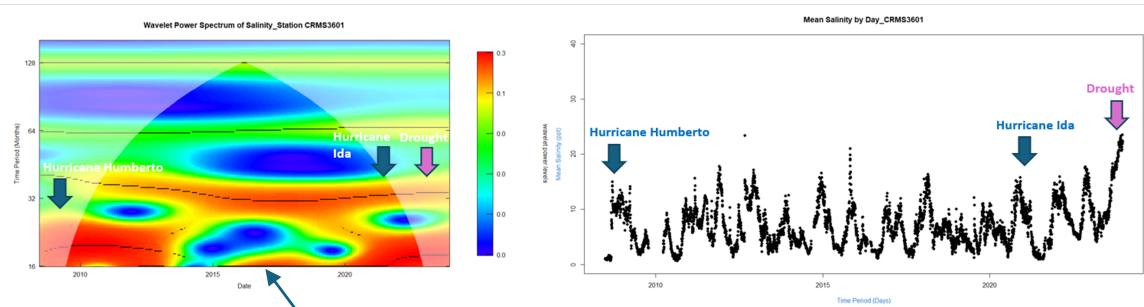
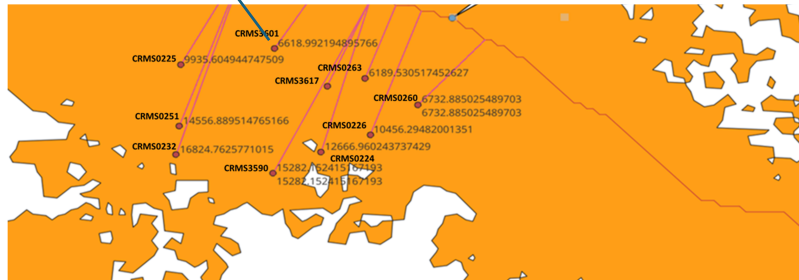
b)











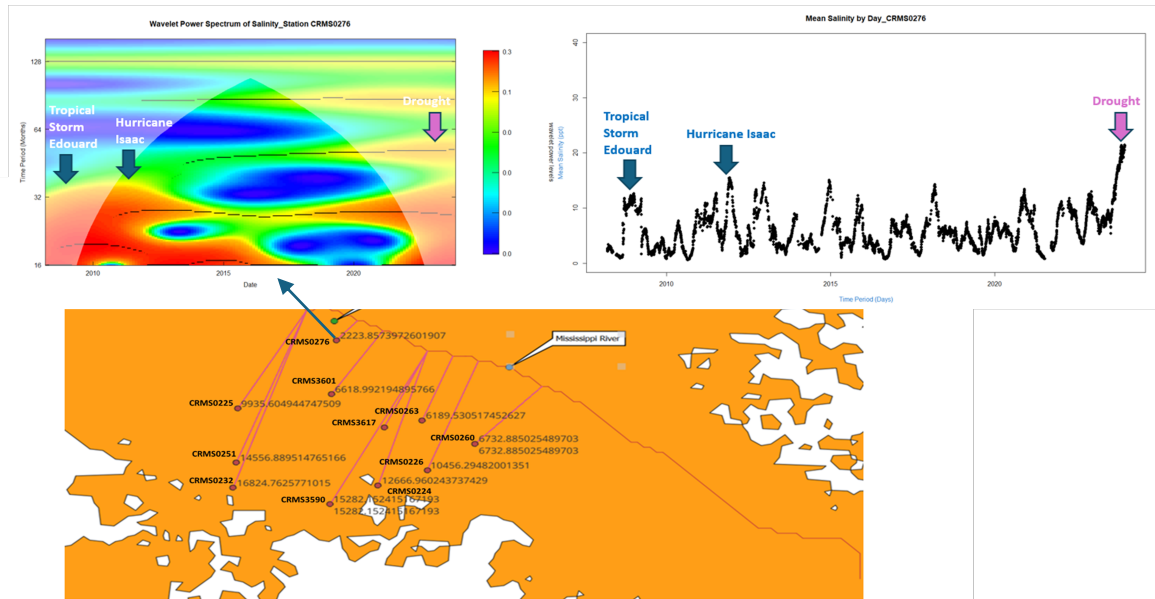


Figure D-3 The Wavelet Power Spectra regarding Diversion as a function of frequency. a) The graphs show that the variance increases in red areas and decreases in blue areas. b) The total mean salinity (ppt) correlations with days for the period 2006-2024.

