

CRANFIELD UNIVERSITY

JAE HUN SHIN

SUSPENDED SEDIMENT TRANSPORT IN RIVERS: NEW
INDICATORS OF TRANSPORT DYNAMICS FOR ANALYSIS OF
CATCHMENT AND CLIMATE CONTROLS

SCHOOL OF WATER, ENERGY AND ENVIRONMENT
Phd In Water

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Academic Year: 2020 - 2023

Supervisor: Dr. Robert Grabowski
Associate Supervisor: Prof. Ian Holman
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the degree of PhD

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ABSTRACT

Suspended sediment is found naturally in rivers but can cause environmental and engineering problems, especially if the quantity or quality has been altered. Many factors affect suspended sediment concentration (SSC), such as land cover, land use, vegetation growth, and weather, making it difficult to predict changes in SSC at a location over short time periods (e.g., days to months). The aim of this research was to improve the scientific understanding of intra-annual variations in SSC through the statistical analysis of SSC timeseries data from rivers across a variety of catchment and climate characteristics. The specific objectives were to: (i) characterise the continental scale spatio-temporal variations in SSC dynamics using new transport indicators, (ii) determine the contribution of climate to these variations, and (iii) identify SS transport dynamic responses to climate oscillations as a means to separate out the effects of shifts in seasonal weather from catchment influences. The study used daily SSC (mg/l) and site attribute data from the US Geological Survey (USGS), which included 1,666 gauging stations of SSC across the continent, Hawaii and Puerto Rico. First, new indicators of SSC dynamics were developed and applied to the data, based on magnitude, frequency and timing (MFT). Through statistical analysis e.g., principal component analysis (PCA) and K-means clustering, new insights in spatial variability of temporal dynamics in SSC were identified e.g., high extreme events in desert and mountainous areas, the longest duration of events in upper Midwest and distinctly different timing of events in Puerto Rico. Next, further statistical analyses (regression and geographically weighted regression) were conducted on a reduced number of sites (n=120) to determine the relative importance of different catchment and climate factors. The MFT indicators of SS enabled identification of short term dynamics and new understandings of varying influence of land use and land cover. The key results were identified that agricultural covers were positively related with low frequency SSC events. Urban and forest covers brought higher frequency events, except in the driest region. Annual average precipitation had a negative relationship with SSC magnitude. Finally, the influence of climate oscillations e.g., El Niño–Southern Oscillation (ENSO), North Atlantic Oscillation (NAO), Pacific Decadal Oscillation (PDO) on SSC transport

dynamic indicators was evaluated for four catchments using continuous and cross wavelet analyses. Periodicities in SSC indicators were identified that match climate oscillations, suggesting that small shifts in seasonal weather (e.g., wetter winters) can cause significant changes in SS transport dynamics in rivers. Future works remain to be using latest SS data in the future or application of latest technology e.g., turbidity as well as optimization of input parameters in modelling by generation of MFT time series. This research provides new understandings of SS transport dynamics in rivers and the relative importance of catchment and climatic factors, which will inform practitioners of SS modelling for better predictability in a changing climate.

Keywords: Suspended sediment dynamic indicators, Magnitude, Frequency and Timing (MFT), Climatic change, Hydrological processes, Wavelet analysis, Climate oscillations, Ordinary Least Square (OLS) Regression, Geographically Weighted Regression (GWR), K-means Clustering

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I really appreciate the opportunity, generously provided by the uni to embark on the Phd journey. My background as an engineer before joining Cranfield can be described as inadequacy and being on a steep learning curve with endless struggling. This lucky opportunity to analyse the speculative unknowns enabled me to be at Cranfield. I've listed my sincere appreciation in this acknowledgement. I've been luckier than any other else having this opportunity to write Acknowledgement.

This writing up stage first brings me to when I considered pursuing a Phd. I still remember my wife's anxiety behind a back seat in my car crossing the river in Seoul when I told her I'm quitting the job to pursue a doctorate. Similar reaction occurred when I told people around me. Then, they replied to me with harsh words or sentences that academics rarely use, but I always had in my mind that life is to follow the law of scarcity. In that sense, I was always thinking, trying a Phd is the best option.

The journey started with a generous acceptance of my naive and inadequate suggestion including a decision on the execution of Alumni bursary. The acceptance is described as an acting of sparing their precious portion of something good hidden. This all happened on the onset of Covid-19 in 2020. I remember that it was a desperate choice and tried to hold a solid rope for a better future, which eventually took me out of the concrete jungle during the last 4 years.

I've been quite lucky as generous ideas about existing applicable raw data have enabled this study. The research was simply possible by the thorough guidance from the supervisors (Dr. Robert Grabowski and Prof Ian Holman). The brilliant insights and applied knowledge are thought to be the right words for their massive help. The guidance incorporated understandings, which were certainly beyond my ability to plan or imagine. There have been numerous hints and guidance, but I couldn't notice quickly because I didn't have that much deeper insight. I felt this feeling many times during the study and lecturing on how to work continued in a similar manner in Msc but in a much more advanced way with a lot more stuff

and depths. The supervisors also gave me a key to open the gate to a different world where scripts boost productivity, which is an independence from making a lot of mistakes by clicking, dragging and checking numbers by eyes. These all highlight my supervisors' high level insights and vision that also emphasizes my unfortunate status of not likely to meet such bosses in anywhere else but obviously every boss at Cranfield is exceptional including the director of the theme, Prof Paul Jeffrey as well as within the team in 2 weeks interval for Cop meeting, Prof Jerry Knox and Prof Tim Hess. Sharp reviews by Prof Neil Harris and Dr Andrea Momblanch were very appreciated. I also really thank the effort of proof reading by Dr Andrea Momblanch and Dr Niranjana Panigrahi in the submission stage of the thesis. The constructive feedback from the examiners (Prof Jane Rickson and Prof Nicholas Howden) after Viva were highly valued. I'm giving special thanks to Dr Katy Wiltshire and Dr Ben Exton for comments during correction stage. I appreciate all of the people involved in this study for their gentle influences to me, which is world class.

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River environment is much more complex than I thought. My study is not the end of finding processes of good justification of climate on suspended sediment as the nature is continuously evolving and better data will be accumulated. I hope this research well serves as a footstep for next people who would like to make things better. Natural phenomena are somehow speculative by anybody on their own but numerically quantifying them requires aids from someone who knows really well about it. The rope, thrown to me pulled out by the people at Cranfield had led me to be a much better person indeed. Many thanks.

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LIST OF ABBREVIATIONS

AGNPS	AGricultural Non-Point Source Pollution Model
Agperc	Percentage of agricultural land
AI	Artificial Intelligence
AIC	Akaike Information Criterion
AMO	Atlantic Multi-decadal Oscillation
ANFIS	Adaptive Neuro-Fuzzy Inference Systems
ANN	Artificial Neural Networks
ANOVA	Analysis of Variance
ANSWERS	Areal Non point Source Watershed Environment Response Simulation
AO	Arctic Oscillation
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
BFI	Avg. baseflow index (%)
BIC	Bayesian Information Criteria
C.of.e	Avg. annual number of SSC events
Catch.A	Upstream drainage area (sq. miles)
CC	Climate Change
Clay	Avg. percentage of soil clay content (%)
D	Avg. annual duration of SSC events, in days
DJF	December-January-February
Eco L1 Code	Level I Ecoregion Code
ENSO	El Niño-Southern Oscillation
ETF	Eastern Temperate Forest
F.r	Avg. annual daily falling rate in SSC
Flow.50p	50 th percentile of daily flows
Flow.95p	95 th percentile of daily flows
FNU	Formazin Nephelometric Units
Forestperc	Percentage of forest land
GAGES	Geospatial attributes of gages for evaluating stream flow
GHG	Greenhouse Gases
GP	Great Plains
GWR	Geographically Weighted Regression
InVEST	Integrated Valuation of Ecosystem Services and Tradeoffs
JJA	Jun-July-August
Kfact	Avg. K-factor for the uppermost soil horizon (unitless)
Loess	Locally weighted scatterplot smoothing
LULC	Land Use and Land Covers
M25	Avg. annual 25 th percentiles of SSC
M50	Avg. annual 50 th percentiles of SSC
M75	Avg. annual 75 th percentiles of SSC
M95	Avg. annual 95 th percentiles of SSC
Major_Dams	Number of dams
MAM	March-April-May
MC	Mediterranean California
MFT	Magnitude, Frequency and Timing
MK	Mann Kendall
Month.i.p.max	Month with the maximum number of events
Month.max.sum	Month with the maximum total SSC
M-SVR	Multi-output Support Vector Regression

MUSLE	Modified Universal Soil Loss Equation
MWC	Multiple Wavelet Coherence
MWCF	Marine West Coast Forest
NAD	North American Deserts
NAO	North Atlantic Oscillation
NFM	Northwestern Forested Mountains
NLCD	National Land Cover Database
NOAA	National Oceanic and Atmospheric Administration
OLS	Ordinary Least Squares
P.p.e	Avg. annual number of peaks per SSC event
PCA	Principal Component Analysis
PDO	Pacific Decadal Oscillation
Perm	Soil permeability
PPT30	30-year rainfall and runoff factor
R.r	Rising rate
R.storage	Dam storage
RE	Rainfall erosion
Rfact	30-year rainfall and runoff factor
RUSLE	Revised Universal Soil Loss Equation
s.e.	Standard errors
Sand	Sand content
SDR	Sediment Delivery Ratio
SHETRAN	SHE (Système Hydrologique Européen), TRAN (Transport)
Silt	Silt content
SON	September-October-November
SSC	Suspended Sediment Concentration
SST	Sea Surface Temperature
Stdev.max	Standard deviation of monthly maximum SSC
Stdev.min	Standard deviation of monthly min SSC
SVM	Support Vector Machine
SWAT	Sediment Water Assessment Tool
Urbanperc	Percentage of urban land
USGS	United States Geological Survey
WEPP	WEPP
WLS	Weighted Least Square

1 Introduction

Suspended sediment is a natural part of river systems and important for structuring landscapes (Bywater-Reyes *et al.*, 2018), maintaining ecological habitats and nutrient transport (Boota *et al.*, 2022). Alterations to the quantity and quality of fine sediment can have negative impacts on local ecology, increasing flooding and management of infrastructure (Vercruysse *et al.*, 2017). Suspended sediment in rivers deteriorates water quality through physical, ecological and chemical impacts and can be especially problematic when the particles deposit in the bottom of rivers causing colmation (Wharton *et al.*, 2017; de Oliveira *et al.*, 2021). Additionally, because of its nature to adsorb contaminants (Desrosiers *et al.*, 2020), fine sediment deposits can be stores of harmful pollutants and microbes that further impact economic activity and ecological communities (Costa *et al.*, 2018). Thus, when fine sediment is mobilized (e.g. soil, river bank and riverbed sediment erosion), it creates additional water quality challenges for the aquatic ecosystem and society (e.g. water abstraction). The prediction of suspended sediment concentrations in rivers is important for environmental, human health and water supply reasons. However, suspended sediment transport is influenced by numerous natural and anthropogenic factors (Zhang *et al.*, 2018), making it challenging to predict using existing approaches (Vercruysse *et al.*, 2017; 2020).

1.1 Climate and catchment influences on suspended sediment transport in rivers

Climate change (CC) is predicted to affect the flux of suspended sediment in river systems and change rainfall, temperature and carbon dioxide (CO₂) concentrations, which is expected to alter the forces of climate in association with soil erosion and factors of moderation of such phenomena e.g., vegetation growth (Naylor *et al.*, 2017; Lowe *et al.*, 2018; IPCC, 2019). Such moderation occurs naturally and via anthropogenic activity, including changes to LULC in response to or as part of mitigating actions against climate change such as changes of crop types or conversion of agricultural land to forest (Murphy, 2020). Relative influences of CC on hydrological cycles e.g., temperature, precipitation and

evaporation patterns, caused spatially and temporally varying changes in water and sediment sources across the world (Barnett *et al.*, 2008, Zhang *et al.*, 2013, Miga and Philip, 2014, Zhang *et al.*, 2020). There have been many research, conducted on the impact of LULC and climate change on annual sediment load (i.e. sediment yield) at catchment scales (Dai *et al.*, 2009; Hung *et al.*, 2014; Camilo and Restrepo, 2017; Kemper *et al.*, 2019) and at continental scales (Syvitski, 2003; Walling and Fang, 2003; Wang *et al.*, 2011; Syvitski *et al.*, 2014; Moragoda and Cohen, 2020). However, less focus was identified on how these factors and their interactions influence SS transport dynamics, i.e. short-term variation of SSC at a location over days to months (Mount and Abrahart, 2011; Roman *et al.*, 2012; Murphy, 2020).

Changes to SS transport processes are expected from climate change e.g., alteration of precipitation patterns and change of magnitude and frequency of runoff (Farzin and Anaraki, 2021; Hobeichi *et al.*, 2022) including increases of soil moisture (Zimmermann *et al.*, 2012). Impacts of climate change on hydrology is inevitable that increasing rarer precipitation events lead to more frequent floodings. CC intensifies more extreme precipitation (Xiao *et al.*, 2017; Tabari, 2020) and drought (Abdourahamane and Acar, 2018; Javadinejad, 2021; Abdelkader and Yerdelen, 2022). Due to climate change, precipitation varies seasonally differently (Le *et al.*, 2023), and drought is more severely exposed (Javadinejad, 2021). Changes of magnitude and frequency of precipitation and snowfall are occurring (Whitfield and Shook, 2020). Snowmelt flows are related with shapes of hydrograph and peak flows (Neupane *et al.*, 2018). The climate change also impacts on ground water in mountains (Immerzeel *et al.*, 2020).

The impacts of CC on SS transport dynamics have drawn significant uncertainties (Coulthard *et al.*, 2012; Bussi *et al.*, 2016; Shrestha & Wang, 2018). More intensified human activities and climate change were of primary importance for studying hydrological responses of rivers (Xu, 2009; Yao & Xu, 2013; Wei *et al.*, 2016). Therefore, it requires thorough knowledge about its impacts on SS for better prediction accuracy (Basher *et al.*, 2020; Murphy, 2020). SS generation needs efficient management of sources from catchments in various sizes under

this combination of difficult circumstances (Murphy, 2020). Thus, fundamental importance is recognized in CC impacts on LULC i.e., process based understandings (Girolamo *et al.*, 2015). These all emphasize a growing importance of better understanding suspended sediment transport due to climate change (Costa *et al.*, 2018).

Uncertainty of SSC dynamics exist because numerous factors affect suspended sediment transport. Climate, LULC and human activities all affect the magnitude, frequency and timing of SS events (Vercruysse *et al.*, 2017). Climate change is shifting temperatures and rainfall, but it is also altering the frequency and magnitude of extreme weather events (van de Pol *et al.*, 2010). These climate influences can directly affect SS generation and transport, through rainfall led soil erosion and resuspension of sediment deposition over land and in river channels. Precipitation is the primary driver of soil erosion and mass movements that provide the raw material for SS transport in rivers (Ampomah *et al.*, 2020; Çakmak *et al.*, 2021; Guduru and Jilo, 2023). However, the relationship between precipitation and soil erosion rates is non-linear because of spatial differences in catchment characteristics, like topography, slope, geology, soil hydraulic conductivity and soil erodibility, and antecedent conditions (e.g. soil moisture) that affect the availability of sediment, the partitioning of rainfall at the soil surface and the generation of overland flow, which drives soil erosion (Trenberth, 2011; Javanshiri *et al.*, 2023). Anthropogenic alterations to catchment characteristics affect hydrological responses such as runoff generation and sediment dynamics (Ashraf *et al.*, 2016; Yang *et al.*, 2018; Wu *et al.*, 2023). Similarly, river discharge is the primary driver of resuspension and transport within river networks, which is affected by similar factors that influence the amount, timing and flow of water across and within the landscape (Mcgregor, 2019). However, again, there are non-linear relationships between river discharge and SSC due to temporal changes in sediment supply (Jothityangkoon and Sivapalan, 2009; Megnounif *et al.*, 2013; Wang *et al.*, 2018; Mcgregor, 2019; Moragoda and Cohen, 2020; Szalińska, Orlińska-Woźniak and Wilk, 2020; Syvitski *et al.*, 2022). For example the exhaustion of intermediate sediment stores during a storm event or the input of sediment from new sources (e.g. bank erosion) (Vercruysse *et al.* 2017).

Climate change can also, both positively and negatively alter suspended sediment flux at catchment scale through indirect effects on vegetation growth. The combined effect can lead to multiple possible future trajectories in SSC dynamics in rivers with climate change. Increased vegetation from higher temperatures and CO₂ concentrations in the air will reduce soil erosion, despite a higher frequency and magnitude of precipitation events and runoff (Tietjen *et al.*, 2017). Rainfall also was known to have less effect on sediment generation than the catchment hydrological regime (Fortesa *et al.*, 2021). Other hydrological variables like evapotranspiration have been linked with large scale climate oscillations (Xu, 2019). Natural responses to climate change could be mitigated by LULC changes, installing engineering infrastructures and implementing erosion control methods across the landscape. However, SS transport is not linearly responsive to natural processes or anthropogenic activities (Bussi *et al.*, 2016). While rainfall and discharge are often used to predict suspended sediment transport, relationships between these drivers and SSC are not constant in different space and time due to impacts by various processes (Vercruysse *et al.*, 2017). Therefore, better prediction of future changes to SSC transport dynamics requires further research on the climate and catchment factors that interact to affect the frequency and timing of high SSC events.

There is complexity in sediment generation processes and their interactions due to multiple erosion and physical processes from various sources (Worrall *et al.*, 2013; Licciardello *et al.*, 2019; Misset *et al.*, 2019). Process-based understanding is required as there is importance of understanding hydrological catchments and their interactions with variability of climatic influences (Girolamo *et al.*, 2015; Guan *et al.*, 2018). It is worth understanding how further impacts on hydrological cycles and catchment scale processes including runoff, evaporation rates, erosion and sediment transport. Despite many efforts, there have been clear gaps on lack of understanding of spatial and temporal distribution of SS transport.



1.2 Previous research on suspended sediment transport in rivers

The prediction of suspended sediment transport dynamics in rivers is complicated by the large number of sediment sources in a river network and catchment and the large number of factors influencing erosion and transport at multiple spatial and temporal scales (Vercruysse *et al.*, 2020). A variety of statistical and modelling approaches have been used to investigate transport dynamics and the climate and catchment factors. Relatively few studies investigated short term dynamics from SS transport. Sediment loads were mostly used to investigate SS transport, which would be more suited to longer time frame e.g., annual distribution. Therefore, it is much more worthwhile to analyse intra-annual variations using approaches available in other hydrology and water quality studies. Such uncertainties also are doubled by climate change.

Previous research has studied the effects of rainfall over small catchments and large rivers on water yield and suspended sediment (López-tarazón *et al.*, 2009; Oeurng *et al.*, 2010; Nu-fang *et al.*, 2011; Chen *et al.*, 2014; Sun *et al.*, 2016). Studies have used daily SS loads due to the links to soil erosion processes and sediment transport e.g., soil loss degradation and areas of deposition (Walling & Fang, 2003; Achite & Ouillon, 2016; Pandey *et al.*, 2016; Basher *et al.*, 2020). Also, many studies across different spatial and temporal scales were tried using an SS load approach (Roman *et al.*, 2012; Das, 2021). However, it does not allow us to separate out SSC and discharge as it is multiplied by water discharge (Porterfield, 1972). They often resulted in inconsistency from different catchments with different controls in SS generation such as close correlations between rainfall, runoff and soil erodibility (Nu-fang *et al.*, 2011; Chen *et al.*, 2014; Sun *et al.*, 2016). Despite the challenges in reaching acceptable range of accuracy, it is important to point out appropriate modelling practices for prediction of suspended sediment transport (Farzin and Anaraki, 2021).

There also have been much emphasis on implementing empirical and process based modelling approaches for analysing SS transport (Alewell *et al.*, 2019; Batista *et al.*, 2019). Empirical models utilize characteristics between data and

values from observation (Sulaiman and Al-ansari, 2021). Conceptual models are in the middle position between empirical and physical models as of limited physical interpretability. Physically or process based models use parameters of physics e.g., mass transfer, momentum and energy (Pandey *et al.*, 2016). However, results from daily SS physical models on loads are unable to link with event-based variation, which is crucial to improve understandings of impact of SS (Vercruysse *et al.*, 2017). Those models have been used but need to use real data. Thus, there is necessity of bringing in other approaches available in hydrology and water quality to analyze intra annual variations in SS. Nonetheless, the magnitude and extent of climate change impacts on suspended sediment dynamics are not thoroughly understood due to the large number of different factors involved (Peizhen *et al.*, 2001; Pruski and Nearing, 2002; Bussi *et al.*, 2016).

1.3 Research gaps in suspended sediment transport dynamics

Despite decades of research, spatial and temporal dimensions of suspended sediment transport and processes have not been fully understood (Vercruysse *et al.*, 2017). Recent research suggests that there are two main areas for an investigation such as better understandings of spatio-temporal dimension of SSC and processes (Rodríguez-blanco *et al.*, 2016; Zuo *et al.*, 2016) and combined impacts of climate and land-use changes on sediment (Bussi *et al.*, 2016; Rodríguez-blanco *et al.*, 2016; Asadi *et al.*, 2017; Han *et al.*, 2020; Khatri *et al.*, 2019; Shrestha *et al.*, 2018), which would be advanced through the development of new indicators of suspended sediment transport dynamics

1.3.1 Indicators of intra-annual variations in suspended sediment transport

High variability in SS transport dynamics poses a tough challenge for management due to a wide range of climate and catchment factors. SSC studies are beneficial to decision making processes on water resources management e.g., management of water infrastructure. However, deeper understanding of SSC transport dynamics is required as there are varying flux changes and increasing uncertainties from climate change. MFT (Magnitude, frequency and

timing) approach, widely applied in other fields of hydrology is potentially useful to generate temporal variability of SS transport. Each magnitude, frequency, timing can be associated with significant processes of SS in current knowledge.

Conventional approaches using sediment load lacks better indication of spatio-temporal patterns i.e., shorter term dynamics. The MFT approach is useful for overcoming limitation of analyzing a single temporal scale from most of SS transport studies (Francke *et al.*, 2014; Vercruysse *et al.*, 2017). Despite recent studies by multiscale approach using turbidity as a surrogate (Wang & Steinschneider, 2022), impacts of stability of turbidity discharge relationships were discovered. However, MFT approach of the efficient description of hydrological systems is expected to deliver detailed representation of contribution factors of SS transport over landscape (Mize *et al.*, 2018; Misset *et al.*, 2019).

It compels a better understanding of spatio-temporal distribution of SS in the dynamics perspective, especially in the concept of magnitude, frequency and timing (MFT) (Kemper *et al.*, 2019). Better understanding of the whole system can be enhanced by developing new indicators of SSC dynamics. MFT approach provides greater detail on the dynamics of SSC. The MFT indicators allow richer representation of varying magnitudes and frequencies in specified periods e.g., magnitudes represented as percentiles and peaks as well as event numbers and durations (Reckendorfer, 2019; Matthews *et al.*, 2022). Event-based dynamics indicators can enhance the analytical approach e.g., empirical approaches employing indicators in MFT. SS event is defined as concentration being elevated after rainfall events from climate, specific processes, physiographic settings and anthropogenic activities and lowered as such impacts are minimized until to a specific reference timing, which vary in length from short to long duration (Amos *et al.*, 2004). Characterization of spatial patterns are possible using those MFT indicators calculated (Kourouma *et al.*, 2022). The MFT indicators also can offer a fresh perspective on better understanding of temporal distribution of SS generation (Karimipour *et al.*, 2018), allowing identification of shorter term dynamics of fluvial SS (Bussi *et al.*, 2016). For instance, spatially coherent patterns were used to check hydrological similarity (Papacharalampous *et al.*,

2021), enabling additional spatial analyses from its representation of forces shaping hydrological environment e.g., morphometry (McKee *et al.*, 2002). Later on, application of big data management tools can bring more realistic modelling results (Slater *et al.*, 2019). Associated research gaps have been identified as lack of understanding spatio-temporal dimensions of SSC and processes and understanding shorter term dynamics of SSC (Rodríguez-blanco *et al.*, 2016; Zuo *et al.*, 2016). A key research question is that has LULC received changes by climate and climate regions?

1.3.2 Climate vs catchment drivers of suspended sediment transport dynamics

Climate change and SS generation in river systems are inextricably intertwined that climate factors can both positively or negatively influence soil erodibility (Naylor *et al.*, 2017; Lowe *et al.*, 2018; IPCC, 2019). Despite considerable research, conducted on impacts of LULC and climate change on SS load at various scales, it was not entirely about influencing factors to SS transport dynamics in MFT e.g., changes of SSC in short period. Better understanding of MFT is helpful for reducing uncertainty of SS dynamics and the impact of underlying factors (Girolamo *et al.*, 2015; Nosrati *et al.*, 2021).

Different LULC have been found to strongly affect SS magnitude (Uwimana *et al.*, 2017; Op *et al.*, 2019; Uwimana *et al.*, 2020). In general, correlations between discharge, baseflow and suspended sediment concentration were identified (Sun *et al.*, 2016), but anthropogenic factors were highlighted in studies, such as the impacts of reservoirs (Sun *et al.*, 2016; Walling & Fang, 2003), soil and water conservation measures, water diversion and reforestation (Sun *et al.*, 2016). SS generation processes in nature (Szalińska *et al.*, 2020) are also governed by many factors that generate sediment including discharge conditions, sources of sediment, climate, lithology, tectonics and human activities (Sun *et al.*, 2016). In addition, nonlinear responses exist between climatic variables and sediment concentrations (Shrestha and Wang, 2018). The non-linear nature of system responses is in the joint impacts of climate change and sedimentation because of possible synergistic effects exist in climate and sediment delivery (Lane *et al.*,

2007) in addition to the effects from the complexity and non-linear responses from environmental systems to extrinsic and intrinsic forcings (Cohen *et al.*, 2013).

Large scale climate mechanisms affect sediment transport dynamics by controlling the hydrological cycle of a region (Mortensen *et al.*, 2018). Climate factors determine the amount, timing and partitioning of precipitation at the land surface (e.g. infiltration vs overland flow) and influences LULC. There is a broad range of climate factors that affect SS dynamics, directly through erosion and transport and indirectly through linkages between climate oscillations, precipitation and soil moisture content (Trenberth, 2011; Javanshiri *et al.*, 2023). The primary driver of soil erosion is regarded as precipitation, and the mass movements provide the raw material for SS transport in rivers (Ampomah *et al.*, 2020; Çakmak *et al.*, 2021; Guduru and Jilo, 2023). Intense storm events cause the mobilization of sediment overland (Sherri *et al.*, 2016) by soil erosion (Li & Fang, 2016), overland flow erosion (Mu *et al.*, 2019; Anis and Rode, 2021) and transport in channels (Debnath & Ghoshal, 2021; Liu, 2016). Besides, broader links from climate to the hydrological environment that generate suspended sediment is very complicating as also affected by various human activities (Murphy, 2020).

The MFT indicators would allow greater interrogation of the influence of climate and catchment factors on SSC dynamics indicators. Each magnitude, frequency and timing indicator produces different values and correlation with catchment characteristics, providing better understanding of sources or processes (Tang *et al.*, 2018). Right level of understanding mechanisms behind differences in time and space scales has pretty much been drawn attention (Wang *et al.*, 2015; Gao *et al.*, 2017). The climatic driven and shifted water and runoff cycles can impose profound impacts on natural processes with spatio-temporal variability. Therefore, there is a need to investigate SSC events and how there are impacts by climate and other factors using empirical models as a whole system within catchment boundaries.

An empirical approach using the MFT indicators with SSC could advance knowledge in this area (Kemper *et al.*, 2019; Whipple *et al.*, 2017; Zhang *et al.*,

2016). Multiple linear regression is a commonly used approach to find relationships between continuous dependent variables and two or more independent variables (Grauso *et al.*, 2021). The status of ephemeral rivers should also be considered in the data pre-processing in creating the static MFT data (Goodrich *et al.*, 2018). Furthermore, clustering analysis can observe nonlinear relationships between sources of contaminants, clearing spatio-temporal heterogeneity (Wu, 2022). In aid of GWR, K-means clustering can also compensate nonlinear effects (He *et al.*, 2019). By investigating spatial patterns (Jothityangkoon & Sivapalan, 2009; Guse *et al.*, 2019), how catchment and climate factors interact and its influences to SS transport dynamics can be better understood in various seasons (Guse *et al.*, 2019). Recognizing these, the associated research gap that will be addressed in the thesis are identified as understanding combined impacts of climate and land-use changes on sediment (e.g., agricultural area receives more frequent rainfall increasing soil erosion, and precipitation mobilizes erodible materials over slopes that can be transported to watercourses) (Bussi *et al.*, 2016; Rodríguez-blanco *et al.*, 2016; Asadi *et al.*, 2017; Han *et al.*, 2020; Khatri *et al.*, 2019; Shrestha *et al.*, 2018). A key research question is that what are uncharted catchment and climate controls on specific processes of suspended sediment regardless of being in similar climatic boundary?

1.3.3 Climate oscillations and climate change

Climate oscillations may provide a good natural experiment to determine the relative impact of catchment and climate factors on SS transport in rivers. They may also provide a good analogue to climate change impacts as they were used to understand the nonstationary nature of small shifts in weather (Thomson *et al.*, 2003; He *et al.*, 2020; Hund *et al.*, 2021). The distinctive climate over North America may exploit the meaningful interpretations between SS transport dynamics, associated processes and large scale atmospheric circulations i.e., Climate oscillations (Polade *et al.*, 2013; Tamaddun *et al.*, 2019). Considering impact of climate on river systems, it is worthwhile to expand knowledge in process based understandings of SS transport with the evidence based approach

of climate oscillations and climate variability (Rasouli *et al.*, 2020; Schillerberg and Tian, 2020).

SS dynamics indicators may have unique relationships with each different climate oscillation (Shin *et al.*, 2023). There is an innate tendency, identified from climate oscillations, having strong correlations with regional hydrology, providing a better chance of long-term hydrological forecasting (Wanders and Wada, 2015). Climate oscillations cause changes in weather over multi-year cycles due to large scale ocean atmospheric circulations (Schillerberg & Tian, 2020). A broad range of elements from climate subsequently affect SS dynamics e.g., possibility of linkages between sea surface temperature (SST), precipitation and soil moisture content (Trenberth, 2011). There is challenge of using long-term datasets to quantify for CC impacts in SSC dynamics (e.g., covariation between many variables and lack of enough variables representing spatio-temporal differences) (Vercruysse *et al.*, 2017). However, there is potential to differentiate the impacts of climate factors from catchments using climate oscillations (Nalley *et al.*, 2019). Inter-annual variation in SSC is useful in analysing impacts of climate and LULC. These shifts materialize in different ways, depending on the type of oscillation and location, e.g. ENSO impacts on wetter winter in western US (Tian and Quiring, 2017) as well as PDO and AMO influences on summer climate (Kamae *et al.*, 2017). Research about SS and climatic oscillation cycles (Gray *et al.*, 2015) provides an opportunity for identifying potential links between hydrological processes and new indicators of SS transport dynamics, which can improve understandings of SS generation environment. Thus, applying climate oscillations as a baseline is useful to anticipate changes in SS dynamics with climate change. The associated research gap is identified as evidence of climate oscillations on SSC and underlying causes (Krishnamurthy & Krishnamurthy, 2017; Liu *et al.*, 2017). A key research question is that what are the hidden roles of climate oscillations on certain suspended sediment dynamics?

It is important to adopt new ways to improve understandings of suspended sediment transport to predict impacts due to climate change. Because of the influence of CC on modelling approaches e.g., accelerated soil erosion (Owens

et al., 2005, Le Gall *et al.*, 2017) and alteration of hydraulic properties (Hirmas *et al.*, 2018), it requires pointing out appropriate ways to improve modelling practices (Lehner *et al.*, 2006; Kundzewicz *et al.*, 2009; Bilotta *et al.*, 2010; Farzin & Anaraki, 2021). There have been many attempts to improve predictability of SS transport by modelling SSC magnitudes, especially with sediment loads. However, they are insufficient for predicting the short-term fluctuations in SSC that impact ecology, water quality and infrastructure. This research applied an MFT dynamics indicator approach to SSC data within a spatial context and in consideration of climate oscillations to help differentiate the impacts of catchment and climate factors to inform predictions of SS transport in a changing climate. An example of the possible limitations from unverifiable surrogation exists in the daily SS data from United States Geological Survey (USGS). However, USGS provides the most continuous and high quality SSC time series data from the rivers in the nation, which is widely utilized in research and monitoring purposes for characterizing fluvial sediment delivery (Sommerfield, 2016). Taking the continental scale of US also has advantage of covering various ecoregions that each represents similar collective patterns of SS generation environment (Omernik and Griffith, 2014).

1.4 Thesis aim and objectives

The aim of the thesis is to improve the scientific understanding of the impact of climate change on intra-annual variations in suspended sediment concentrations in rivers. The specific objectives are to:

- 1) Characterise the continental scale spatio-temporal variations in the intra and inter-annual patterns in suspended sediment dynamics in rivers (e.g., magnitude, timing and/or frequency of high daily SSC events),
- 2) Determine the contribution of climate to the spatio-temporal variations in suspended sediment dynamics in rivers,
- 3) Provide evidence of associated seasonal effects of climate oscillations (e.g., PDO and ENSO) on different climatic zones over the continental US and evaluate intra and inter-annual suspended sediment dynamics in rivers to identify the important processes underlying those effects.

Chapter 2 describes developing SS dynamics indicators and their spatial distribution over the continent (Objective 1). Chapter 3 develops MFT indicators to link with catchment processes (Objective 2). Chapter 4 creates annual time series from MFT indicators then find relationships with climate oscillations (Objective 3). Chapter 5 discusses findings from these chapters. The flow diagram of this thesis is as attached in Figure 1-2.

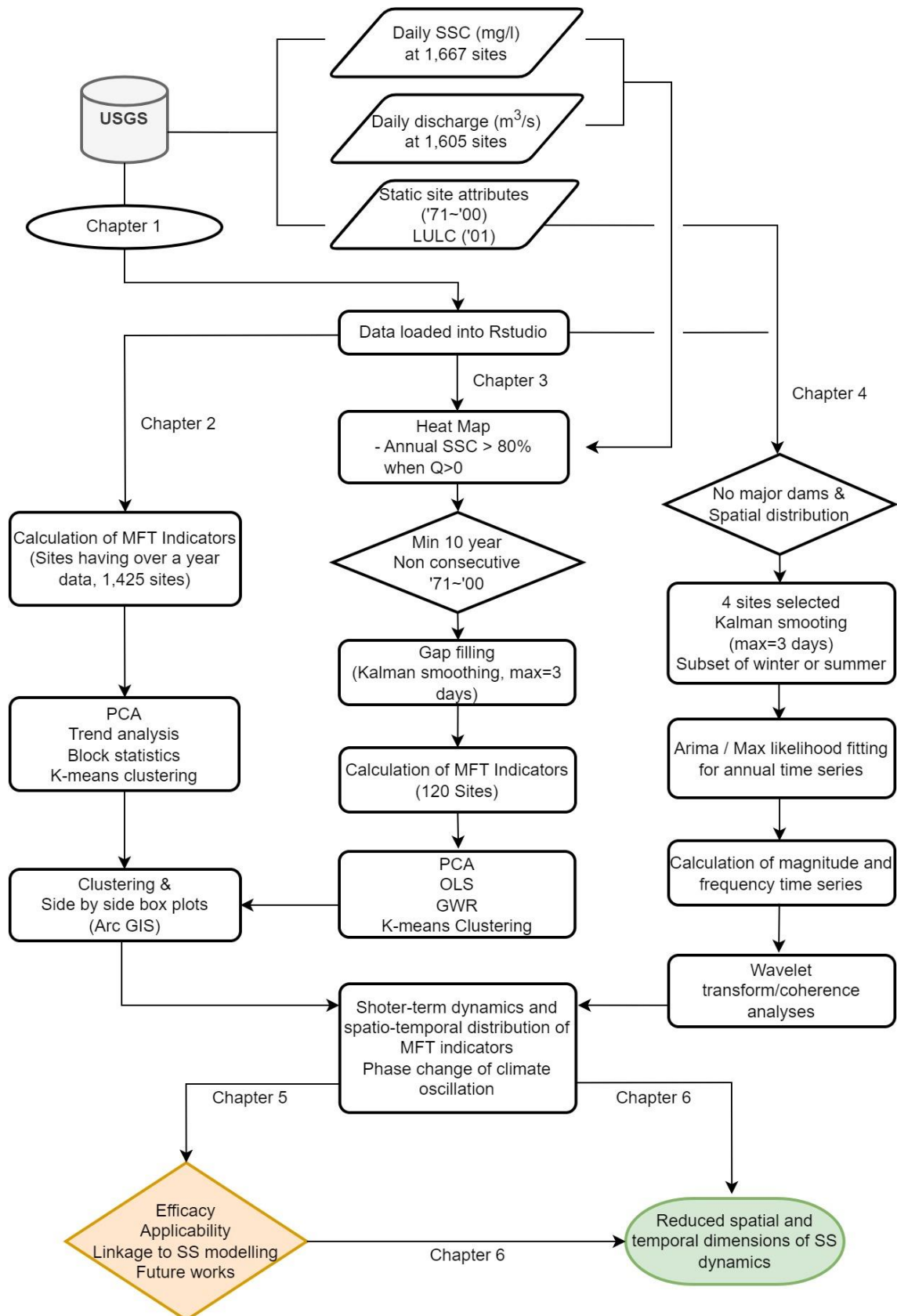


Figure 1-2. An illustration of flow chart providing thesis structure and applied methodology

This chapter is a modified version of 'Indicators of Suspended Sediment Transport Dynamics in Rivers' published in Hydrology Research (Shin *et al.*, 2023).

2 Indicators of Suspended Sediment Transport Dynamics in Rivers

2.1 Introduction

Suspended sediment (SS) is an important part of river systems but is challenging to manage due to the high variability in SS transport dynamics (Cohen *et al.*, 2022), caused by a wide range of climate and catchment factors (Vercruysse *et al.*, 2017). SS concentrations and their temporal dynamics affect aquatic ecological communities and the geomorphic evolution of river systems (Bilotta & Brazier, 2008; Neachell, 2014; Poepl *et al.*, 2019; Wharton *et al.*, 2017) and influence decision-making for water resources management, such as the control of intakes for water abstraction and hydropower operations to prevent SS inflows into the systems (Tsyplenkov *et al.*, 2021). With decadal trends in SS flux and increased uncertainties with climate change (Moragoda and Cohen, 2020), a deeper understanding of SS transport dynamics is needed.

SS transport dynamics studies focus typically on the calculation and analysis of sediment load, which is the mass of sediment transported per unit time (month or year) based on SS concentration and discharge data (Roman *et al.*, 2012; Yilmaz *et al.*, 2018). Sediment load is useful for calculation of total flux of SS, and in conjunction with the hysteresis in SS rating curves, it can be related to catchment hydrological and geomorphic processes (Horowitz, 2003; Misset *et al.*, 2019). Studies on sediment load have identified the relative impacts of factors operating at different spatial and temporal scales, such as different vegetation cover and erosion factors, e.g. gullies (Vercruysse *et al.*, 2017), and relationships between the two main drivers of SS transport, discharge and rainfall (Khan *et al.*, 2016; Kemper *et al.*, 2019). However, it remains difficult to identify the spatio-temporal patterns in, and drivers of, shorter time scales of transport dynamics (days to months) due to the paucity of data.

Most SS transport studies use data from a single temporal scale, often with substantial spatial and temporal gaps, which limits our understanding of drivers

(Francke *et al.*, 2014; Vercruysse *et al.*, 2017). A recent study has helped to address this challenge through a multi-scale analysis of the variability in the rating curve relationship between SS transport and river discharge, using turbidity as a surrogate (Wang & Steinschneider, 2022). The approach allowed the identification of catchment characteristics that affect the stability of turbidity-discharge relationships, such as stream network complexity, perennial snow coverage, saturation-excess overland flow. The incorporation of transport dynamic indicators into these multi-scale analyses, i.e. magnitude, frequency and timing (MFT) of events, as is done for other areas of hydrology and water quality, has the potential to further specify the contribution of different factors to SS transport dynamics (Mize *et al.*, 2018; Misset *et al.*, 2019).

An MFT approach has the potential to generate a richer representation of temporal variability of SS transport, which can be combined with analytical approaches, like multivariate data mining techniques to relate to underlying environmental or human factors (Vercruysse *et al.*, 2017). Magnitude indicators, especially those that capture extreme values, like 95th percentile, are useful to link with extreme values of precipitation, especially flows and sediment yield (Stryker *et al.*, 2018; Whitfield and Shook, 2020). Indicators of frequency relate to both the number of events per unit time and the duration of those events, which can help to identify the underlying factors affecting the hydrological responsiveness of the catchment and sediment generation and transport mechanisms. For example, long duration SSC events can indicate large catchments and large weather-related drivers, such as hurricanes or monsoons, whilst short events can relate to convective storms that might be frequent (continental climate) or infrequent (arid climate) (Alexandrov *et al.*, 2007; Yao *et al.*, 2022). The timing of high SSC can be influenced by factors such as climate or land use that influence the generation, mobilization and delivery of SS (Rose and Karwan, 2021). These underlying factors can be better understood when a hierarchy of temporal scales and frequency are considered. Previous research has used monthly (Girolamo *et al.*, 2015) and event-based scales (Nosrati *et al.*, 2021) to investigate sediment transport dynamics within watersheds (Kemper *et al.*, 2019).

The study aim is to use a MFT approach to determine the spatial patterns and temporal trends in short-term (daily to monthly) SS transport dynamics that exist at a continental scale. The objectives of the study are to (i) develop and evaluate new indicators of SS dynamics based on magnitude, frequency and timing, (ii) determine how the new indicators are distributed across the continent and identify spatial patterns and heterogeneity, and (iii) evaluate the indicators to provide recommendations for future studies. Spatial patterns in SS indicators could provide insights into catchment and climate controls on SS generation and transport that could inform environmental water management practices.

2.2 Study area and data

The study area was the contiguous US and the islands of Hawaii and Puerto Rico, which encompasses a diversity of climates, landscapes, and land use and land cover (LULC) (Liu *et al.*, 2020a) that could influence sediment transport regimes and SSC dynamics. The US Geological Survey (USGS) provides daily SSC data at 1,667 monitoring sites on rivers, including in overseas territories. A text file format of the SSC data (Parameter code: 80154) was obtained from USGS (U.S. Geological Survey, 2016) (Figure 2-1). This dataset is described as ‘sediment suspended (milligrams per liter)’ and is derived from instantaneous suspended-sediment concentration collected from water samples using an approved sampling method (Edward and Glysson, 1999), discharge-weighted to correct for spatial variations in SSC at a monitoring station cross-section and temporal variations over the day, and where necessary, flow-weighted based on hydraulic data to fill temporal gaps in data collection and generate the daily SSC dataset (Porterfield, 1972; Sommerfield, 2016). Previous research highlighted two uncertainties with the ‘sediment suspended (milligrams per liter)’ that affect its use in studies of temporal dynamics: (i) the parameter code 80154 was used for both discrete SSC samples and the daily mean SSC dataset, and (ii) the precise methods and data used for discharge- and flow-weighting for each site, and the resulting weighting relationships, are not reported by the USGS. The first uncertainty was addressed at data acquisition, when only the daily mean data were downloaded from the USGS data portal. The second uncertainty was

addressed in this chapter through exploration of correlations between different SS datasets (described in a later subsection) and in the next two thesis chapters through stricter filtering and quality control (please see later chapters). For more information on the data, please see the subsections below that (i) describe in greater detail the approaches that the USGS uses to collect, process and summarize SSC data and (ii) outline the assumptions and limitations of using discharge- and flow-weighted estimates of SSC for an analysis of temporal dynamics.

Filtering and processing were kept to a minimum to retain the greatest number of sites to test the new indicators and investigate spatial patterns in SSC transport dynamics at catchment scale. Sites were selected that had greater than 365 days of record and a minimum of 200 days of SSC data. In total 1,425 sites were selected with an average record length of 9 years (min = 1 year, max = 80 years) and SSC data covering an average of 83.6% of days per site and period of record (min = 6.2% and max = 100% of available daily data). Gap filling was not implemented to avoid adding further uncertainties into the daily SSC datasets. Gaps in the USGS daily mean SSC dataset indicate that collection of discrete samples was deemed inadequate during those periods to permit accurate estimation of daily SSC based on hydraulic parameters and/or SSC at neighbouring sites. Please see the supplementary material for more information on the sites, catchment areas, and length and completion of SSC records (Figure A2-1).

The limited filtering and processing retained the greatest number of sample sites for exploration and evaluation of the new SSC transport dynamic indicators. The inclusion of sites with very limited records helped to identify indicators that were sensitive to long or frequent gaps in the record. However, for the illustration of spatial patterns, it assumes that indicators derived for sites with short duration and incomplete data are comparable to sites with more complete and longer multi-year datasets. To limit erroneous conclusions being drawn based on the spatial patterns, data analyses in this chapter were limited to descriptive summaries using statistical methodologies with limited assumptions. To ensure

transparency, these differences in the length and completeness are illustrated in Figure 2-1. To address this assumption in later chapters, additional data quality control was conducted.

Sampling procedure, lab analyses, and discharge-weighting SSC

The USGS uses several sampling methods to collect instantaneous SSC (i.e. discrete sampling), depending on the river and site, underpinned by decades of research to standardize SSC measurements (Edwards and Glysson, 1999). The primary methods for sample collection are depth-integrating and point-integrating. Depth-integrating samplers are lowered and raised through the water column, continuously collecting water and sediment. The point-integrated sampler is lowered to a defined depth, opened and closed, to collect water and sediment at a specific point within a depth profile and/or channel cross section. These samplers are referred to as isokinetic because their shape and inlet design do not affect river flow velocities (Edwards and Glysson, 1999). SSC is calculated by measuring the mass of the dry sediment, following evaporation or filtration in the laboratory, dividing it by the mass of sediment and water in the sampler and converting the units to mg/l (Guy, 1969; Edwards and Glysson, 1999).

An isokinetic sampler design ensures that the particle size distribution of the sediment in the sample is representative. However, it introduces complications when calculating SSC, because a greater volume of water is sampled when the water velocity is faster. Therefore, the USGS adjusts the SSC based on the water velocity in the channel. This process is known as discharge-weighting and generates a discharge-weighted SSC concentration (Porterfield, 1972).