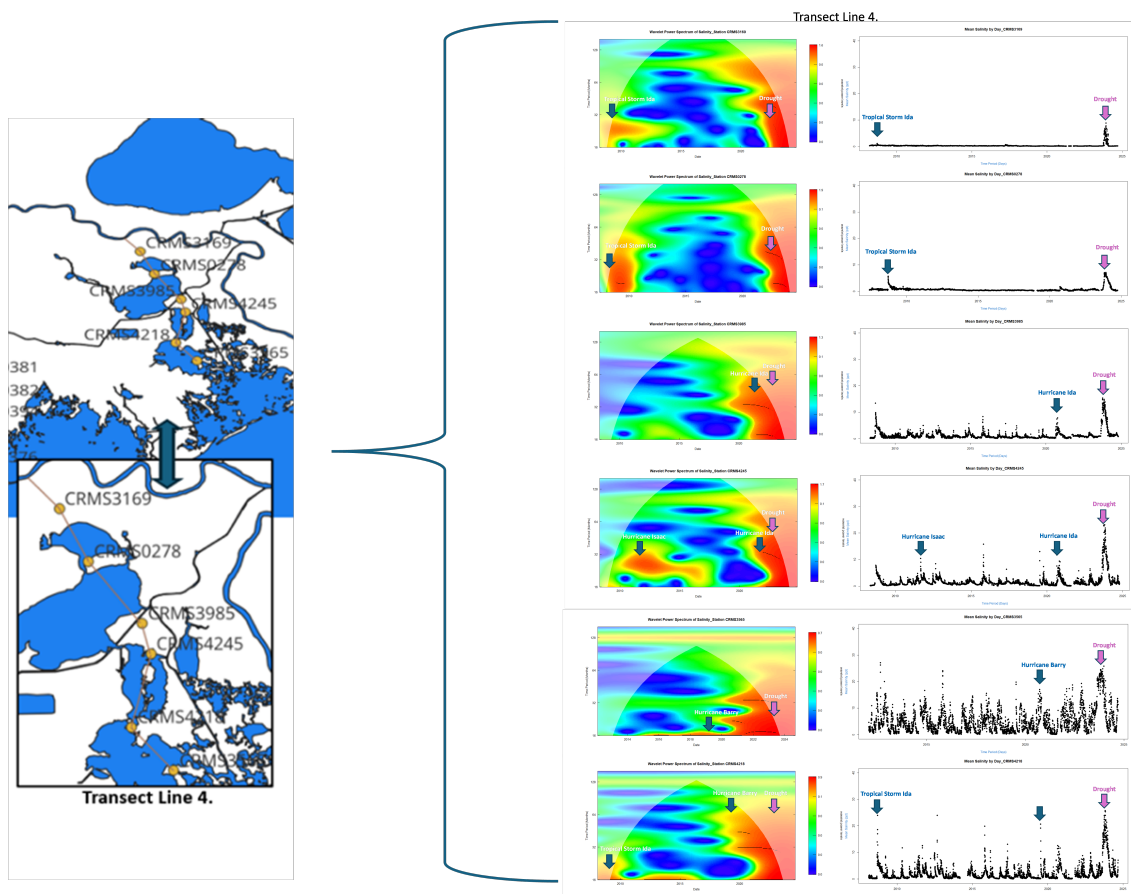


Figure D-4 The wavelet power spectra summary for the Transect Line 4 as well as the extreme events representation through years of the period 2010-2020 regarding the total mean salinity in parts per thousand (‰).

D.2 Python and R software Model's Codes

The link with new Repository on **GitHub** is provided below:

<https://github.com/NikolaosCranfield/NikolaosT.bTest>