Discharge-weighting is essential for reporting of accurate SSC measurements that are representative of the whole channel, because sediment concentrations and flow velocities are not uniform across a channel (Porterfield, 1972). For example, a single-vertical SSC might be higher or lower than the mean for the cross-section, depending on the location of tributary junctions, channel planform (e.g. meander bend), bedforms, sediment type and source.

If a point-integrating sampler is used to collect multiple samples vertically (i.e. single-vertical concentration), the SSC is weighted by the velocity at each depth (Porterfield, 1972). The approach is very similar to the calculation of stream discharge when multiple measurements are taken (Edwards and Glysson, 1999), with the added step of multiplying discharge (Q_w) per depth interval by the SSC to calculate sediment discharge (mg/s), summing the sediment discharge for all depth intervals, and dividing by the total discharge e.g., derived from $Q_s = Q_w \cdot C_s \cdot k$, where Q_s is sediment discharge (tons/day). Q_w is water discharge (cfs). C_s is SSC (mg/l). k is coefficient from unit of water discharge, assuming a specific weight of 2.65 from SS weight (Porterfield, 1972).

From field sampling, each vertical of the mean discharge weighted concentration, c is defined as Eq.2-1 (Edwards and Glysson, 1999).

$$c = \frac{k_1 v^2}{k_2 d} \quad \text{Eq. 2-1}$$

Where, k_1 is a constant for a given depth, particle size and temperature derived,
 k_2 is another constant from sand discharge equation $Q_s = k_2 c v d$,
 v is a mean velocity,
 d is the total sample depth.

A similar discharge-weighting process is conducted when multiple samples are taken across the channel (i.e. cross-sectional concentration). Where single-vertical concentrations are taken at a site, USGS scientists will have developed a cross-section coefficient to convert it to a discharge-weighted average based on additional information (e.g. historical measurements of cross-sectional velocity and SSC at different discharges and seasons). If more than one SSC sample is taken per day, the values would also be discharge-weighted based on velocities at the times of sampling. Thus, a compound ratio, $v^2 d(\text{max})/v^2 d$ is applied to account for variability of concentration at different sampling verticals (Edwards and Glysson, 1999).

These methods and the analytical approaches used prior to the computers (arithmetic and graphical approaches) are described by the USGS (Porterfield, 1972). For an example of the graphical approaches for applying correction factor

and calculating a daily SSC mean from sub-daily measurements of cross-section SSC, please see Appendix Figure A2-2 and A2-3. In addition, Table A2-1 summarizes the methodologies and parameters used for computation of daily SSC and measurement of discrete samples. Please note that the data time periods, sampling approach, cross-sectional averaging method and coefficient used at each site are not publicly available (Sommerfield, 2016).

Estimation of daily mean SSC from discrete data (flow-weighting)

Flow-weighting is used by the USGS to generate a daily SSC time series based on discharge-weighted daily mean SSC values. Similar to discharge-weighting, the exact methods and data used for flow-weighting each site are not publicly available from the USGS (Somerfield, 2015). Therefore, a summary of the flow-weighting approach, data sources used, assumptions, and limitations are provided here.

Flow-weighting involves the development of an empirical relationship between measured SSC and flow conditions at a location to estimate daily mean SSC when discrete samples are not collected. Whilst it was commonly referred to a 'ratings curve', river discharge or gauge height was not used to create a regression-style ratings curve with SSC, as it is commonly done in hydrometry when estimating water discharge from stage. SS discharges computed from sediment rating (or transport) curves are known to be less accurate (Porterfield, 1972). Instead, an empirical relationship was developed for a location between discharge-weighted SSC and variety of available hydraulic parameters e.g., gauging heights, discharge rating curves and flow duration curves. Flow duration curves were widely used with rating curves from sub or daily SS to derive instantaneous or daily mean SS concentrations (Porterfield, 1972). The method is used due to its convenience in computing the concentrations, which was important in the past prior to limitations in computing power.

Fundamentally, the accuracy of the flow-weighted SSC timeseries for a site is dependent on the measurement of SSC and hydraulic parameters over a range of conditions. Whilst precise data requirements are not stated, USGS documentation describes principles and a range of methods that were used to

ensure temporal variations in hydraulic and SSC relationship were captured (Porterfield, 1972). These methods start with the derivation of cross-sectional coefficients based on repeated sampling of SSC and hydraulic parameters, which were then adjusted based on observed seasonal variations (Figure A2-4). These relationships were evaluated after storm events. Then, temporal concentration graphs were developed. The USGS methodology states the need to obtain a larger number of discrete SSC samples for sites with more variable SSC-hydraulic relationships and argues that it is less expensive (or was at the time that the report was written) to collect additional data than to estimate the concentration graph. It states that each sampling station would have had a bespoke sampling program to ensure accuracy of the SSC record. SSC time series were generated by hand by local hydrologists based on the relationship between SSC and hydraulic parameters. For short gaps in discrete data (20 minutes to several days), the hydrologist estimated SSC based on temporal variations in streamflow. For longer gaps, daily SSC was estimated based on historical flow-sediment relationships coupled with interstation correlations or comparison between upstream and downstream data. The SSC record was judged to be inadequate when it could not be 'defined within probable limits of 5 or 10 percent'. This strict threshold is the reason why there are many gaps in the flow-weighted time series datasets.

Due to the site-specific application of the flow-weighting, the lack of transparency in the specific data and methods used and reliance on human judgement at various steps, the flow-weighted daily SSC dataset has limitations. It assumes that SSC is primarily dependent on river hydraulic parameters. Whilst USGS guidance states that local hydrologist should consider the availability of sediment that might impact these relationships, based on their understanding of the effects of diverse storm periods, tributary inflow and seasonal effects, which aligns with current approaches (Vercruysse et al., 2017), how this was done in practice is not known. Furthermore, there were many opportunities for human error, including SSC data collection, calculation of discharge-weighting using graphical methods and the application of conversion factors (Figure A2-2 and A2-3), and integration of hydrological and sediment data for filling longer gaps (Table A2-1).

Furthermore, due to the complicated and site-specific nature of the derivation of the dataset, daily time weighted SSC values are not retrievable from daily water and sediment discharge data. Thus, a posterior analysis of data quality cannot be done. However, the USGS had clearly defined methods and guidelines for the collection, analysis and reporting of data (Porterfield, 1972), adding confidence to the quality of the reported data. Ultimately, no other daily SSC dataset exists from other countries that can match for the USGS dataset in terms of length of records, number of sampling locations, transparency in methods, and availability.

For this thesis, additional quality control checks were conducted by comparing daily mean of instantaneous SSC and daily mean SSC available on the same day at the same site (Figure A2-5 and A2-6). For 128 sites, linear regression was implemented, and the median value of R^2 is 0.735. It suggests that a relatively good correlation exists between instantaneous SSC samples and daily mean SSC. Figure A2-7 shows spatial distribution of R^2 between discrete and daily SSC available at the sites used in Chapter 2. Few sites have R^2 less than 0.3. Figure A2-8 shows R^2 that were used in Chapter 3. Five sites had R^2 less than 0.4. Figure A2-9 shows the sites used in Chapter 4 that a site has relatively less R^2 , which is 0.646. It is important to note that a high correlation between instantaneous SSC and daily mean SSC should not be universally expected. Some sites will have high spatial variation in SSC across the channel and/or high temporal variations in a day, which is why the USGS engineers applied discharge weighting methods.

Previous research identified limitations in USGS SSC data that can affect annual SS load calculations (Sommerfield, 2016), which has led some researchers to use turbidity as a proxy for SSC (Wang & Steinschneider, 2022). For added confirmation, linear regression between SSC and turbidity and a visual assessment of the timing and duration of 'events' based on the two datasets was conducted for the subset of sites selected for further analysis in Chapter 3 on the catchment and climate drivers (Shin *et al.*, 2023a). Those additional analyses showed that daily mean SSC data had strong correlation with turbidity and a coherence in the timing and duration of events (Figure A3-1). The turbidity

dataset was not used in this study because it contained fewer sites (n=1,090) with shorter duration timeseries (min- 0.07, max- 26.71, mean- 6.81 years). Please note that stricter filtering rules were used in Chapter 3 on catchment and climate drivers (Section 3.3).

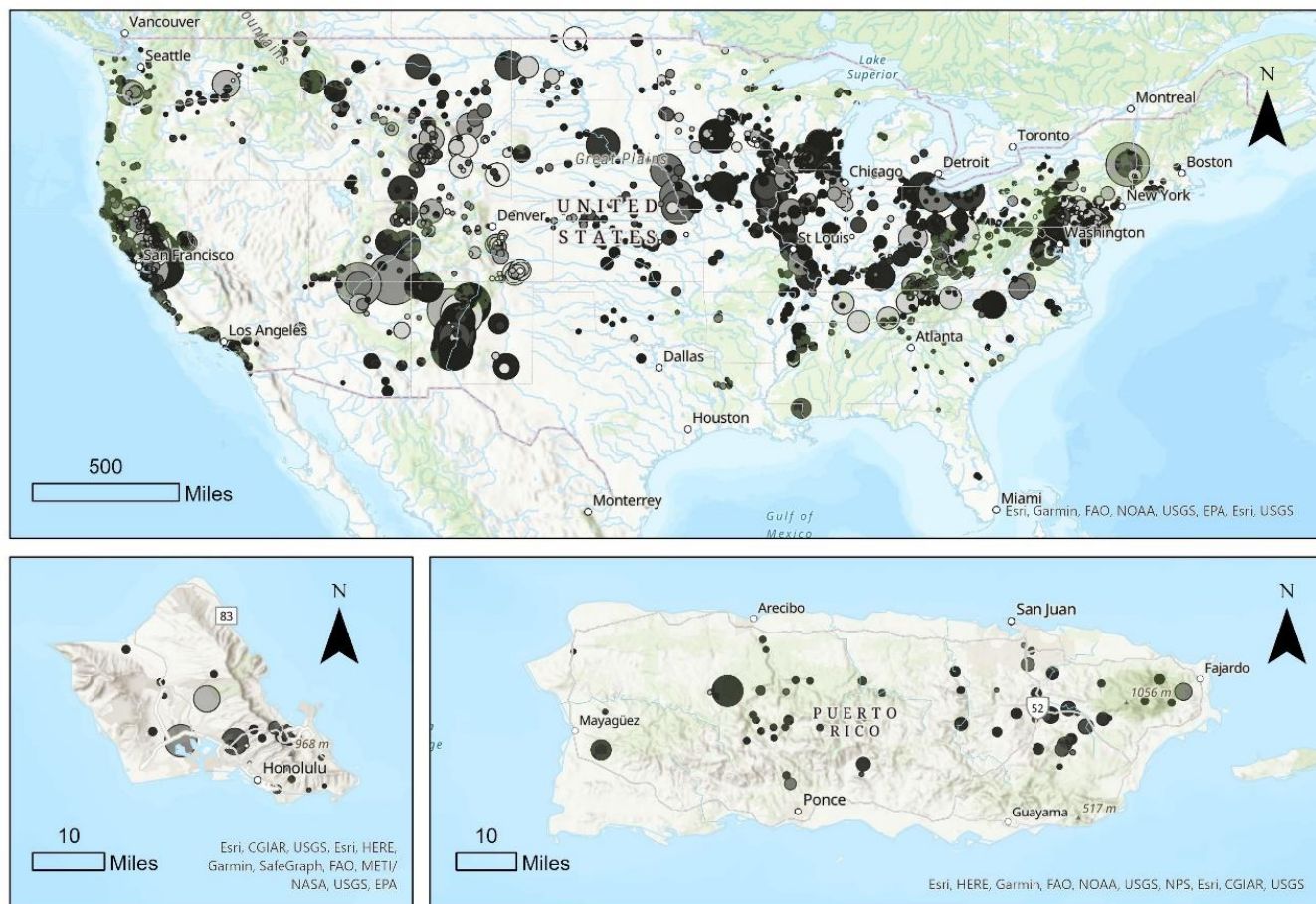


Figure 2-1. Locations and quality of daily mean SSC from USGS gauging stations: Symbol sizes are proportional to the duration of monitoring record (min – 1 year, max – 80 years). Colour indicates completeness of the monitoring records (min – 6.2 %, max – 100 %). More blackish circles represent higher data completeness. – Top: continental US (1,329 sites), Bottom Left: Honolulu, Hawaii (35 sites), Bottom Right: Puerto Rico (61 sites)

2.3 Methods

The methodology comprised several steps: (i) developing MFT indicators that characterise short-term variations in daily SSC; (ii) evaluating covariation in the MFT indicators using multivariate approaches (Principal Component Analysis, PCA) to reduce the number of indicators; (iii) visualising the spatial patterns in MFT indicators; and (iv) analysing their spatial variability using spatial statistics, clustering and temporal trends using trend analysis.

2.3.1 Indicators to describe SS dynamics

Indicators to describe SSC dynamics were developed on an average annual basis to capture variation in the magnitude, frequency and timing of SS transport (Table 2-1 & Figure 2-2). Previous studies have used various approaches to develop indicators from timeseries of hydrological and water quality data, depending on their research aim and data limitations (Vercruysse *et al.*, 2017; Stryker *et al.*, 2018; Whitfield and Shook, 2020). The approach taken in this study was informed by these studies but was tailored to meet two key criteria. First, indicators must be able to be calculated on an annual basis to permit temporal analysis for application to the study of climate variability later in the thesis (climate oscillations; Chapter 4) and for application to climate change in later studies. Second, indicators must not be disproportionately influenced by extreme SSC outliers. It is common in the analysis of hydrological time series to summarize extreme high and lows based on probability of exceedance or non-exceedance, rather than absolute minimum and maximum (Shaw *et al.*, 2010). The same approach was applied to SSC data for the magnitude indicators. This approach facilitates later analysis of statistical analysis of the indicators, as the use of maxima and minima often requires developing nonlinear optimization (Sohn *et al.*, 2004). It also reduces the impact of SSC outliers in a large dataset (1,425/1,666 sites) that is difficult to manually identify and quality control, which could have been introduced during sample collection, processing, data entry or archiving by 3rd parties.

Where indicators calculated on an annual basis need to be compiled over a longer time period of record, the mean was used. The mean was selected for practical reasons. It would be more influenced by extreme indicator values, which was important for the magnitude indicators, especially M95. To illustrate this, pairwise comparisons of mean and median values of annual indicators was conducted, which confirmed that there were limited differences, then, slightly lower median values for the magnitude indicators were identified (Figure A2-10~15). These differences were caused by few extreme values in magnitude (e.g., M95 and Rr). However, frequency indicators were less affected by substantially different outliers compared with mean values across the alpha values (Figure A2-16~17). As the SSC data were already quality controlled by the USGS, it was felt that these extreme values were unlikely to be outliers and, thus, it should be represented in the summary of annual indicator values. Calculation of indicators was conducted in RStudio based on daily mean SSC (Posit team, 2022).

Table 2-1. Indicators to describe temporal variations in SSC (daily mean) based on magnitude, frequency and timing: As duration of events are inversely proportional to count of events, duration of events were included in the frequency category.

Symbols		Indicators	Description
Magnitude	M95	95 th percentile	Avg. annual 95 th percentiles of SSC
	M75	75 th percentile	Avg. annual 75 th percentiles of SSC
	M50	50 th percentile	Avg. annual 50 th percentiles of SSC
	M25	25 th percentile	Avg. annual 25 th percentiles of SSC
	R.r	Rising rates	Avg. annual daily increase in SSC
	F.r	Falling rates	Avg. annual daily decrease in SSC
	Stdev.max	Standard deviation of monthly max values	Avg. annual values of standard deviation of monthly maximum SSC
	Stdev.min	Standard deviation of monthly min values	Avg. annual values of standard deviation of monthly min SSC
Frequency	D	Duration of events	Avg. annual duration of SSC events, in days, for four different frequencies (α)
	C.of.e	Count of events	Avg. annual number of SSC events for four different frequencies (α)
	P.p.e	Number of peaks per event	Avg. annual number of peaks per SSC event for four different frequencies (α)
Timing	Month.max.sum	Month of max total SSC	Month with the maximum total SSC, summed across the time series of record
	Month.i.p.max	Month of max number of inflection points	Month with the maximum number of events, defined as inflection points in the SSC timeseries

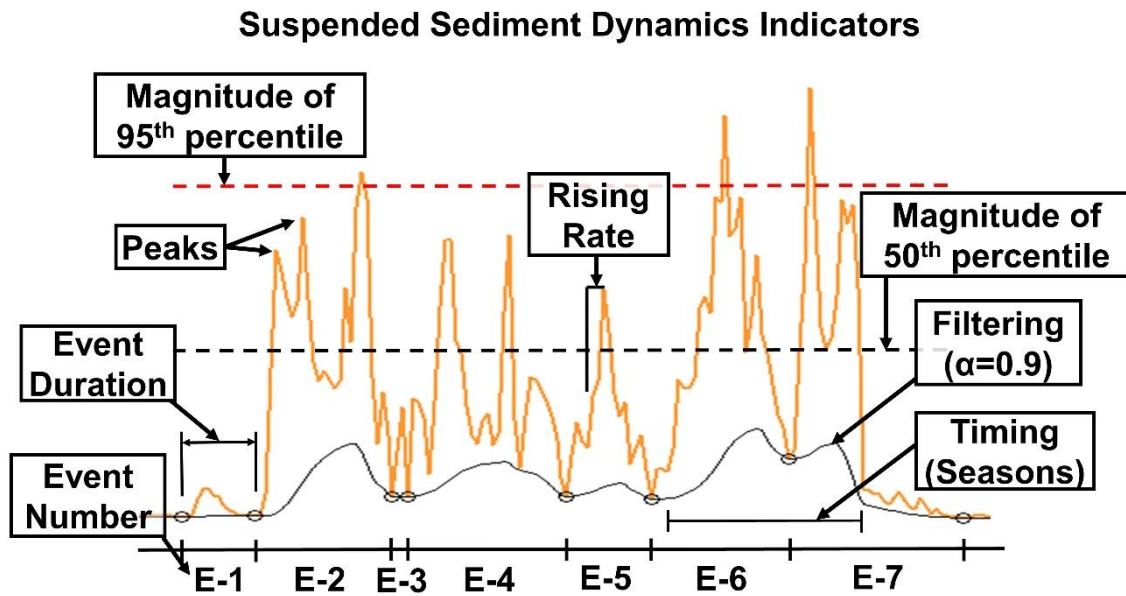


Figure 2-2. Indicators of suspended sediment dynamics in rivers. The SS dynamics indicators were developed based on the magnitude, frequency and timing of changes in suspended sediment concentration.

2.3.2 Magnitude Indicators

Magnitude indicators were developed to capture intra- and inter-annual changes in SSC (Figure 2-2). Annual values were calculated for each indicator in each water year (Oct-Sep). Magnitude of different percentiles (95th, 75th, 50th, 25th) were calculated for each year of record and averaged across the number of years per record (M95, M75, M50, M25). 95th and 75th percentiles were used to capture extreme and high climatic events, as done in climate studies about precipitation (Alexander *et al.*, 2006; Gao *et al.*, 2023), considering the precipitation as a main erosional factor. Threshold for determining moderate is 50th percentile for rain events (Ayantobo *et al.*, 2022). This is supported by quartile based distribution e.g., 25th (Q1), 50th (Q2), 75th (Q3), which was used to better understand sources of SS (Lim *et al.*, 2014). Other percentiles could have been used for extreme SSC magnitude, such as 90th or 99th percentile (Alexander *et al.*, 2006). However, 95th percentile was recommended in other studies for water quality standards, reducing a false sense of uncertainty (Hunter, 2002; Alexander *et al.*, 2006), and a study, used a GIS-based stream sediment geochemical model, also supports this decision (Ali *et al.*, 2015). Rising and falling rates (i.e. positive and negative

changes in SSC per day, respectively) were calculated by subtracting the previous day values from current day values, as the time series consisted of daily data, and then averaged across the period of record (rising rate – R.r, falling rate – F.r). Those indicators were chosen as rising and falling limbs are difficult to capture especially over long period events (Vercruysse *et al.*, 2020). Finally, the standard deviation of monthly minimum and maximum values was calculated (Sd.min and S.d max, respectively), aiming at better reflection of inter-annual variations for identification of possible shifts in dominant sources of SSC (Vercruysse *et al.*, 2017). Thus, non-normal data with outliers were fully used without trimming (Abu-Shawiesh *et al.*, 2020).

2.3.3 Frequency Indicators

Frequency indicators were developed to capture event-based SS transport dynamics: the duration of a high SSC event (event duration), number of SSC events per year (event count) and the number of SSC peaks within an event (peaks per event) (Figure 2-2). The Lyne-Hollick filter was used to identify SSC events. This approach has several benefits over alternative methods (e.g. percentiles or rising and falling limbs from raw SSC curves), including (i) it is commonly used in hydrology to separate events from background variability (e.g. baseflow from streamflow) (T, Chapman, 1991; Ladson *et al.*, 2013; Xu-dong Huang *et al.*, 2016), (ii) it is not affected by shifts in SSC magnitude over time like percentiles (i.e. an event does not need to be the same magnitude or relative increase in magnitude), and (iii) it is able to identify peaks of differing duration. The final point is particularly important, as there is no single definition of a high fluvial SSC event (Sallenger, 1992; Vercruysse, *et al.*, 2017). High SSC events can vary in length from short duration (e.g. hours to days) to long duration (e.g. months), depending on the physiographic setting, catchment size, climate, flow regime, sediment sources and types. For example, short duration and high magnitude events occur with high discharge events after intense rainfall (Amos *et al.*, 2004). In Yunnan and Tibet, 86 % of SS transport occur during four months of monsoon from June to September (Henck *et al.*, 2014).

The ‘baseflows’ package in R was used to identify where daily SSC values in a time series deviate over time, in a process akin to baseflow separation for river flows (Ladson *et al.*, 2013). The analysis draws filtering (e.g. baseflow) curves with a Lyne & Hollick’s filter (Eq. 2-2 and 2-3) and identifies contact points in the SSC data, where the SSC timeseries data make contact with and then separate from the curve.

$$c_f(i) = \begin{cases} \alpha c_f(i-1) + \frac{(1+\alpha)}{2} [c(i) - c(i-1)] & \text{for } c_f(i) > 0 \\ 0 & \text{otherwise} \end{cases} \quad \text{Eq. 2-2}$$

$$c_b(i) = c(i) - c_f(i) \quad \text{Eq. 2-3}$$

Where, $c_f(i)$ is a peak at i^{th} sampling. $c(i)$ is the original concentration at i^{th} sampling. $c_b(i)$ is the baseline at the i^{th} sampling. α is the filter parameter controlling the shape of the baseflow line.

In recursive digital filters for hydrological analyses, Lyne and Hollick filter has better filtering performance than Boughton two-parameter and Eckhardt filters (Li *et al.*, 2014). The filtering enables characterization of diverse typology (Marsi *et al.*, 2006). Differing alpha values can detect multiple values ranging short to longer durations. As the alpha value increases, duration of event decreases but number of event increases. Increasing alpha value creates low pass filter and vice versa. Four α values (0.975, 0.9, 0.6, 0.2) were used to capture SSC events lasting a range of durations, from months to days. The choice of alpha values before implementing calculation of all eligible sites were also confirmed from five different sites across the continent by manually observing the durations of events (Please see Table A2-2 for rationale for the choice and the results section for an example). Use of other alpha values are also not generating substantially different duration of events (Figure A2-19~21 for additional alpha values). The number of days was set to 30 for filtering at the start and end of time series, based on initial testing and previous studies (Ladson *et al.*, 2013). Whilst the filtering process worked well overall, it encountered problems when applied to the longest frequencies due to the presence of data gaps in some sites. Consequently,

frequency indicator values were not able to be calculated for the 0.975 and 0.9 α values at 29 and 6 of the 1,425 sites, respectively.

The event duration was calculated based on the contact points identified in the 'baseflow' filtering, i.e. the dates when the SSC data and filtering curves had the same value, subtracting end date from start date. The analysis was conducted for all four α values (D0.975, D0.9, D0.6, D0.2). As α values become smaller, the filtering curves plot closer to the SSC curve, and short duration events are identified. The number of events per year was counted and then averaged across the number of years per record (count of events – C.of.e). The analysis was conducted for all four α values (C.of.e0.975, C.of.e0.9, C.of.e0.6, C.of.e0.2). Finally, SSC peaks that occurred during a SSC event were counted. Peaks in the SSC record were identified from the rising/falling rate time series by detecting positive to negative inflection points, with a maximum peak duration of the same value set at 7 days. Peaks of the same value more than 8 days were not counted as a peak (Yu & Disse, 2017). The number of peaks per year was calculated and then averaged across the number of years per record. The date of each peak was exported for use as a timing indicator, more information below. The analysis was conducted for all four α values (P.p.e0.975, P.p.e0.9, P.p.e0.6, P.p.e0.2). Duration and counts were recorded at the event end dates and averaged across the number of years.

2.3.4 Timing indicators

Two indicators of the timing of high SSC were developed and calculated, relating to magnitude and frequency (Figure 2-2). First, the month with the highest SSC (i.e. magnitude) was identified by totalling the daily SSC values for each month across the time series of record at 1,425 sites. Second, the month with the highest number of SSC peaks (i.e. frequency) was determined by totalling the number of contact points (i.e. inflection points at local minima where SSC data and the filtering curves have the same value for the date), as described in the frequency section above, for different α values (0.975, 0.9, 0.6, 0.2) for each month across the timeseries of record. Sites having the same monthly values in different seasons were removed in the end to avoid selecting median month value (α =

0.975, 1,008 sites; $\alpha = 0.9$, 1,085 sites; $\alpha = 0.6$, 1,213 sites, $\alpha 0.2 = 1,248$ sites). The results were aggregated and reported based on season: winter – December, January & February (DJF); spring – March, April, May (MAM); summer – June, July and August (JJA); and autumn – September, October and November (SON).

2.4 Data analysis

2.4.1 Principal component analysis

A PCA was conducted with the SS transport dynamics indicators using “factoextra” package in R as an initial data simplification step (Hegde, 2016). The sole purpose of the PCA was to explore covariation of the indicators and identify a reduced number to visualize later using the spatial statistics approach. PCA identified covariance between indicators by extracting original information on linear composites of variables (Niu et al., 2011). This approach is particularly useful for extraction of meaningful indicators from the large dataset as repeating various verification for time series from each site would require considerable amount of time. There are several alternatives to PCA. However, the purposes were not completely in line with the fact that PCA yields representative variables and captures as much as information possible. Cause-effect relationships by implementing direct gradient analysis may partially be more suitable for next chapter (Evans *et al.*, 2010; Peres-Neto and Kembel, 2015). For this chapter, identifying uncovered structure between indicators through exploratory factor analysis were not necessarily important (Park et al., 2002; Adachi, 2019). Furthermore, PCA is not likely to be affected by possible serious overfitting by random forest during generation of decision trees and its unsuitability to high dimensional data containing irrelevant and redundant features (Feng *et al.*, 2020). Assumption was taken that all magnitude and frequency indicators developed are continuous variables. ‘factoextra’ package produced contribution factors, and optimal directions in PCA are computed to produce biplot (Sandström *et al.*, 2020; Wu *et al.*, 2022). Generating scree plot was created to better understand dimensions (X axis) and percentage of variables explained (Y axis). Indicators were selected for further analyses based on being associated with different axes

to remove indicators with high degrees of covariation. Following removal of sites with gaps in indicators, a total of 1,364 sites were included in the analysis.

2.4.2 Trend analysis

A Mann Kendall trend analysis from R package 'Kendall' was used to detect trends in all average annual magnitude and frequency indicators, for each site (Kar and Sarkar, 2021). The MK method was selected because it is designed to detect gradual and monotonic trends (Vercruysse *et al.*, 2020), which was the intention in this study. It is also not affected by distribution of dataset and gaps, and has been used in other hydrological studies (Hu *et al.*, 2020; Vercruysse *et al.*, 2020; Kar and Sarkar, 2021). Sites with significant trends (p value < 0.05) were identified and selected for visualisation and discussion. Field significance was applied to the trend analysis by taking account of False discovery rate (FDR) (Figure A2-22). MK test was chosen over other trend analyses e.g., Pettitt's test, sen's slope, and Coefficient of variation. Pettitt's test is for changing point detection (Sun *et al.*, 2016). MK test was used rather than Sen's slope to take outliers into data as it is suitable for linear slopes from median values (Jiqin and Gelata, 2023; Sudarsan and Lasitha, 2023). The gaps in SS data also supports use of MK rather than Coefficient of Variation, which is for comparison of separate data in different units by calculating ratio of standard deviation to mean (Chankham *et al.*, 2019).

2.4.3 Block statistics

Large-scale spatial patterns in the SS indicators across the study area were visualised with block statistics in Arc GIS 3.1.0 (Yang *et al.*, 2021). The spatial moving window data aggregation, the most basic spatial statistics approach, was selected because of the previously mentioned concerns about variable quality of SSC data. The approach has limited assumptions and does not assume a covariance structure. The size of pixels for block statistics were determined based on the density of SS sample points to capture minimum a single site. The block statistics enable objective comparison of the spatially varying values from statistics within fixed windows or neighbourhoods. Each cell reads data once, thus there is no repetition of values within the defined window (Stepišnik and

Trenchovska, 2018; Yang *et al.*, 2021). Other approaches could have been used, such as kriging, but they make assumptions about the covariance structure, which were unlikely to be valid for this dataset (Krivoruchko and Gribov, 2019; Afu *et al.*, 2021). First, the SSC indicators were generated from SSC timeseries that ranged in length and completeness, thus nearby sites might have different periods of record. Secondly, SSC monitoring stations are distributed along linear river networks, within a nested hierarchical catchment structure. Thus, there is often greater similarity in SSC with a site much further upstream or downstream, than in a neighbouring catchment or subcatchment (e.g. stations at the confluence of a main river and small tributary). Raster files were created for each indicator based on the site of each monitoring station (cell size: 0.087 radian). The coarse resolution raster output had an average of 1.17 sites per cell (min: 1 and max: 7). The outputs of the Block statistics were mean and standard deviation of indicators summarized over larger area (20 x 20 cells, rectangle), resulting in a coarser-resolution raster. Block statistics were not conducted on the sites with statistically significant trends, due to the low point density.

2.4.4 Clustering analysis

K-means cluster analysis was used to integrate the findings across the indicators to find general patterns that might relate to natural and anthropogenic factors (Plexida *et al.*, 2014; Celestino *et al.*, 2018; Fang *et al.*, 2021). K-means clustering was conducted in ArcGIS Pro 3.1.0 using the multivariate clustering function. Magnitude and frequency indicators were log transformed (Tomlinson *et al.*, 2018), and timing indicators were left untransformed. The number of clusters was assessed by Elbow and Silhouette methods (Masud *et al.*, 2018). Silhouette method with a clustering number of 4 was adopted, because an obvious break in slope was not visible using the Elbow method in Figure A2-25 (C. Shi *et al.*, 2021).

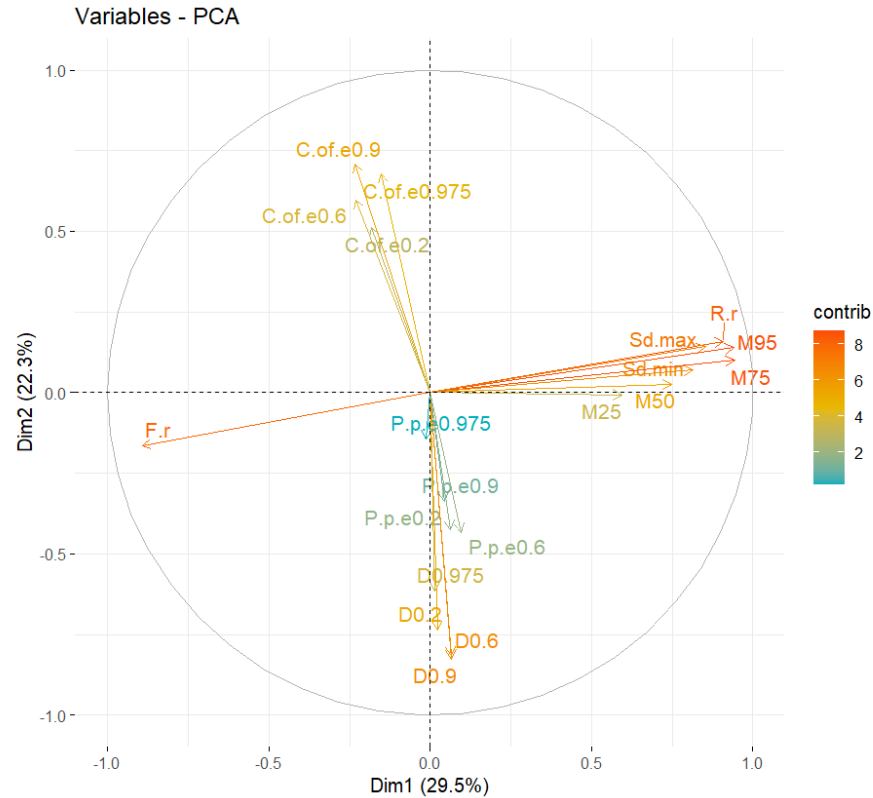
2.5 Results

2.5.1 PCA

The PCA identified considerable covariance between SS transport dynamic indicators, suggesting that a reduced number of indicators could be used for

visualization and analysis (Figure 2-3). PCA was a preliminary step to identify a reduced number of indicators to use prior to the regression (Wuttichaikitcharoen and Babel, 2014). Magnitude indicators were aligned with PCA axis 1, which explained 29.5% of the variance in the dataset. The strongest positive scores related to M95, M75 and rising rate (R.r), whilst the only negative score was falling rate (F.r), which was opposite to R.r. Frequency indicators were aligned closely with PCA axis 2, which explained 22.3% of the variance in the data. Despite the low variance, PCA result provided sufficient information on the choice of indicators to be taken forward. Generally, the number of events (C.of.e.) had positive scores, whilst peaks per event (P.p.e) and event duration (D) were negative. From this analysis, a selection of magnitude, duration and peaks per event indicators were taken forward in the analysis, subselecting those that occupy different dimensions of the PCA plots (M95, M25, D0.9, D0.6, P.p.e 0.6). Note: C.of.e indicators were not taken forward as there was little differentiation between these vectors, and indicators with $\alpha = 0.975$ were not used due to the previously mentioned issue with calculation the indicators when there were gaps in SSC record.

a) PCA result



b) Scree plot

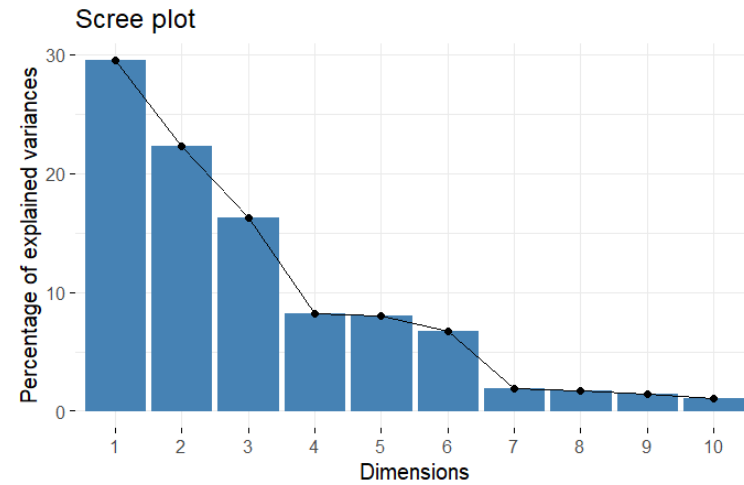


Figure 2-3. PCA result (a) and scree plot (b) of magnitude and frequency indicators for the mean annual indicators. Magnitude: M95, M75, M50 and M25 – daily SSC at different percentiles; R.r - rising rate; F.r - falling rate; Sd.max and Sd.min - standard deviation of monthly max and min values. Frequency: D - duration of events; C.of.e - count of events; P.p.e – Peaks per event. 'contrib': Contributions of variables. The PC1 and PC2 explains 51.8 % of variance observed. The PC3 and PC4 explains 24.5 % of variance.

2.5.2 Block statistics

Magnitude Indicators

Spatial patterns of extreme high and low SSC were evident from the magnitude indicators (Figure 2-4). Both M95 and M25 had similar spatial patterns across the continental US, with generally low values across most of the US, but with higher SSC in the driest regions of the country and a single site in the Eastern Temperate Forest ecoregion, around Atlanta, Georgia (Figure 2-4a,c). The highest extreme SSC values (M95) were found in the Rocky Mountains, Great Plains, and southern deserts (Figure 2-4a). A notable outlier is the extremely high SSC values in the Northwest, which relate to the Mount St. Helens eruption in 1984 (Figure 2-4a,c). Elevated M25 was found at similar sites as M95. However, some areas, e.g. Rocky Mountains and deserts, had generally lower M25 relative to their high M95, whilst others e.g. Great Plains had higher M25 (Figure 2-4a,c). Standard deviation (Stdev) of magnitude values was generally low across the US and areas of high Stdev were located in areas of high M95 or M25 (Figure 2-4b,d).

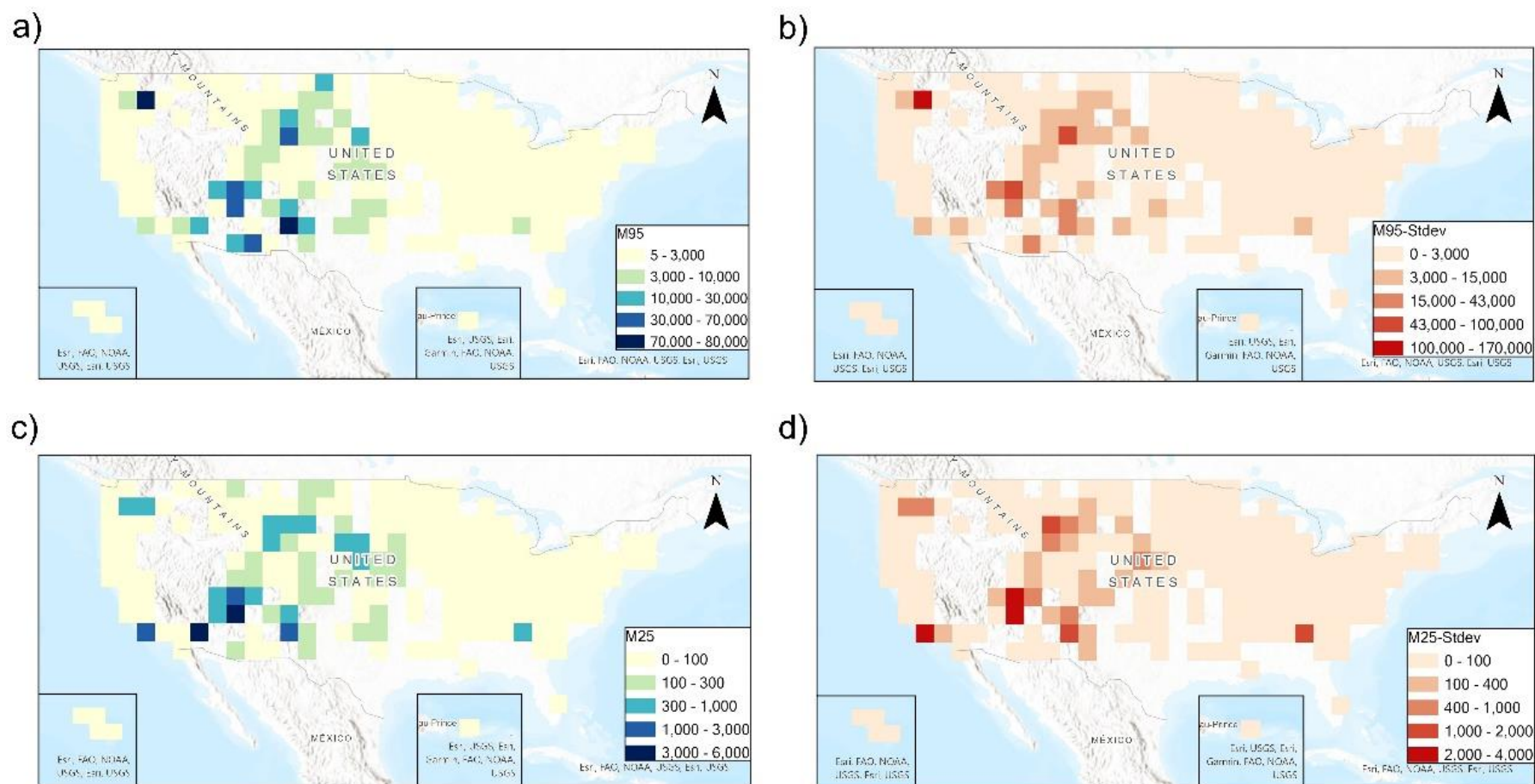
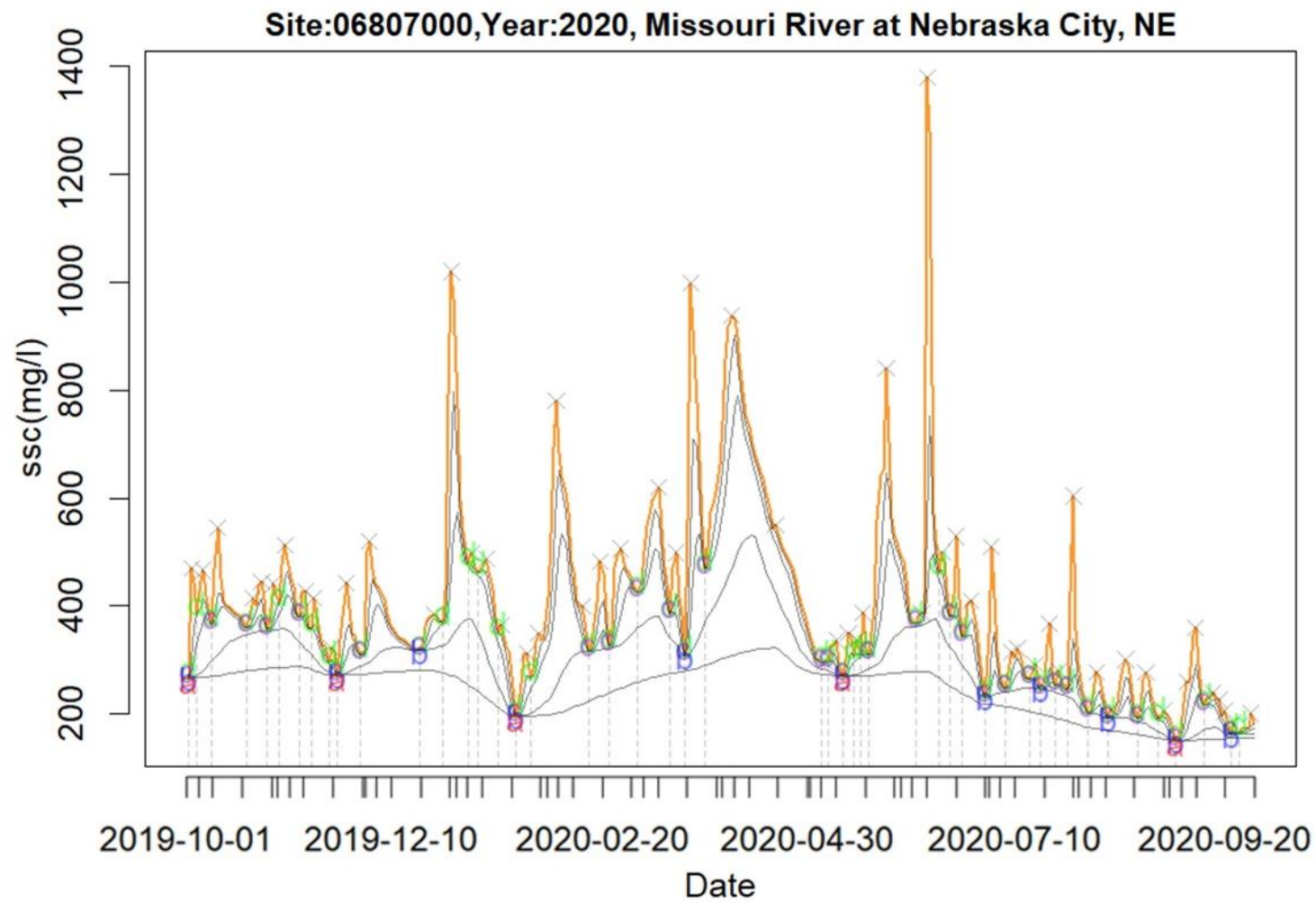


Figure 2-4. Spatial distribution of M95 and M25 including standard deviation (mg/l): M95 and M25 represent magnitude of 95th and 25th percentiles (a and c), respectively. Stdev is standard deviation (b and d).

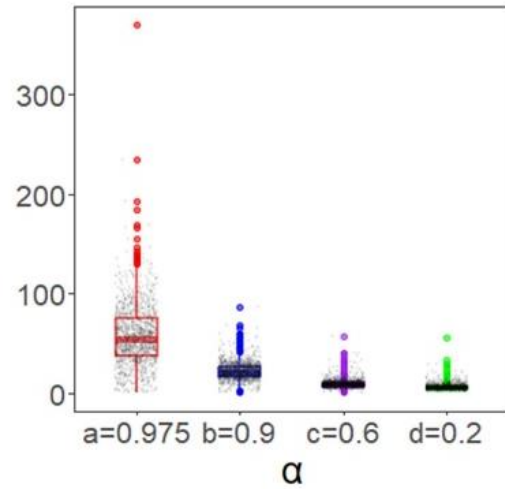
Frequency Indicators

The use of multiple α values allowed the calculation of frequency indicators for SSC events occurring across a broad range of temporal scales, with lower α values identifying shorter duration events (Figure 2-5). The largest α value (0.975) identified the longest duration events, i.e. multi-month (Figure 2-5a), which ranged in length from 1 to 370 days (mean = 57.2) (Figure 2-5b). An α of 0.9 identified events that lasted approximately one month in duration, ranging in length from 1.5 to 86.5 days (mean = 22.3). The smaller α values identified events that lasted a single day to weeks. The duration of events for 0.6 ranged in length from 1 to 57.9 days (mean = 9.56), whilst for 0.2, it ranged in length from 1 to 55.3 days (mean = 6.3) (Figure 2-5b). As α value decreased, the count of event increased and number of peaks per event decreased (Figure 2-5c,d).

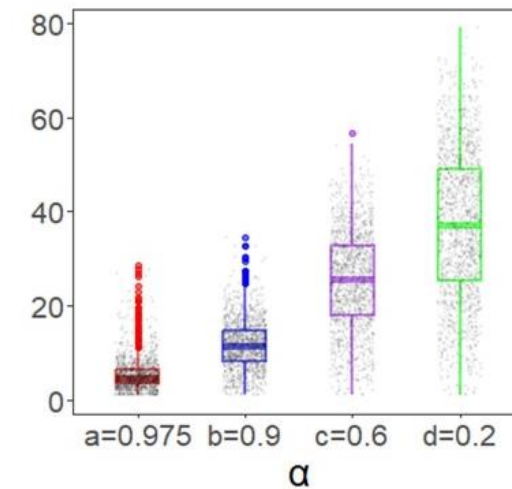
a) Filtering curves by different α values



b) Duration of event (D)



c) Count of event (C.of.e)



d) Peaks per event (P.p.e)

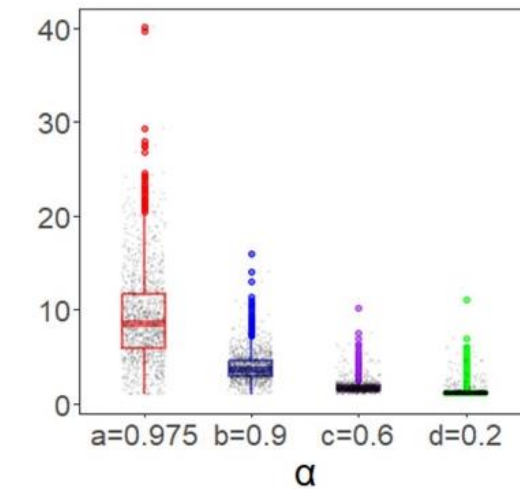
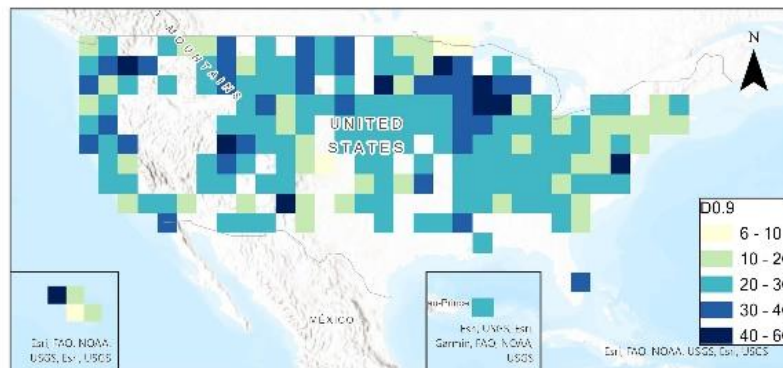


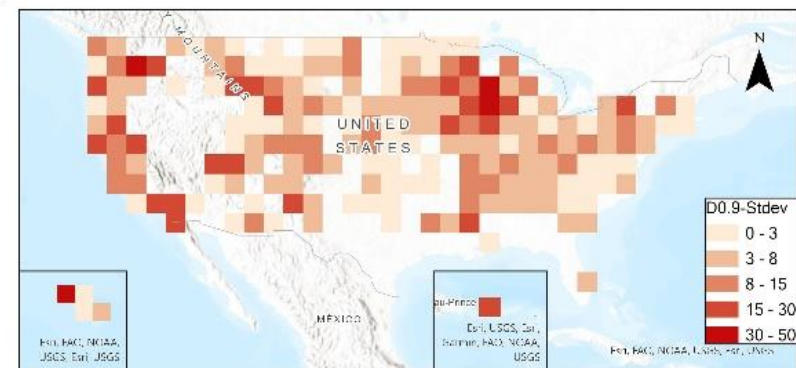
Figure 2-5. Impact of α value on the frequency indicators for all available time series. An example SSC timeseries (Orange) illustrating the length of SSC events at different α (Red=0.975, Blue=0.9, Purple=0.6, Green=0.2)(a). The start/end of events are located where the filtering curves make contacts with the SSC (i.e. pairs of the same letters in the same colours) - Higher alpha values created baseflow recession curves (Grey) with more gentle slopes, whilst lower alpha values generate curves with steeper slopes and more contact points with the SSC timeseries. Duration of event (Days) (b). Count of events (c). Peaks per event (d).

The frequency indicators had different spatial patterns from the magnitude indicators, which also varied by α value (Figure 2-6). The duration of events at $\alpha=0.9$ were around 20-30 days for much of the US, with a cluster of longer durations in the upper Midwest and scattered in sites in California, the Northwest, Rocky Mountains and Puerto Rico (Figure 2-6a). Durations of events at $\alpha=0.6$ showed greater spatial heterogeneity, with a cluster of short durations in the Appalachian region, lasting 8-10 days, and similar sites of long durations, lasting 20-30 days, as for $\alpha=0.9$. Peaks per event also had high spatial variability, with a slightly higher numbers in the inland and overseas territories (Figure 2-6e). Standard deviations were the highest in sites with the highest durations and peaks per event (Figures 2-6b,d,f).

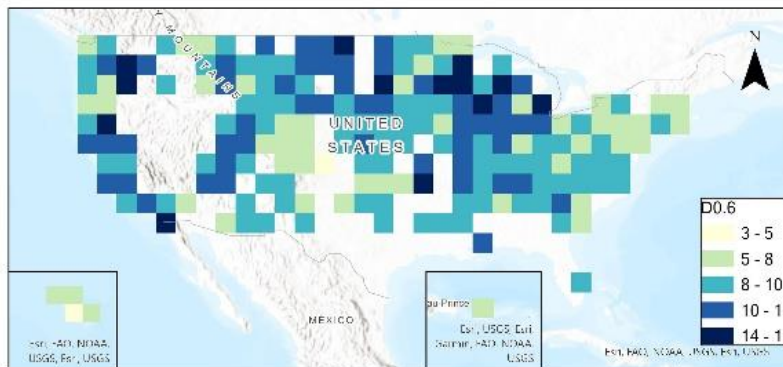
a)



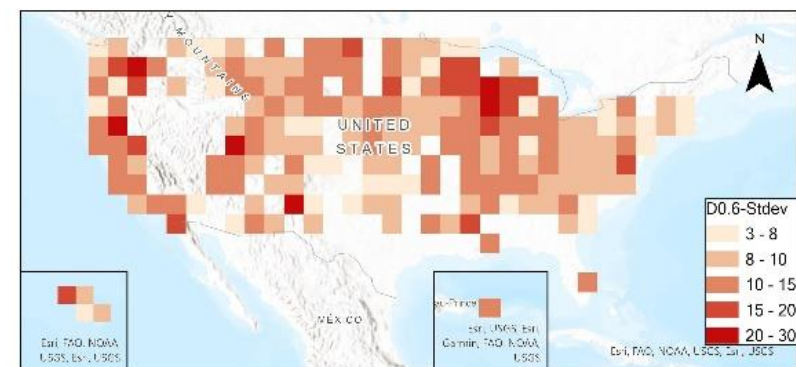
b)



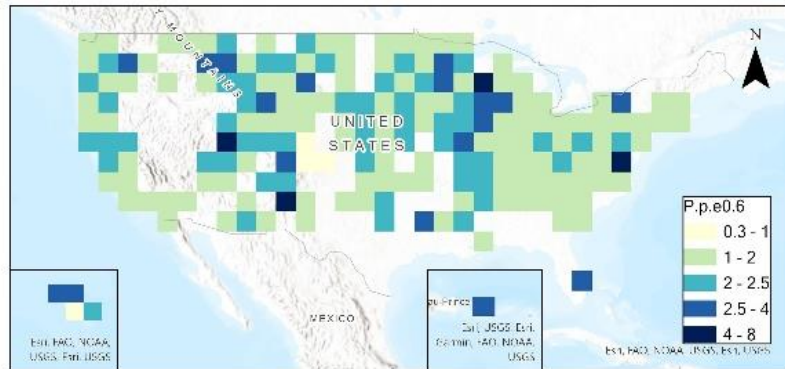
c)



d)



e)



f)

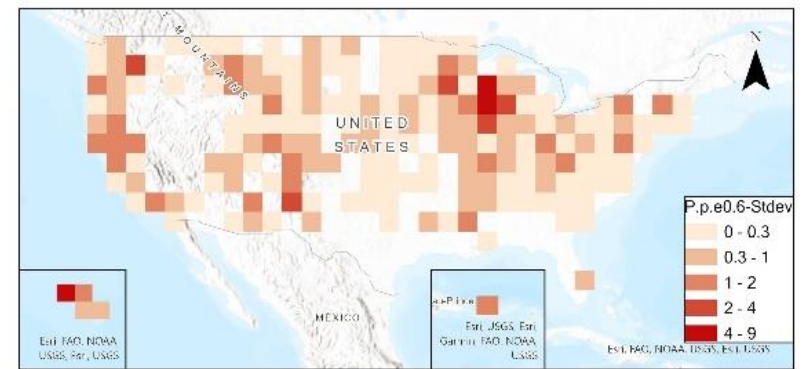
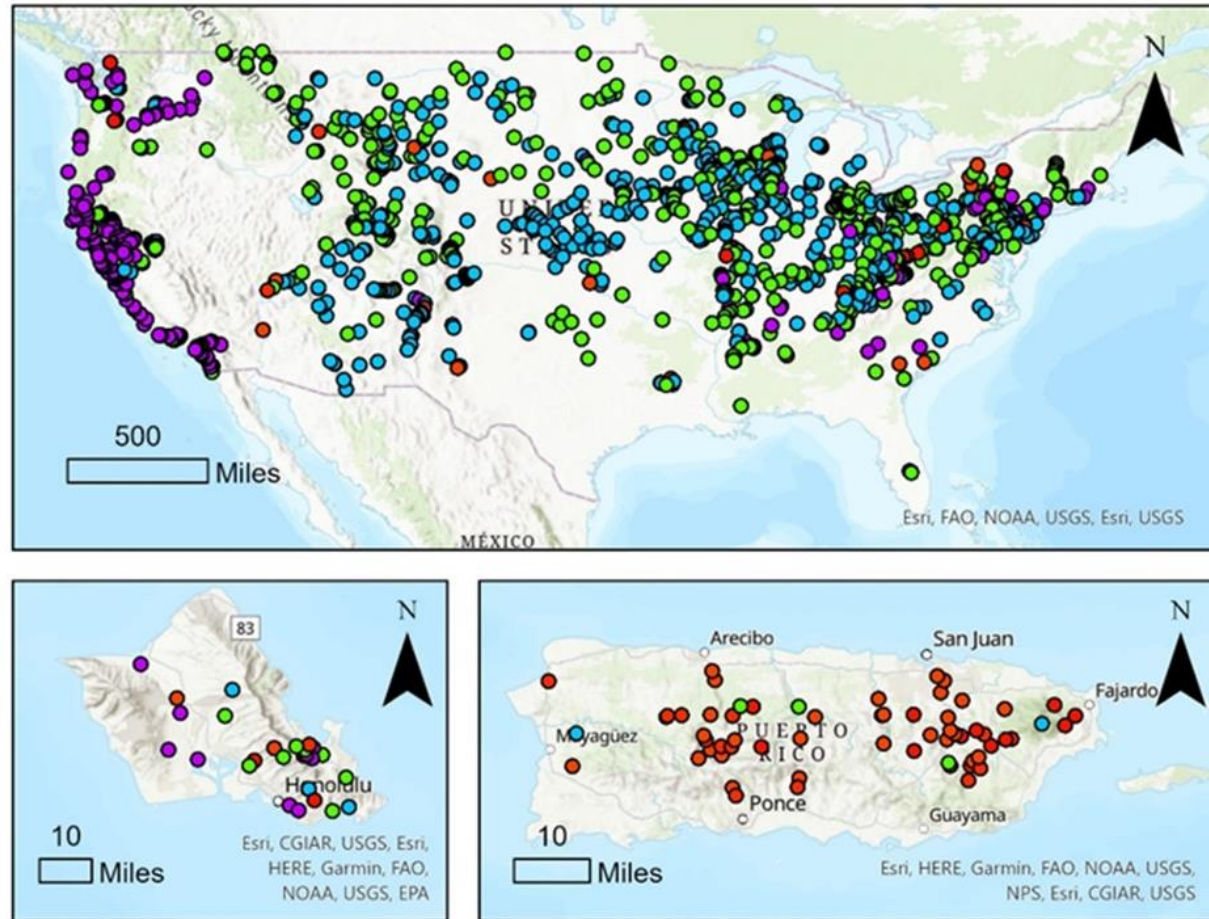


Figure 2-6. Spatial distribution of selected frequency indicators and standard deviation: Duration of events at α values of 0.9 (D0.9; a) and 0.6 (D0.6; c); peaks per event at α value of 0.6 (P.p.e0.6; e). Stdev represent standard deviation (b,d,f).

Timing Indicators

Spatial patterns were observed in the SSC timing indicators, though these were more pronounced for magnitude than frequency (Figure 2-7). The maximum SSC was consistently found in the winter months (DJF) in the West Coast (e.g. California and Washington State; Figure 2-7a, purple) and in the autumn (SON) for Puerto Rico (Figure 2-7a, red). The Great Plains and Midwest regions had their greatest SSC in spring and summer (Figure 2-7a, green and blue). The season with the highest number of SSC events had greater variability across the US, with no clear spatial patterns ($\alpha=0.6$; Figure 2-7b). The choice of α value may potentially be important for this indicator; more sites had an autumn (SON) timing with higher α values (e.g. longer duration events), whilst more sites had a summer (JJA) timing at lower α values (e.g. shorter duration events; Figures A2-23 & A2-24).

a)



b)

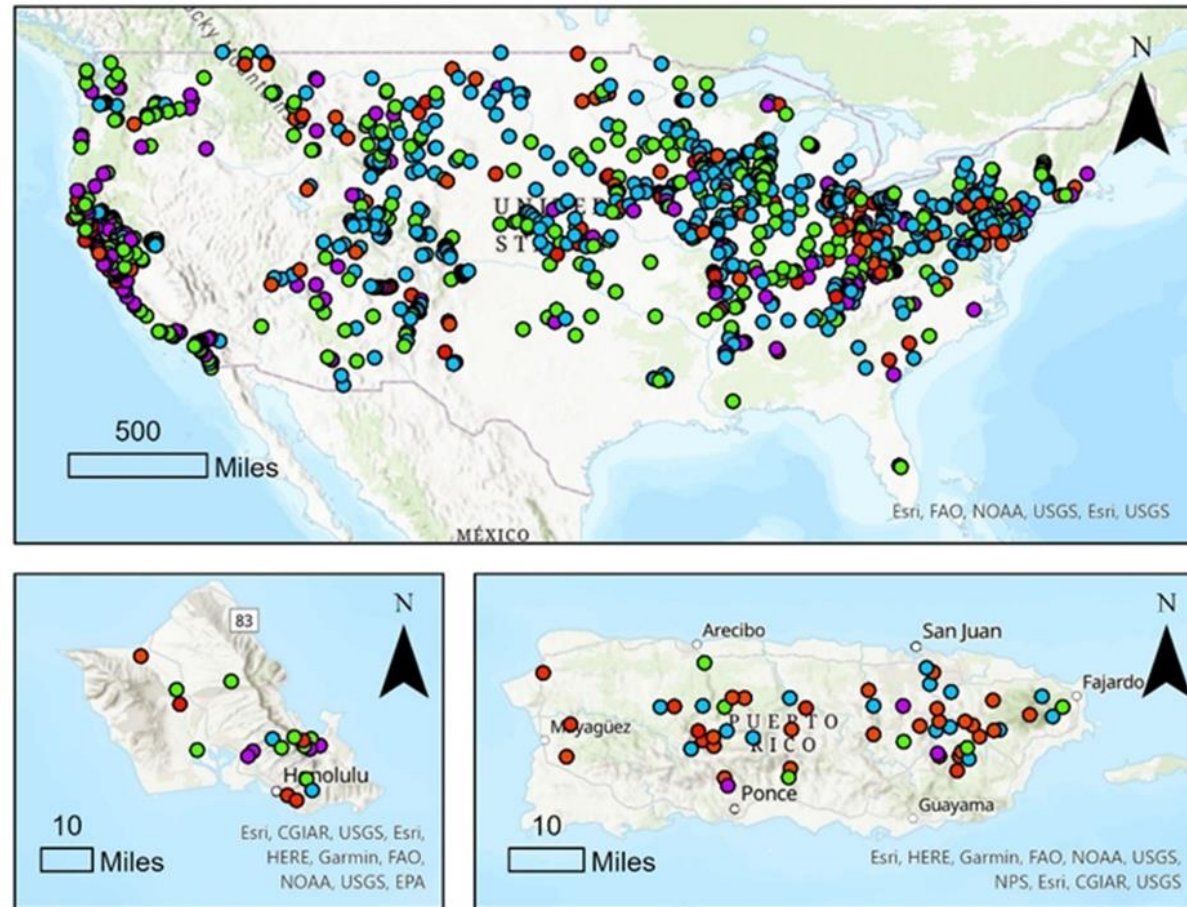
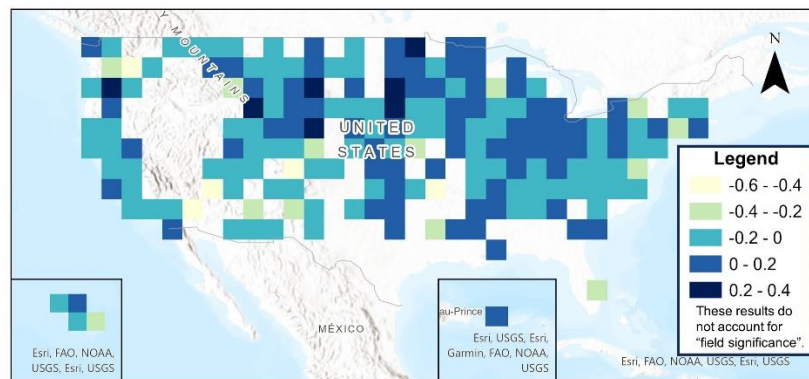


Figure 2-7. Seasons with the maximum SSC per month (magnitude; a) and the maximum number of SSC events at α of 0.6 (frequency; b): Winter (DJF) - Purple, Spring (MAM) – Green; Summer (JJA) - Blue; Autumn (SON) – Red.

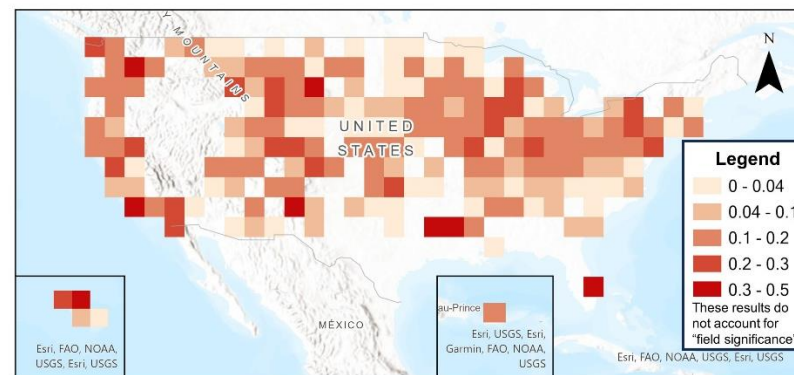
2.5.3 Trend Analysis

The trend analysis shows a mixture of increasing and decreasing trends (Figure 2-8), but by applying Field significance (stricter p value from Walker's p), more obvious decreasing trends with much smaller number of valid results were identified (Figure A2-22). When all sites are included in the analysis, SSC values appear to be increasing over time, without any obvious spatial patterns in the magnitude of the trend (Figure 2-8a) or standard deviation (Figure 2-8b). However, when only statistically significant trends are shown (1,159 sites from all time series, 168 from M95, 92 sites from D0.9, 125 sites from D0.6, 75 sites from Ppe0.6), it becomes clear that there is a generally negative trend in M95 (Figure 2-8c). Event durations show a more mixed distribution with both increasing and decreasing durations for long (i.e. seasonal) and medium-length (i.e. monthly) events, though there is a greater number of sites showing increasing trends in duration for D0.6 than D0.9 (Figure 2-8d,e). P.p.e0.6 had a mixture of increasing and decreasing trends (Figure 2-8f).

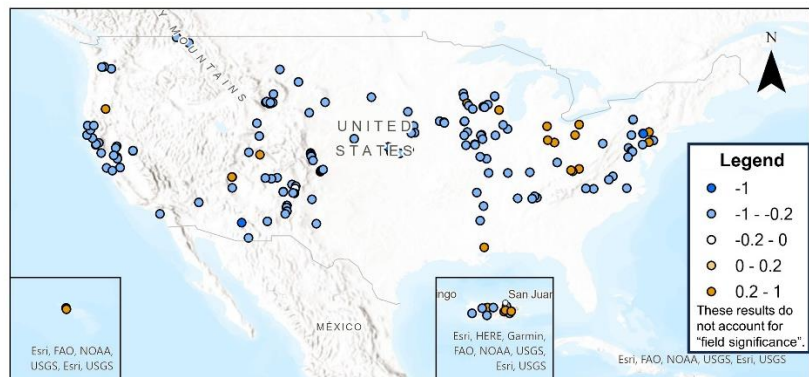
a) MK - All time series



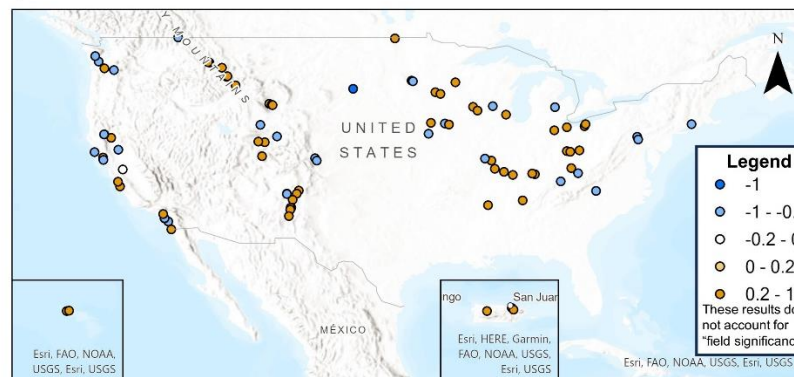
b) MK-Stdev



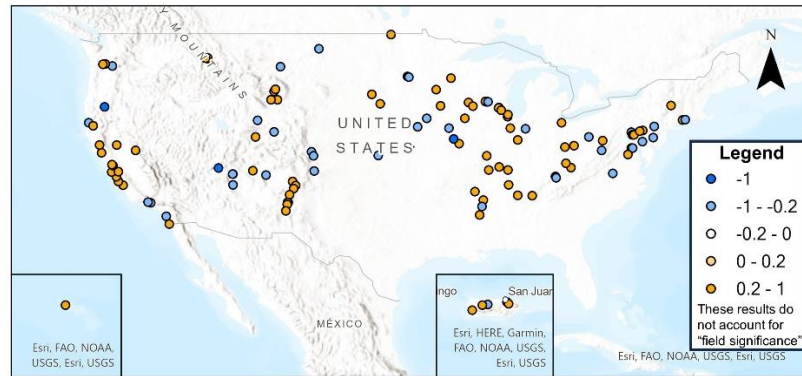
c) MK-M95



d) MK-D0.9



e) MK-D0.6



f) MK-P.p.e0.6

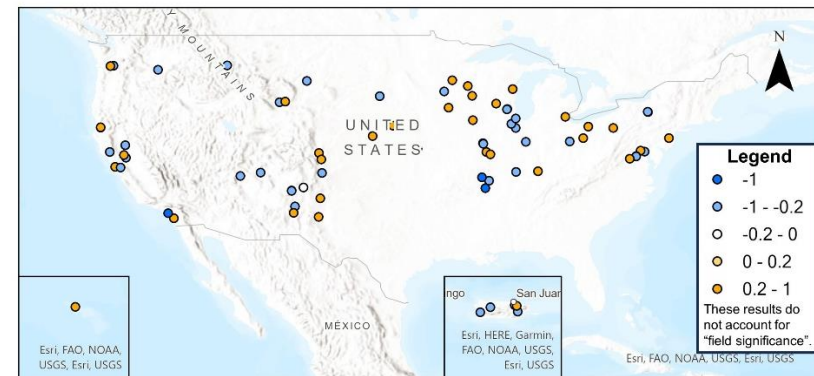
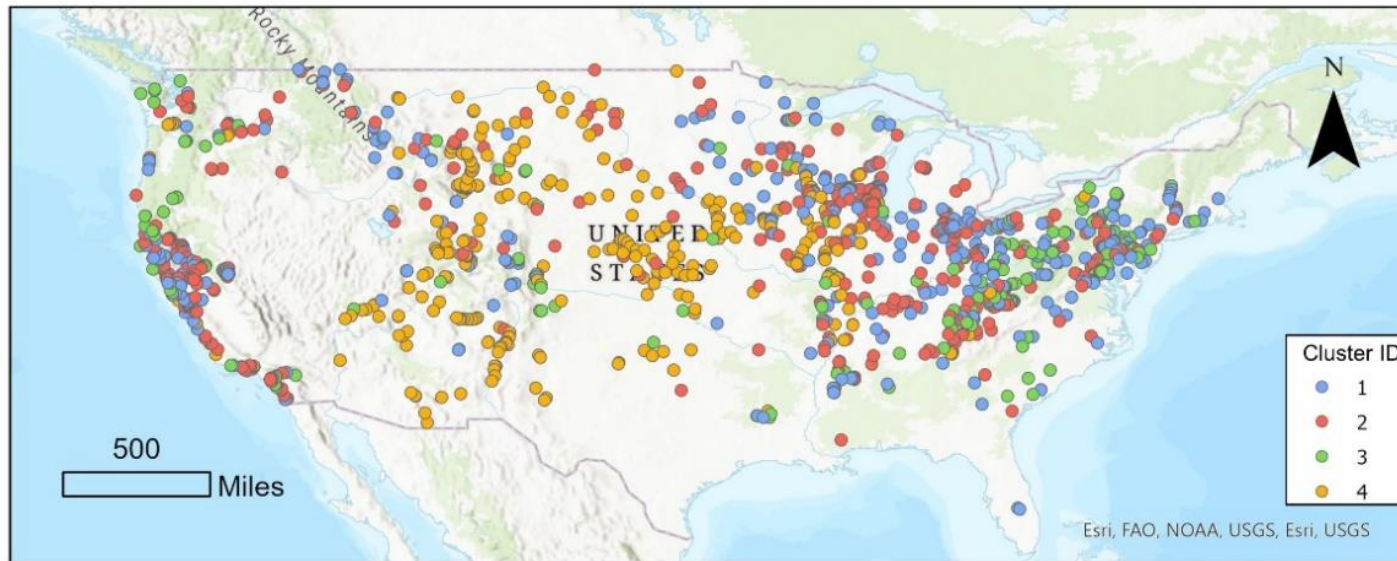
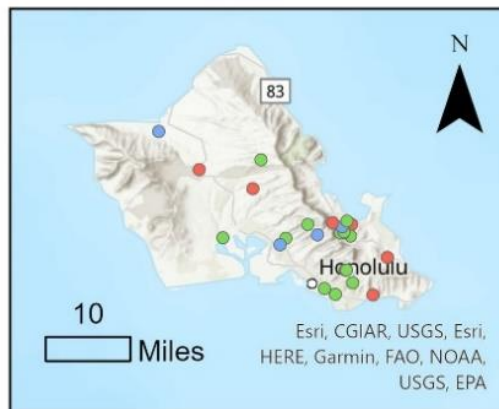
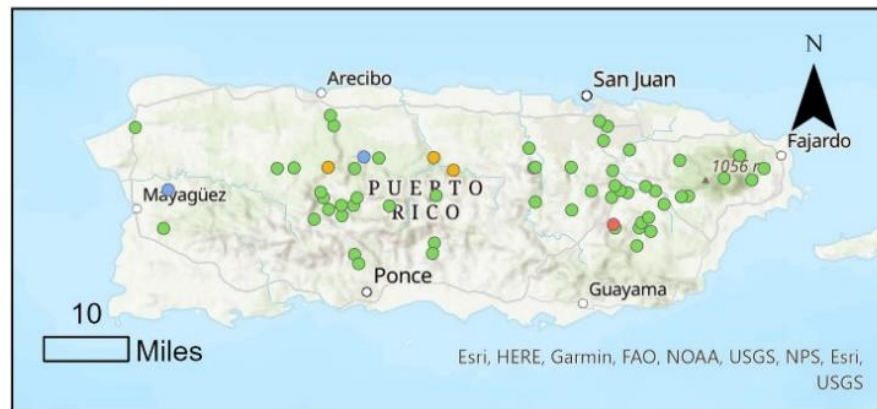


Figure 2-8. Results of trend analyses: MK means Mann Kendall trend analysis: magnitude of 95th percentiles (M95), duration of events (D), count of events (C.of.e), and peaks per event (P.p.e). The Block statistics results (a,b) provide MK trend analysis results from all daily time series. Results of MK trend analysis on the indicator calculation are shown in c,d,e,f, calculated from average annual time series ($p < .05$) with more sediment and blue colours, representing increasing / decreasing trends. Trend analysis results applying the field significance is attached in Figure A2-22.

Cluster analysis

K-means clustering was conducted using selected magnitude, frequency and timing indicators. Four clusters were selected based on the results of Silhouette method (Figure A2-25). The clustering results show clear spatial patterns at the continental scale (Figure 2-9a). A broad cluster of sites with high M50 and R.r was found distributed across the central US, spanning the Rocky Mountain, desert, and Great Plains regions (Figure 2-9, cluster 4, yellow). Sites with a longer duration of SSC events ($\alpha=0.6$) were found across the US but appear to be clustered in the Midwest and California (Cluster 2, red), along with the Appalachian region. The timing of the maximum monthly SSC was later in the year for the islands and the eastern US region (Cluster 3, green), especially compared to the rest of the inland area, e.g. Midwest and broader Mississippi basin (Clusters 1 and 2, blue and red, respectively). For the season with the greatest number of events (Max i.p months), the irregular patterns observed at continental scale (Figure 2-7b), were reflected in the clustering analysis (1,3 and 4, blue, green and yellow, Figure 2-9).

a)



b)

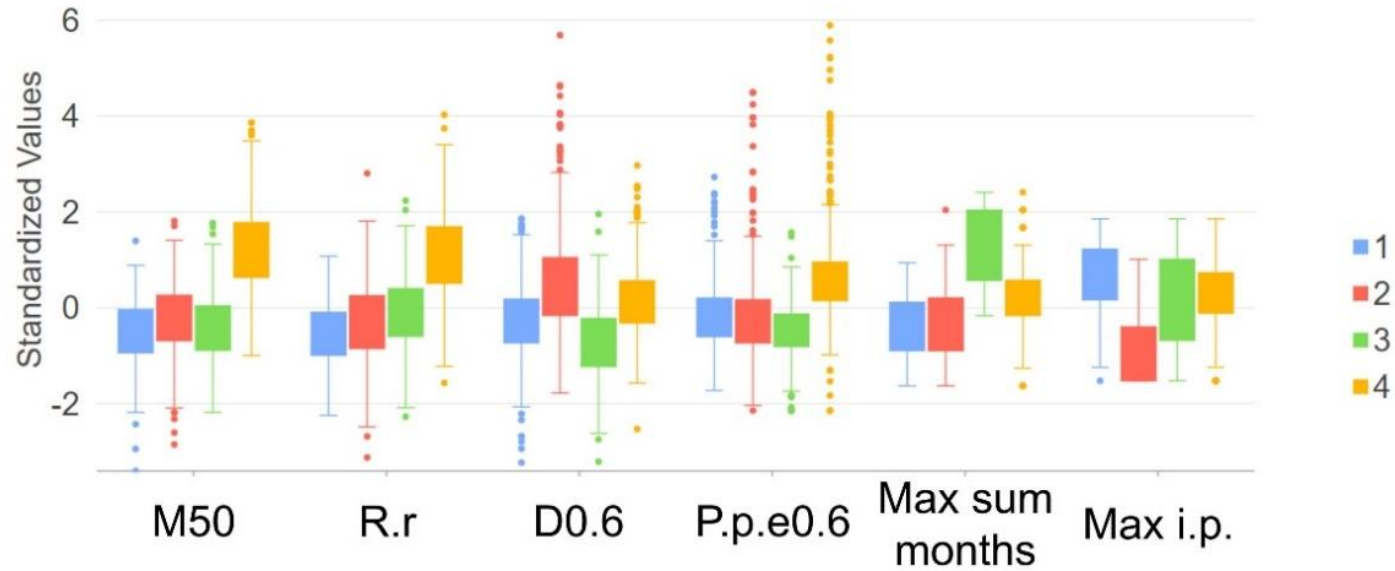


Figure 2-9. Clustering of MFT: Variables consist of log transformed median SSC (M50), rising rate (R.r), event duration at $\alpha=0.6$ (D0.6), peaks per event at $\alpha=0.6$ (P.p.e0.6) and months of maximum SSC (max sum months) and max number of SSC events (max i.p.) without transformation, showing the spatial distribution of the clusters in the continental US (a) and the relative differences between clusters for each indicator (b).

2.6 Discussion

This study analysed timeseries of SSC data from river monitoring stations using newly developed indicators of SS transport dynamics based on magnitude, frequency and timing. Clear spatial patterns were observed for some indicators and indicator classes, which suggest that these SSC indicators are driven by large-scale factors, such as climate or LULC. Other indicators had more complex, and heterogenous spatial distributions, suggesting more localised influences in SS transport dynamics. In this section, we summarize these findings on the spatial patterns in SS transport dynamics indicators and make recommendations for their future use in studies to determine the influence of catchment and climate factors.

Of the SSC dynamics indicators, M95 had the most distinctive spatial pattern. M95 and the standard deviation of M95 were low across most of the US (Figure 2-4). However, elevated values were observed in dry and mountainous regions, especially the Rocky Mountain, North American desert and western Great Plains regions (Li *et al.*, 2020). The high SSC values detected near Mount St. Helens are a clear illustration of the influence of volcanic and other tectonic events on SS transport dynamics, which also impact local ecosystems (Uhrich *et al.*, 2021). It highlights the importance of sediment retention systems near possible eruption areas (Hoess and Geist, 2021). There was a strong correlation between the magnitude indicators (Figure 2-3), thus future studies may only require the inclusion of a single magnitude indicator (e.g. M50 or M95), or perhaps a reduced number with slightly different alignment along the PCA axes (e.g. M95 and M25), to investigate climate and catchment controls.

Frequency indicators had continental scale spatial patterns that were distinctly different to magnitude (Figure 2-6). SSC events were longer in the upper Midwest and lower in the eastern US at all α values (Figure 2-6a,c). These results could be caused by spatial patterns in climate and precipitation (Akinsanola *et al.*, 2020). The duration of shorter events (i.e. 1 - 2 week duration) had slightly more defined clusters than long duration events, especially in the upper Midwest, upper Great Plains and west coast (Figure 2-6c). P.p.e was generally low across the US, and

high values were widely distributed. However, there is a suggestion of a cluster of moderate to high values along the Mississippi River, especially in the upper Midwest (Figure 2-6e), which may be due to short-duration intense precipitation in the summer (Alexandrov *et al.*, 2007). Again, the strong covariation between the duration indicators suggests that a single indicator (e.g. D0.6) may be appropriate for further research (Figure 2-3).

The spatial pattern of the timing of SSC events suggests a strong climatic signal for magnitude but not frequency. The highest SSC values were found to occur almost exclusively in winter (DJF) in the west coast region of the US and in autumn in Puerto Rico (Figure 2-7a; purple). These results correlate to periods of high rainfall and availability of erodible materials (Guirguis *et al.*, 2019), for example the late summer and autumn Atlantic hurricane season for Puerto Rico. The majority of sites across the US had their highest SSC in spring and summer, but there was no clear spatial pattern, suggesting influences of local factors that affect sediment availability (LULC) overlain onto climatic patterns. For example, the sites with summer (JJA, blue) could be caused by higher and more intense rainfall in this period, whilst the spring sites might be influenced by agricultural management practices (e.g. ploughing and sowing). Whilst some clusters of high frequency SSC events are apparent (e.g. upper Midwest in summer) that may relate to climate (e.g. convective storms), more research is needed to determine the utility of this indicator (Figure 2-7b).

The trend analysis identified largely decreasing trends in magnitude (Figure 2-8a,c) in accordance with the overall decreasing trend of SSC (Li *et al.*, 2020), which is believed to be due to SS management, e.g. soil conservation (Paolo and Minella, 2020). However, increasing trends were identified for duration and frequency indicators over large areas of the country (Figure 2-8 d,e,f). Thus, whilst SSC magnitude is decreasing, periods of elevated SSC (relative to the annual average) are lasting longer in rivers. These results align with a hypothesis that improved soil management is decreasing rainfall-induced erosion and transport to river channels, resulting in a less anthropogenically-influenced, flashy SS regime. The localised areas of increasing magnitude might be due to changes

of land uses (Murphy, 2020). However, due to the limitations and uncertainties in the daily SSC dataset (Sommerfield, 2016), interpretation of new indicators about trend analysis requires consideration of uncertainty.

The spatial patterns for magnitude, frequency and timing indicators were integrated in the cluster analysis, which, despite considerable heterogeneity, showed some important large scale spatial patterns (Figure 2-9). Sites in the Great Plains, central Rocky Mountain, and North American Desert regions were associated with the highest M50, R.r. and P.p.e0.6, which may be associated with LULC and availability of erodible materials, perhaps due to agriculture. Sites with a low M50 and low R.r. with the greatest number of SSC events in summer (i.e. a high month of max i.p in the hydrological year) were found across the Midwest, Appalachian and northern Rocky Mountain regions. Sites with a moderate M50 and R.r, low D0.6, and a timing of highest SSC in autumn (green) were identified across the US, but a pronounced cluster was found in the Appalachian region, northern California and in pockets on the west coast. The spatial patterns are likely due to a mixture of human impacts and LULC, e.g. higher impacts of magnitude in the driest and mountainous regions, longer duration of events from urban areas, and peaks per event from areas where receives frequent precipitation events (Li *et al.*, 2020a; Taszarek *et al.*, 2020). For future studies we recommend the use of a combination of magnitude (e.g. M50 or M95, R.r.), frequency (e.g. D0.6 and/or P.p.e0.6) and timing (e.g. Max sum months and Max i.p.), especially when climate is a factor.

The use of daily SSC data has implication on the results presented. Despite the unavailability of which methods were taken for each daily SSC computation, the SS dynamics may include covariance with water. There is uncertainty that SSC could be over or underestimated. It is recommended to compare the results with other available local SS data e.g., discrete SSC, turbidity, sediment discharge etc. However, measuring turbidity also has different type of uncertainty e.g., differing turbidity measurement by sensor type and inclusion of organic matter, microscopic organisms, etc (Williamson and Crawford, 2011).

As in all studies, choices made in data processing and analyses may have influenced the spatial patterns. Use of turbidity and/or stricter completeness thresholds for SSC time series might have resulted in less localized variation in indicators, as some of the observed variation might be caused by differences in the time periods, e.g., intense storms and representativeness of seasonal variations. The patterns including outliers identified were the results from taking arithmetic mean of percentiles, which yielded generally higher values than taking median (Figure A2-10~15). However, median instead of mean had minor impacts though using median value may have produced less extreme values. Instead of monthly maxima or minima, standard deviation of seasonal mean may produce different results (Yunus *et al.*, 2008).

Current choice of alpha values captured event duration in weeks to months, which is sufficient to the research objectives given the volume of interpretation and not significantly different durations observed between those alpha values e.g., 0.1, 0.4, 0.75 and 0.9375 (Figure A2-19). The research also used the first forward filter only to define events from Lyne and Hollick filter. Examples of distortion between several forward and backward pass filters with subsequently varying exponential decays were identified as the alpha value becomes higher (Figure A2-18). If different orders of forward or backward pass filters were used, all frequency indicators may have produced different values. From the examples in A2-18, further longer duration of events, lower number of events and more number of peaks per event would have been derived accordingly. Future work should find minimum distortion between different pass filters.

The number of statistically significant trend analysis result also imply the limitations identified in the data filtering that the discrepancy of multiyear temporal dimension is not visible in the maps from static data (Wang *et al.*, 2017). Furthermore, the interpretation of Block statistics result should consider non-uniform number of points in each pixel.

2.7 Conclusions

New indicators of SS transport dynamics were used to characterize the magnitude, frequency and timing of SS transport dynamics. Large scale patterns

in magnitude and frequency indicators were identified, which could be caused by climate and land use. Sites with the highest SSC events (M95) were located in the desert and mountainous regions, whilst sites with the longest duration SSC events were found in the upper Midwest. Timing indicators showed varying patterns with clear dominant seasons for higher SSC in the western US and Puerto Rico but a high spatial heterogeneity for the season with the most events (Max i.p). The trend analysis confirmed the decreasing trend in SSC magnitude reported by other studies but provides new evidence of increasing trends for the duration of SSC events and the number of peaks per events. These indicators provide new insights into the spatial variability of temporal dynamics in SSC in rivers and can be used by studies to determine the catchment and climatic controls. We recommend the use of a magnitude, frequency and timing indicator for future studies, particularly $\alpha=0.6$ to capture short-term dynamics, which may be useful coupled with M95 and R.r for climate change impact studies. A deeper understanding of the drivers of SSC dynamics will support the prediction of climate change impacts on SSC and develop mitigation measures to reduce the ecological and societal impacts of SS transport.

This chapter is a modified version of 'Spatio-Temporal Variations in Suspended Sediment Transport Dynamics in Rivers: Catchment and Climatic Influences' published in Hydrology Research (Shin *et al.*, 2023a).

3 Spatio-Temporal Variations in Suspended Sediment Transport Dynamics in Rivers: Catchment and Climatic Influences

3.1 Introduction

Climate change is predicted to affect the flux of suspended sediment in river systems. Changes in rainfall, temperature and CO₂ concentrations are expected to alter the forces (i.e. rainfall intensity, river discharge and wind) that drive erosion and transport but also the factors that moderate these forces, such as vegetation growth (Naylor *et al.*, 2017; Lowe *et al.*, 2018; IPCC, 2019). These moderating factors operate naturally and via anthropogenic activity, including changes to land use and land cover (LULC) in response to or as part of mitigating actions against climate change, e.g. shifts in crop types or conversion of agricultural land to forest (Murphy, 2020). Considerable research has been conducted on the impact of LULC and climate change on annual sediment load (i.e. sediment yield) at catchment scales (Dai *et al.*, 2009; Hung *et al.*, 2014; Camilo and Restrepo, 2017; Kemper *et al.*, 2019) and at continental scales (Syvitski, 2003; Walling and Fang, 2003; Wang *et al.*, 2011; Syvitski *et al.*, 2014; Moragoda and Cohen, 2020). However, there has been less focus on how these factors and their interactions affect suspended sediment transport dynamics, i.e. short-term changes in suspended sediment concentration (SSC) at a site over days to months (Mount and Abrahart, 2011; Roman *et al.*, 2012; Murphy, 2020).

Uncertain future trajectories in SSC dynamics exist because numerous factors affect SS transport. Climate, LULC and human activities all affect the magnitude, frequency and timing of SS events (Vercruysse *et al.*, 2017). Climate change is shifting temperatures and rainfall, but is also altering the frequency and magnitude of extreme weather events (van de Pol *et al.*, 2010). These climate perturbations can influence SS generation and transport directly, through rainfall-induced detachment of soil particles and resuspension of stored sediment on land

and in river channels. They can also alter SS flux at catchment scale through indirect effects on vegetation growth, both positive and negative. The combined effect can lead to multiple possible future trajectories in SSC dynamics in rivers with climate change. Some studies suggest that increased vegetation growth triggered by higher temperatures and carbon dioxide concentrations in the air will reduce soil erosion, despite a higher frequency and magnitude of precipitation events and runoff (Tietjen *et al.*, 2017). Other studies conclude that rainfall has less effect on sediment generation than the catchment hydrological regime, controlled by lithology and geological characteristics, which determines the partitioning of rainfall on the land surface (Fortesa *et al.*, 2021). Natural responses to climate change could be compounded or mitigated by human activity, such as LULC changes, engineering infrastructure and erosion control methods implemented across the landscape. However, suspended sediment transport is not linearly responsive to natural processes or anthropogenic activities (Bussi *et al.*, 2016). While rainfall and discharge are often used to predict suspended sediment transport, relationships between these drivers and SSC are variable in space and time due to impacts by different processes (Vercruysse *et al.*, 2017). Thus, to better predict future changes to SSC transport dynamics (i.e. sediment regime), further research is needed on the climate and catchment factors that interact to affect the magnitude, frequency and timing of high magnitude SSC events in rivers.

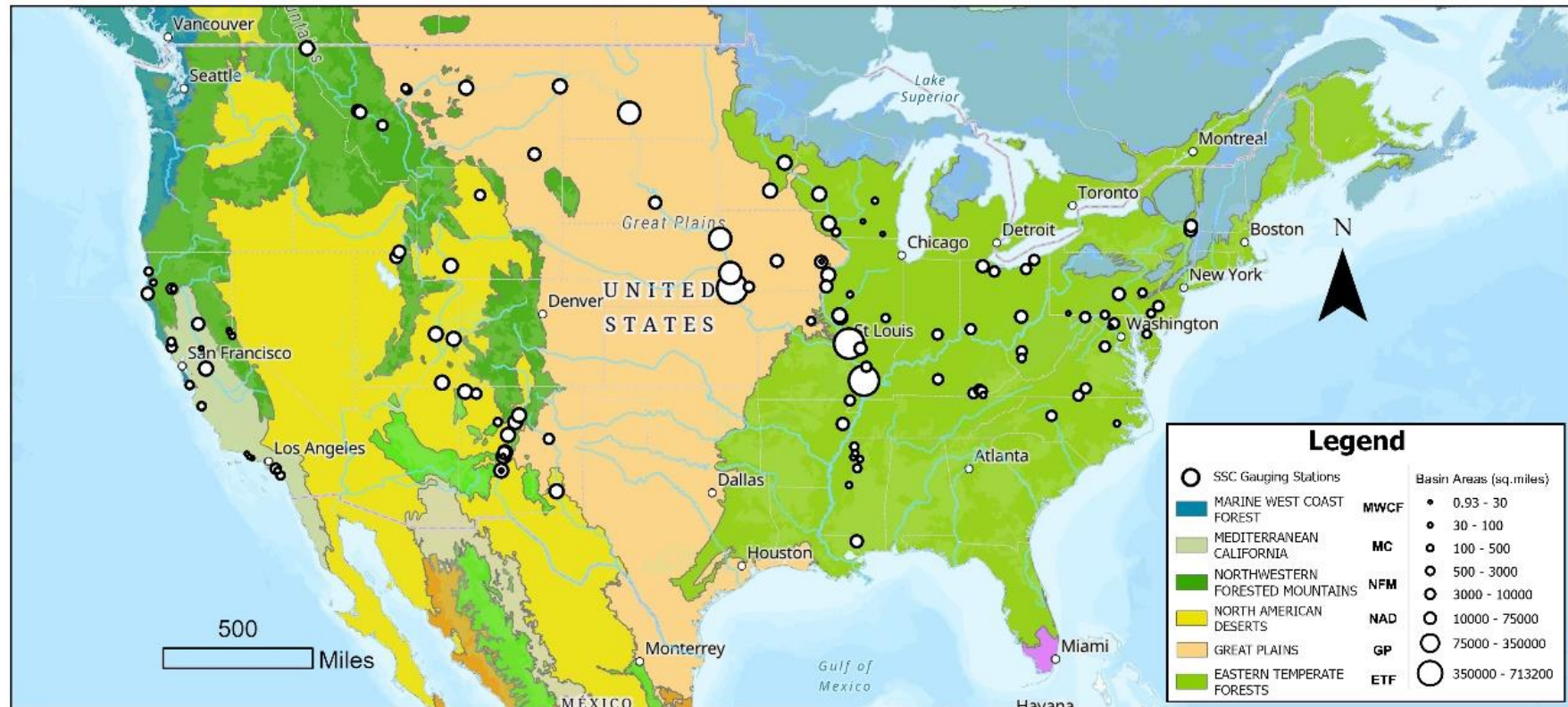
Suspended sediment transport dynamics are often investigated explicitly with discharge, either in the form of rating curves or sediment loads (Vercruysse *et al.*, 2017), but an approach that considers the magnitude, frequency and timing of high SSC events is important for sediment management (Reckendorfer, 2019; Shin *et al.*, 2023). A magnitude, frequency, timing approach can also be analysed using regression approaches to determine the contribution of climate and catchment factors, as done in previous research to predict long term mean annual SS loads (Roman *et al.*, 2012; Grauso *et al.*, 2021) and total SS loads (Ayadi *et al.*, 2010). A deeper understanding of climate and LULC controls on SSC and their interactions with catchment characteristics is crucial to predicting changes in the magnitude, frequency and timing of high SSC in rivers in the future.

The aim of this study is to determine the influence of climate and catchment characteristics on suspended sediment transport dynamics in rivers. The objectives are to (i) develop statistical and spatial models of indicators of SSC dynamics (magnitude, frequency and timing) at annual and seasonal scales in order to (ii) assess the relative contribution of climate and catchment characteristics. The aims and objectives are achieved through analysis of long time series of SSC data from river gauging stations distributed across the contiguous United States of America (USA). This statistical approach can generate empirical models capable of differentiating the relative contributions of climate (Roman *et al.*, 2012; Eurich *et al.*, 2021) that have the potential to be more transferable than process-based modelling (Girolamo *et al.*, 2015).

3.2 Study area and data

SSC data were obtained from the United States Geological Survey (USGS), which has a large database of SS monitoring data, collected over a long time period, and encompassing a range of climatic regions and catchment characteristics. The study started with the daily mean SSC (mg/l) data from 1,667 sites, as in Chapter 2, and daily discharge (m^3/s) from 1,605 sites from USGS distributed across the continent and overseas territories of the US. Text files containing each SSC (Parameter code: 80154) and discharge (Parameter code: 00060) were downloaded from USGS Surface-Water Daily Data for the Nation. More information on the collection and processing of the SSC data can be found in (Shin *et al.*, 2023). For more information on the daily mean SSC dataset, how it was collected and analysed, and its limitations, please see section 2.3.1. The spatial extent of the study was reduced to the contiguous U.S., due to limitation of the site characteristics datasets in Geospatial Attributes of Gages for Evaluating Streamflow (GAGES) (e.g. environmental features and anthropogenic influences) in the remaining areas of the USA (Falcone *et al.*, 2010). The number of sites was then reduced further due to SS data availability and the application of site selection criteria.

a)



b)

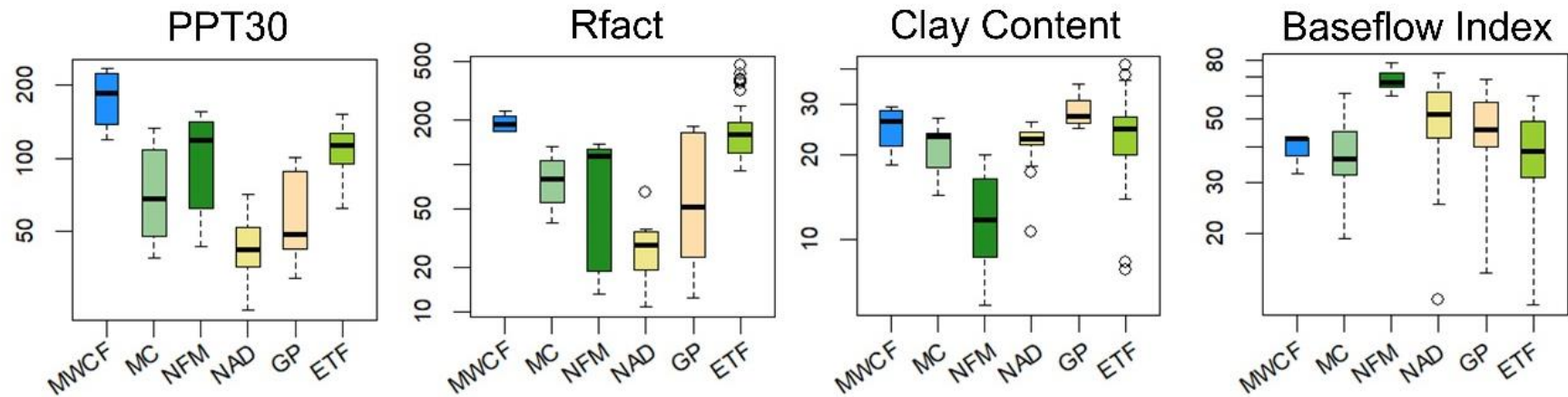


Figure 3-1. a) Data were analysed from 120 sites across the contiguous USA, which encompasses 6 ecoregions (level-I; Falcone *et al.*, 2010). b) Summary of climate and catchment characteristics by ecoregion, including average annual precipitation (PPT30; cm/yr), 30-year rainfall and runoff factor (Rfact; 100's foot tonforce inch per acre per hr per yr) · 10), clay content (%), and baseflow index (%).

3.3 Suspended sediment data and pre-processing

The SSC data were processed, and final sites were selected, according to five steps. First, sediment monitoring sites were filtered to include only those co-located with a river discharge gauging station. Secondly, extreme outlier sites, which could be linked to geological events, were identified and removed. For example, the SSC monitoring site on the Yakima River (Sunnyside, Washington) was removed from the dataset because SSC records were affected by the 1980 Mount Saint Helens volcanic eruption. Thirdly, sites were selected that had a good completeness of SSC data, defined as 80% SSC data per year. To ensure that ephemeral and intermittent rivers were included in the study, this threshold was applied to days on which discharge was recorded at the gauging station (Goodrich *et al.*, 2018). Fourthly, sites were filtered further by selecting those that had at least 10 years of data (non-consecutive) within the 30-year period, 1971-2000. This time period was selected because it corresponded with the period used for estimation of catchment characteristics (Falcone *et al.*, 2010) and is consistent with climate change impact studies (Yue *et al.*, 2020). The filtering is based on the assumptions that uniform influence of climate representing 30 year is on various hydrological processes over the land surface. The limitation is that the filtering technique has not applied the fact that data are from nested catchments. Finally, gaps were filled to avoid misleading calculation of MFT indicators. The gap filling was done using Kalman's smoothing for short gaps in data (≤ 3 days), because the approach to calculate the frequency of high SSC events is sensitive to gaps (Moritz and Bartz-beielstein, 2017) and its suitability with daily SSC over time averaging approach e.g., linear or cubic spline interpolation and linear regression with other explanatory variables e.g., discharge (Holtschlag, 2001). Assumption of using Kalman's smoothing is that the filtering can only be used with linear models and Gaussian distribution noise (Chiang *et al.*, 2012). Limitation from Kalman's smoothing is that it may worsen final error levels (Panomruttanarug and Longman, 2008). A total of 120 sites passed the selection process and were included in this study (Figure 3-1).

The daily mean SSC dataset was used, despite concerns raised by previous research regarding its use for calculating annual sediment yield (Sommerfield, 2016). That research used four example case studies to illustrate that there are low correlations between discrete and daily mean SSC and a lack of homogeneity in discrete SSC over time. However, preliminary analyses for this study found generally high R^2 between instantaneous SSC, daily mean SSC and turbidity (FNU). Median value of R^2 between instantaneous SSC and daily SSC is 0.735, and R^2 ranges between 0.73~0.95 between daily SSC and FNU. Importantly, there is coherence in the timings of rises and falls between those SSC and FNU (Formazin Nephelometric Unit) turbidity datasets (Figure A2-5~9 and A3-1). The observed correlations for these sites provide confidence in the use of the SSC daily data for this study to investigate catchment and climate influences on suspended sediment dynamics. Though, it is important to note that a high correlation between instantaneous SSC and daily mean SSC should not be universally expected. Some sites will have high spatial variation in SSC across the channel and/or high temporal variations in a day, which is why the USGS engineers applied discharge weighting methods. Furthermore, the lack of homogeneity identified by Sommerfield (2015) can, as the authors note, be caused by numerous factors, including changing upstream sediment supply.

Site attribution data

The study used summary data on climatic and catchment characteristics from USGS for all 120 sites (Table 3-1). This dataset aligns with the SSC data pre-processing period; climate data was compiled from the 30 year time period (1971-2000) (Daly *et al.*, 2008) and LULC calculated for the year 2001 (GAGES) (Falcone *et al.*, 2010). The site attribute data are broadly grouped into climate, land use, land cover, soils, and river hydrology data. Ecoregion distinguishes areas with internally consistent LULC and climate in consideration of natural vegetation community (Dodds and Whiles, 2004; Omernik and Griffith, 2014). The research used Ecoregion level-I (7.0, 11.0, 6.0, 10.0, 9.0, 8.0), which for this study included Marine West Coast Forest (MWCF), Mediterranean California

(MC), Northwestern Forested Mountains (NFM), North American Deserts (NAD), Great Plains (GP) and Eastern Temperate Forest (ETF).

Table 3-1. Climatic and catchment characteristics (Falcone *et al.*, 2010): NLCD - National Land Cover Database. Slope gradient was not introduced in the predictor variables as there were no significant relationships between flow velocity and slopes exerting impact on SS transport (Zhao *et al.*, 2015).

Category	Abbreviation	Content
Climate	PPT30	Mean annual precipitation (1971-2000, cm)
	Rfact	30-year rainfall and runoff factor (100's ft-tonf in $\text{h}^{-1} \cdot \text{ac}^{-1} \cdot \text{yr}^{-1}$)
Land Use	Agperc	Percentage of agricultural land (sum of NLCD classes 81 and 82, %)
	Urbanperc	Percentage of urban land (sum of NLCD classes 21, 22, 23, and 24, %)
Land Cover	Perm	Avg. soil permeability (inches/hour)
	Kfact	Avg. K-factor for the uppermost soil horizon (unitless)
	Forestperc	Percentage of forest land (sum of NLCD classes 41, 42, and 43, %)
	Silt	Avg. percentage of soil silt content (%)
	Sand	Avg. percentage of soil sand content (%)
	Clay	Avg. percentage of soil clay content (%)
	Eco L1 Code	Level I Ecoregion Code
River Environment	Catch.A	Upstream drainage area (sq. miles)
	BFI	Avg. baseflow index (%)
	Flow.50p	50 th percentile of daily flows
	Flow.95p	95 th percentile of daily flows
	Major_Dams	Number of dams (≥ 50 feet in height or having storage $\geq 5,000$ acre-feet)
	R.storage	Dam storage (acre-feet)

3.4 Methods

The research used a multivariate statistical analysis approach to determine the contribution of catchment and climate explanatory factors to spatial and temporal variations of suspended sediment dynamics. The following steps were used: (i) calculation of SSC dynamics indicators, (ii) data exploration and a principal component analysis (PCA) to inform the reduction in the number of SSC dynamics indicators to model, (iii) regression analysis using ordinary least squares regression and the removal of spatial autocorrelation with geographically-weighted regression (GWR), and (iv) cluster analysis and statistical analysis of GWR coefficients by ecoregions.

3.4.1 Suspended sediment concentration dynamics indicators

Indicators to describe SSC dynamics in magnitude (e.g. percentiles and rates of changes in mg/l), frequency (durations & counts) were calculated at annual and seasonal timescales (Shin *et al.*, 2023). The indicators were calculated from the daily SSC time series, separately for each year of record, and then averaged annually and seasonally. A total of 80 SS dynamics indicators were initially calculated (Table 3-2).

Table 3-2. The indicators calculated to quantify SS dynamics annually and seasonally; Seasonally subset values of Stdev. of monthly max/min as well as counting peaks related indicators were not calculated due to less variance observed in the annual data.

SS Indicators	Indicators calculated for statistical analyses (Average annual)	Abbreviation	Number of Indicators	Seasons (x 4)
Magnitude	1) Magnitudes in percentiles (95th, 75th, 50th, 25th)	M	4	4
	2) Rising/falling rates	R.r/F.r	2	2
	3) Magnitude on a peak day value	Mpkday	1	1
	4) Standard deviation of monthly max/min	StdevMax/ Min	2	x
	5) Annual average change rate	Aacr	1	1
Frequency	1) Event durations ($\alpha = 0.975, 0.9, 0.6, 0.2$)	D	4	3
	2) Counts of events ($\alpha = 0.975, 0.9, 0.6, 0.2$)	C.of.e	4	3
	3) Peaks per event ($\alpha = 0.975, 0.9, 0.6, 0.2$)	P.p.e	4	x
	4) Duration between peaks	D.b.p	1	x

Intra-annual variation in SSC dynamics was investigated seasonally so that the potential impacts of seasonally varying land management practices for the different LULC units (%) could be explored: winter (December, January and February; DJF), spring (March, April and May; MAM), summer (June, July and August; JJA) and autumn (September, October and November; SON) (Table 3-2). All pre-processed time series were divided into seasons, and magnitude and frequency indicators were recalculated. Visual checks of time series were done at each step to verify whether there were impacts from missing months as well as yearly gaps in time series.

3.4.2 Preliminary statistical analysis – Principal Component Analysis

A PCA was conducted, using the “factoextra” package in R (R Core Team, 2023), to explore the multivariate dataset and reduce the number of response variables in the subsequent statistical models (i.e. the SSC dynamics indicators) (Haddadchi and Hicks, 2021). The two step process (PCA and OLS) was conducted because of the desire to use a spatially-explicit regression approach. Otherwise, direct gradient analyses, factor analysis or random forest could have been used to find multivariate relationships between catchment and climate factors, but using those alternatives may have needed additional considerations e.g., inappropriate predictor and response variables and overfitting (Feng *et al.*, 2020). The analyses used all continuous and discrete (e.g. C.of.e and P.p.e) response variables to identify SSC indicators that correspond to different dimensions in the PCA plots, aided by K-means clustering (Fang *et al.*, 2012). Continuous variables and integers were taken in the same PCA plot. The redundant variables with low contribution were removed. PCA minimizes mean square errors and is sensitive to outliers (He *et al.*, 2011).

3.4.3 Regression analysis – OLS and GWR

OLS regression

OLS linear regression analysis was used to determine the relationship between climatic and catchment characteristics (Predictor variables) and the SSC dynamics indicators (Response variables) for the selected 120 sites, annual and

seasonal (Burgers *et al.*, 2014). Data transformation was conducted to produce more symmetric residuals with linearity and homoscedasticity. A log 10 transformation was conducted on the response variables to achieve normality (Cho and Lee, 2018). The OLS linear regression analysis was conducted using a best subset selection approach with the reduced number of response variables identified in the PCA and all predictor variables. In addition to the identified significant predictor variables, the OLS analysis was deemed appropriate to bypass detrending of the input variables prior to exploring the spatial patterns in the GWR. Due to the number of predictor variables (< 30) (Nakariyakul and Casasent, 2007), the 'leaps' package with Branch and Bound method (Fouad *et al.*, 2020; Lumley, 2022) was used to develop parsimonious models in R (R Core Team, 2023). The subset selection process started with five independent variables for each model, which was one more than the number of categories of independent variables (Table 3-1). Variables were added or removed to maximize Adjusted R^2 and minimize Mallows's Cp (Cp, a variant of AIC – Akaike Information Criterion) and the Bayesian information criteria (BIC).

Cross validation of the models (K-fold) was done to determine predictor variables with the least prediction error using the 'caret' package in R (R Core Team, 2023). A 5-fold model was used (Max *et al.*, 2023), informed by recent research in environmental sciences and earth surface processes (Coker *et al.*, 2021; Su *et al.*, 2021), with the data divided into test (20 %) and training (80 %) subsets. The number of independent variables in each model was determined based on the least cross validation errors. Then, the variance inflation factor (VIF) was checked for multicollinearity, removing independent variables with VIF greater than 10 (Arabameri *et al.*, 2020; Wang and Wang, 2022), followed by checking interaction terms between independent variables. Finally, predictor variables with statistical significance greater than p-value of 0.05 were removed.

Geographically Weighted Regression

Geographically Weighted Regression (GWR) was conducted, using the 'spgwr' package in R (Bivand *et al.*, 2023), to reduce the spatial autocorrelation in the linear regression models as a means to explore spatial patterns in the predictor

variables for the SSC indicators (Ha & Tu, 2018). In addition, GWR incorporates non-linear elements between sites allowing independent quantification of regression coefficients between sites by estimation of weighted least squares (Middya and Roy, 2021) (Eq. 3-1).

$$y_i = \beta_{i0} + \sum_{k=1}^n \beta_k(\mu_i, \nu_i) x_{ki} + \delta_i \quad \text{Eq. 3-1}$$

Where, y_i is response variable at site i . β_{i0} is intercept at site i . $\beta_k(\mu_i, \nu_i)$ is local coefficient with coordinates of a site denoted by μ_i and ν_i . x_{ki} is k^{th} predictor variable. n is number of predictor variable. δ_i is random error at site i .

Other approaches e.g., GWR-kriging, local regression-kriging (LRK) and Kriging with an external drift (KED), ordinary kriging (OK) were available, but those were not undertaken to avoid making assumptions about the covariance structure, which were unlikely to be valid for this dataset (Harris *et al.*, 2010; Sun *et al.*, 2012; Sideris *et al.*, 2014; Krivoruchko and Gribov, 2019; Afu *et al.*, 2021). There were also cases that a subtle difference of interpolation was identified between Ordinary kriging (OK) and GWR (Yu, 2009). Assumptions were made that variance of coefficient varies smoothly across space without discontinuities (Páez, 2004).

The Weighted Least Square (WLS) method estimates the local parameters, $\beta_k(\mu_i, \nu_i)$, allocating different weight to each site. The estimation is done in a form of matrix, which is,

$$\hat{\beta}(\mu, \nu) = (X^T W(\mu, \nu) X)^{-1} X^T W(\mu, \nu) Y \quad \text{Eq. 3-2}$$

Where, X is a matrix of predictor variables, Y is a vector of response variables, $\hat{\beta}(\mu, \nu)$ represents a vector of local regression parameters, $W(\mu, \nu)$ represents geographical weighting from regression location as a diagonal matrix, which puts more weights to closer points in the regression.

An important step in GWR is setting the bandwidth for the spatial weighting ($w(g)$), based on a Gaussian scheme (Eq. 3-3). The bandwidth type (e.g. fixed or

adjusted) was selected considering the spatial variability in the density of the gauging stations and modelling performance (e.g. higher R^2 and less AIC).

$$w(g) = \exp \left\{ - \left(\frac{1}{2} \right) \left(\frac{d}{h} \right)^2 \right\} \quad \text{Eq. 3-3}$$

Where, d is the distance between the observations, and h is the bandwidth.

Spatial autocorrelation was calculated using Moran's I for OLS and GWR using the coordinates available for each site and distance of derived bandwidths.

3.4.4 Spatial patterns and differences in GWR coefficients

The spatial distribution of GWR coefficients was investigated directly and indirectly using K-means clustering (Kopczewska and Ćwiakowski, 2021). Patterns in GWR coefficients were related to continental scale variations in precipitation. Those were summarized by Ecoregion Level-I. To aid visual comparison of results, only the two predictor variables with the first and second highest relevant weights are presented in figures in the results (Johnson, 2010). The significant differences in mean values of the GWR coefficients by Ecoregion were evaluated using one-way ANOVA and Tukey's test (Oh *et al.*, 2019).

Finally, given the large number of SSC indicators investigated, K-means clustering was conducted to identify regions of the U.S. with distinct combinations of GWR coefficients (ArcGIS Pro 2.8). All SS dynamics indicators and statistically significant predictor variables were included in the cluster analysis with cluster size determined by the spatial coverage of Ecoregion level-I. Side-by-side boxplots were used to check variability between predictor variables. Maps of standard error (s.e.) of each GWR model were produced to check locally different reliability of the model and possible local multicollinearity due to implicit constraints tied to the local coefficients, i.e. larger deviations in SSC magnitude (Wheeler and Tiefelsdorf, 2005).

K-means clustering was chosen instead of hierarchical clustering due to its greater efficiency with large datasets (Maruthi and Bilas, 2022). As the spatial density of the sites were not directly affected by SS, density based clustering was

also not implemented (Wade, 2023). Other alternatives of data partitioning approaches e.g., K-medoids, Time-series K-means, Bayesian clustering, CLIQUE, SPECTRAL and swarm-based clustering algorithms were not used as GWR does not require prior training (Sobiech and Dierking, 2013). K-medoids is more suitable for data with outliers (Pardeshi and Toshniwal, 2010). Bayesian clustering is based on models or loss function with more assumptions added (Wade, 2023). CLIQUE clustering was not used as the algorithm is biased by density of the points within a grid cell (He *et al.*, 2022). SPECTRAL clustering was not implemented as use of spectral graph theory including similarity matrix does not explain well the complex SS transport systems (Jia *et al.*, 2014). Furthermore, Swarm-based clustering was avoided as the optimization process uses collective intelligence from nonenvironmental factor e.g., birds (Figueiredo *et al.*, 2019).

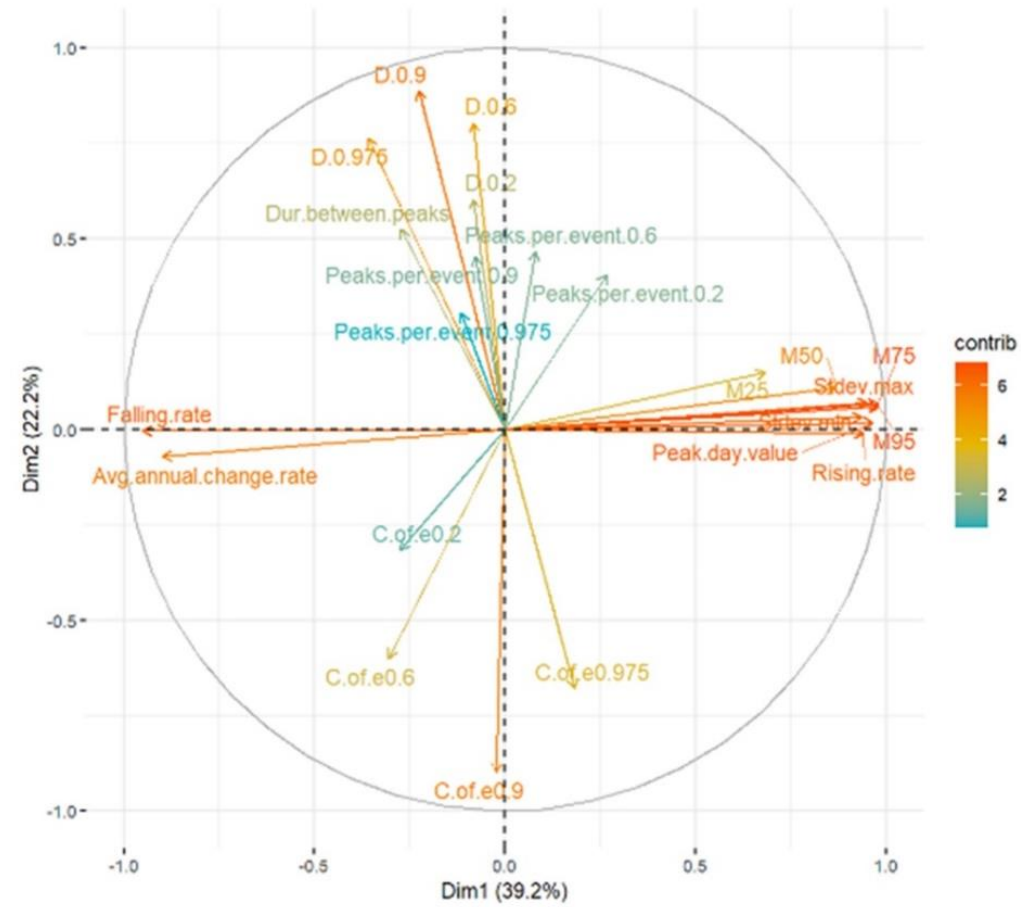
3.5 Results

3.5.1 Preliminary statistical analysis – PCA

The PCA results using the pre-processed SSC data identified covariation in the response variables. The first principal component from the PCA corresponded with the magnitude indicators and rising/falling rates, whereas the second component corresponded with duration and count of events (Figure 3-2a). Magnitude indicators were positively correlated with each other, except for falling rates and annual average change rates. Similarly, for frequency, the duration of events indicators were positively correlated with each other, but negatively correlated with count of events. The K-means clustering analysis applied to check the PCA results identified clear distinction between the magnitude indicators and two clusters of frequency indicators: (i) three magnitude indicators – M95, M50 and R.r, (ii) two frequency indicators related to the duration of events ($\alpha = 0.9$ and 0.6), and (iii) two frequency indicators of count of events ($\alpha = 0.9$ and 0.6 ; Figure 3-2b). The seven indicators were taken forward for further analyses. Similar results were obtained for the PCA with indicators at seasonal resolution (Figure A3-2), therefore, the same sub selection of indicators was used for the seasonal

models. The spatial distribution of indicators is presented in Figure A3-3, and the trend analysis is in Figure A3-4.

a) Result of 24 annual indicators



b) Result of selected indicators

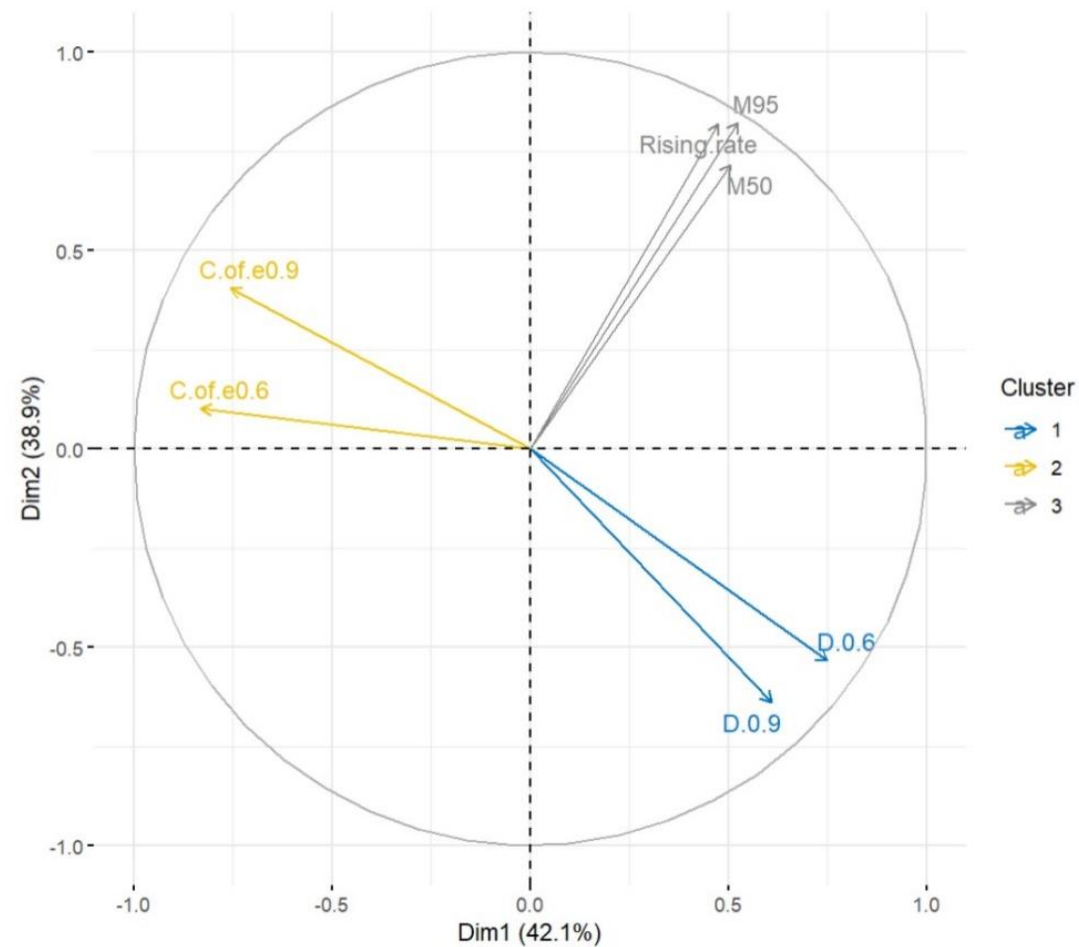


Figure 3-2. PCA results of (a) all annual SSC dynamics indicators and (b) indicators selected with K-means clustering, in which redundant indicators with less significant meanings (Low contribution) were removed.

3.5.2 Regression analyses

For the 7 SSC dynamics indicators identified in the PCA analysis, a total of 35 OLS regression models (annual and seasonal) were initially developed for regression analyses. The regression models included different predictor variables and interactions for the SSC indicators, but the most common predictor variables were LULC (Urbanperc, Agperc, Forestperc), BFI, clay content and PPT30 (Table 3-3). The GWR model with fixed bandwidths accounted for spatial autocorrelation in the regression models, thus yielded models with better R^2 and AIC (Table A3-1). Following tests for significant spatial autocorrelation in the residuals of the GWR model, 23 GWR models had successfully removed autocorrelation and were studied further (Table 3-3).

Table 3-3. Final statistical models without significant autocorrelation in the residuals (n=120, p-value > 0.05)

Response Variable	Season	Intercept	OLS Model															GWR (Fixed bandwidths)	
			PPT30	Rfact	Kfact	BFI	Urbanperc	Agperc	Forestperc	Clay	Sand	BFI x Clay	Rfact x Clay	R.storage	Catch.A	Catch.A x BFI	R ²	R ²	Observed Moran's I
M95	Annual	5.80	-1.00×10 ⁻²			-6.00×10 ⁻²	-1.10×10 ⁻²	-1.00×10 ⁻²		-4.20×10 ⁻²		2.00×10 ⁻³					6.30×10 ⁻¹	8.30×10 ⁻¹	-7.20×10 ⁻²
	DJF	5.44	-5.00×10 ⁻³			-6.30×10 ⁻²		-1.20×10 ⁻²		-4.30×10 ⁻²		2.00×10 ⁻³					5.90×10 ⁻¹	6.80×10 ⁻¹	-2.90×10 ⁻²
	MAM	3.73	-1.00×10 ⁻²			-1.70×10 ⁻²	-9.00×10 ⁻³	-8.00×10 ⁻³		4.00×10 ⁻²							5.50×10 ⁻¹	8.20×10 ⁻¹	-7.40×10 ⁻²
	JJA	2.29	-2.80×10 ⁻²	1.10×10 ⁻²					1.00×10 ⁻²	7.60×10 ⁻²			-2.00×10 ⁻⁴				5.90×10 ⁻¹	8.40×10 ⁻¹	-5.50×10 ⁻²
	SON	3.71	-1.10×10 ⁻²			-2.20×10 ⁻²	-1.20×10 ⁻²	-1.10×10 ⁻²		4.60×10 ⁻²							5.10×10 ⁻¹	8.70×10 ⁻¹	-5.70×10 ⁻²
M50	DJF	4.25	-8.00×10 ⁻³			-4.90×10 ⁻²	-1.10×10 ⁻²			-4.40×10 ⁻²		2.00×10 ⁻³					5.10×10 ⁻¹	7.60×10 ⁻¹	-4.60×10 ⁻²
	MAM	3.06	-1.30×10 ⁻²			-1.30×10 ⁻²	-1.20×10 ⁻²	-6.00×10 ⁻³		3.80×10 ⁻²							6.30×10 ⁻¹	7.90×10 ⁻¹	-3.80×10 ⁻²
R.r	Annual	3.25	-9.00×10 ⁻³			-2.30×10 ⁻²		-1.30×10 ⁻²		3.50×10 ⁻²							4.60×10 ⁻¹	7.70×10 ⁻¹	-6.60×10 ⁻²
	DJF	4.60				-5.60×10 ⁻²		-1.60×10 ⁻²	-7.00×10 ⁻³	-4.20×10 ⁻²		1.00×10 ⁻³					5.40×10 ⁻¹	5.90×10 ⁻¹	-1.30×10 ⁻²
	MAM	3.00	-8.00×10 ⁻³			-2.10×10 ⁻²		-1.00×10 ⁻²		3.90×10 ⁻²							4.60×10 ⁻¹	7.50×10 ⁻¹	-6.80×10 ⁻²
	SON	4.96	-7.00×10 ⁻³			-6.10×10 ⁻²		-1.20×10 ⁻²		-4.60×10 ⁻²		2.00×10 ⁻³					5.20×10 ⁻¹	7.80×10 ⁻¹	-6.10×10 ⁻²
D0.9	DJF	1.12				2.00×10 ⁻³			-1.00×10 ⁻³	6.00×10 ⁻³				8.70×10 ⁻¹⁰			2.70×10 ⁻¹	6.90×10 ⁻¹	-7.90×10 ⁻²
	MAM	1.22				2.00×10 ⁻³		1.00×10 ⁻³							-3.90×10 ⁻⁶	9.50×10 ⁻⁸	2.70×10 ⁻¹	4.20×10 ⁻¹	-3.10×10 ⁻²
	JJA	1.20				2.00×10 ⁻³		2.00×10 ⁻³									1.60×10 ⁻¹	2.70×10 ⁻¹	-3.30×10 ⁻²
	SON	1.36				3.00×10 ⁻³			-2.00×10 ⁻³		-4.00×10 ⁻³						2.70×10 ⁻¹	5.10×10 ⁻¹	-5.20×10 ⁻²
D0.6	JJA	1.20	1.00×10 ⁻³		-8.09×10 ⁻¹				-3.00×10 ⁻³								2.00×10 ⁻¹	5.80×10 ⁻¹	-6.20×10 ⁻²
	SON	1.01							-2.00×10 ⁻³								1.40×10 ⁻¹	7.00×10 ⁻¹	-1.58×10 ⁻¹
C.of.e0.9	Annual	2.81×10 ⁻¹			4.58×10 ⁻¹				3.00×10 ⁻³	-4.00×10 ⁻³				-7.40×10 ⁻¹⁰			3.80×10 ⁻¹	7.10×10 ⁻¹	-7.80×10 ⁻²
	MAM	9.60×10 ⁻²			6.88×10 ⁻¹	-2.00×10 ⁻³	2.00×10 ⁻³		3.00×10 ⁻³		4.00×10 ⁻³						3.40×10 ⁻¹	5.60×10 ⁻¹	-6.80×10 ⁻²
	JJA	1.35×10 ⁻¹			6.15×10 ⁻¹		2.00×10 ⁻³		2.00×10 ⁻³								2.10×10 ⁻¹	4.80×10 ⁻¹	-4.20×10 ⁻²
C.of.e0.6	Annual	1.35	-2.00×10 ⁻³		1.35			4.00×10 ⁻³	8.00×10 ⁻³								1.90×10 ⁻¹	4.50×10 ⁻¹	-2.70×10 ⁻²
	DJF	7.59×10 ⁻¹							2.00×10 ⁻³								6.00×10 ⁻²	4.30×10 ⁻¹	-6.90×10 ⁻²
	SON	8.84×10 ⁻¹							2.00×10 ⁻³		-3.00×10 ⁻³						1.50×10 ⁻¹	4.80×10 ⁻¹	-7.30×10 ⁻²

M95 had the greatest number of models, with statistically significant models created for annual and all four seasons (Table 3-3). For M50, models were generated for winter (DJF) and spring (MAM). For rising rate, models were created for annual and all seasons except summer (JJA). For these magnitude indicators, there were similar predictor variables and directions of effects (positive, +, or negative, -), generally PPT30 (-), BFI (-), Urbanperc (-), Agperc (-), Clay(+/-), and BFI x Clay (+), though Urbanperc was not included in the model for rising rate. There is some suggestion of seasonal variations in the impacts of predictor variables; Forestperc appears in two seasonal models, the direction of the impact of clay content varies considerably between seasons, and BFI x Clay appears in models for winter (DJF).

For the duration of longer events ($\alpha=0.9$), statistically-significant models were created for all four seasons, but few predictor variables were common amongst them, except BFI (+). For the duration of shorter events ($\alpha=0.6$), models were significant for summer (JJA) and autumn (SON) with Forestperc exhibiting a negative effect in both seasons. An annual model and two seasonal models were created for count of events for both longer and short events showing generally positive associations with LULC and, for $\alpha=0.9$, a positive association with Kfact.

Spatial patterns and differences in GWR coefficients

The GWR model adjusts the regression coefficients to account for spatial autocorrelation. The spatial distribution of these coefficients identifies geographical areas in which the influence of a variable is higher or lower than the original regression model. For many of the models, particularly for the magnitude indicators, PPT30 was the variable that explained the most variation in the linear regression, i.e. the highest relative weight based on the heuristic method (Johnson, 2010). PPT30 showed a general spatial pattern of higher GWR coefficients in the coastal regions (MWCF, MC and ETF) and a lower coefficient in the driest region (NAD) (Figures 3-3~3-5), which is similar to the spatial pattern observed for some of the climate and catchment characteristics (Figure 3-1). However, models for the frequency indicators showed distinctly different regional

patterns in the GWR coefficients for LULC (Figures 3-6 & 3-7). The spatial patterns by ecoregion for all GWR coefficients are shown in Figures A3-10~16; only a subset are included here for presentation and later discussion.

GWR coefficients varied spatially and seasonally, suggesting differences and shifts in dominant factors affecting sediment erosion and transport. For example, PPT30 had a negative effect on M95 in all ecoregions, except MWCF, at annual resolution (Figure 3-3). However, the GWR coefficient for PPT30 was positive only in spring (MAM) and autumn (SON) (Figure 3-3). Similarly, GWR coefficients for PPT30 were higher in some of the ecoregions, e.g. MC and NFM, in the autumn (SON), with some shifting to positive, and were much lower in other ecoregions in summer (JJA), e.g. NAD. In general, clay content had the 2nd highest weighting in the linear regressions for M95. At annual resolution, clay content was negatively associated with M95 in all ecoregions, but there were substantial differences seasonally. GWR coefficients for clay content were strongly positive in spring (MAM) and autumn (SON) (Figure 3-3), but negative in winter (DJF) (Figure A3-17). In spring (MAM) and autumn (SON), clay content has the greatest positive effect on M95 in the NFM, NAD and GP ecoregions. Finally, the predictor variables with the highest weighting differed for winter (DJF). BFI had a negative relationship with M95, with the lowest GWR coefficient value in ETF and highest in NAD. Agperc had very different relationships with M95 by ecoregions, with a low negative GWR coefficient in the western MWCF ecoregion rising to a high positive in the eastern ETF ecoregion.

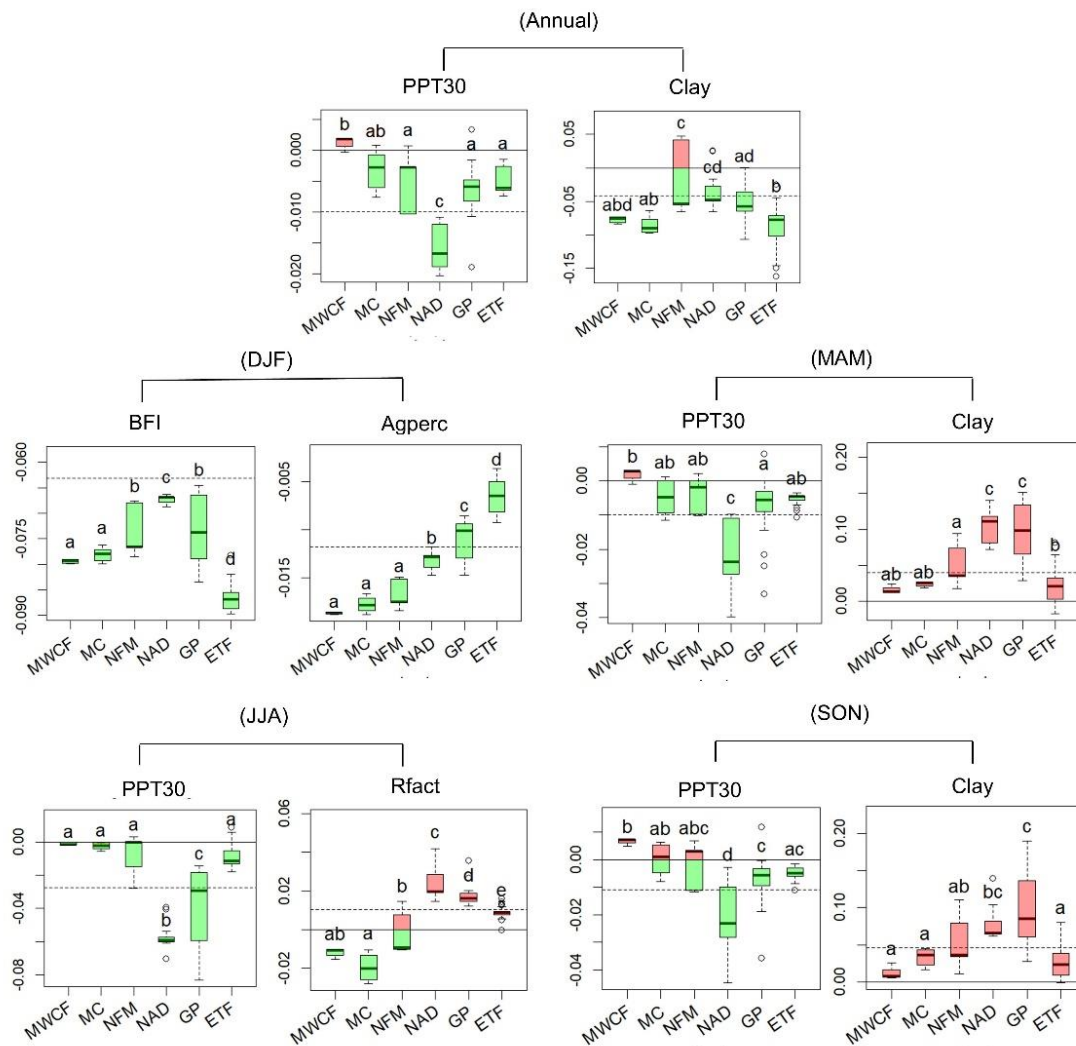


Figure 3-3. GWR coefficients of M95 in different ecoregions (Log10 transformed): Horizontal lines in Black represent zero, and the dashed horizontal lines are OLS coefficients. Similar mean values in each plot from Tukey's tests are in the same initials above each box plots.

Urbanperc, BFI, Agperc, clay cover and PPT30 were the catchment variables affecting M50, mainly in winter (DJF) and spring (MAM) (Table 3-3 and Figure 3-4 & A3-11). PPT30 had a consistently negative association with M50 for winter (DJF) and spring (MAM), though there were significant differences across the ecoregions. The general west-east negative unimodal pattern was observed for both seasons, with a greater range observed in winter (DJF). Clay cover was positively related to M50 but significantly lower in MWCF and ETF than in other ecoregions. BFI was negatively associated with M50 overall (Table 3-3),

especially in the winter (DJF) when GWR coefficients are significantly lower for GP and ETF (Figure 3-4). However, BFI was positively associated with M50 in MWCF and MC in spring (MAM) (Figure A3-11).

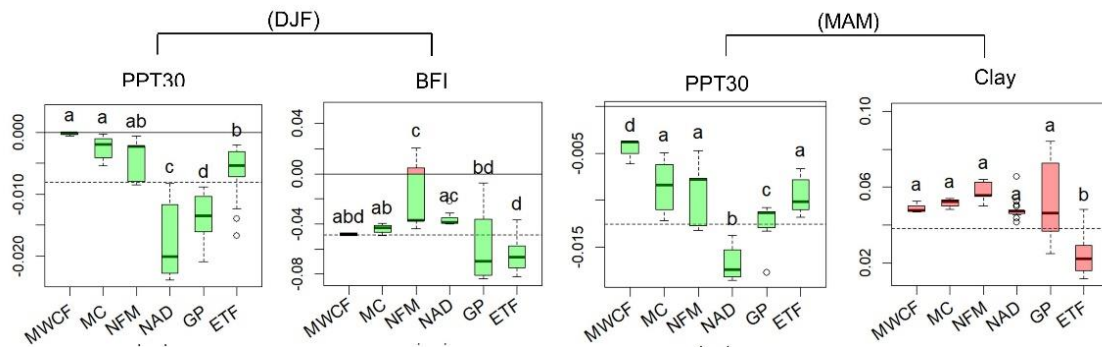


Figure 3-4. GWR coefficients of M50 in different ecoregion (Log10 transformed): PPT30 is mean annual precipitation (1971 ~ 2000, cm). BFI is average baseflow index (%). Clay is average percentage of soil clay content.

The models predicting rising rates were composed of PPT30 and LULC components e.g., Agperc, Forestperc, clay content and BFI x Clay (Table 3-3). However, the predictor variables with the highest weighting were PPT30 and BFI (Figure 3-5). GWR coefficients for PPT30 displayed the negative unimodal distribution across the ecoregions, identified earlier, with the lowest values (Negative) in NAD and highest (Positive) in MWCF and ETF. BFI was generally negatively associated with rising rates with greater differences by ecoregion in winter (DJF) and spring (MAM). Agperc identified solely with negative coefficients without impact from PPT30.

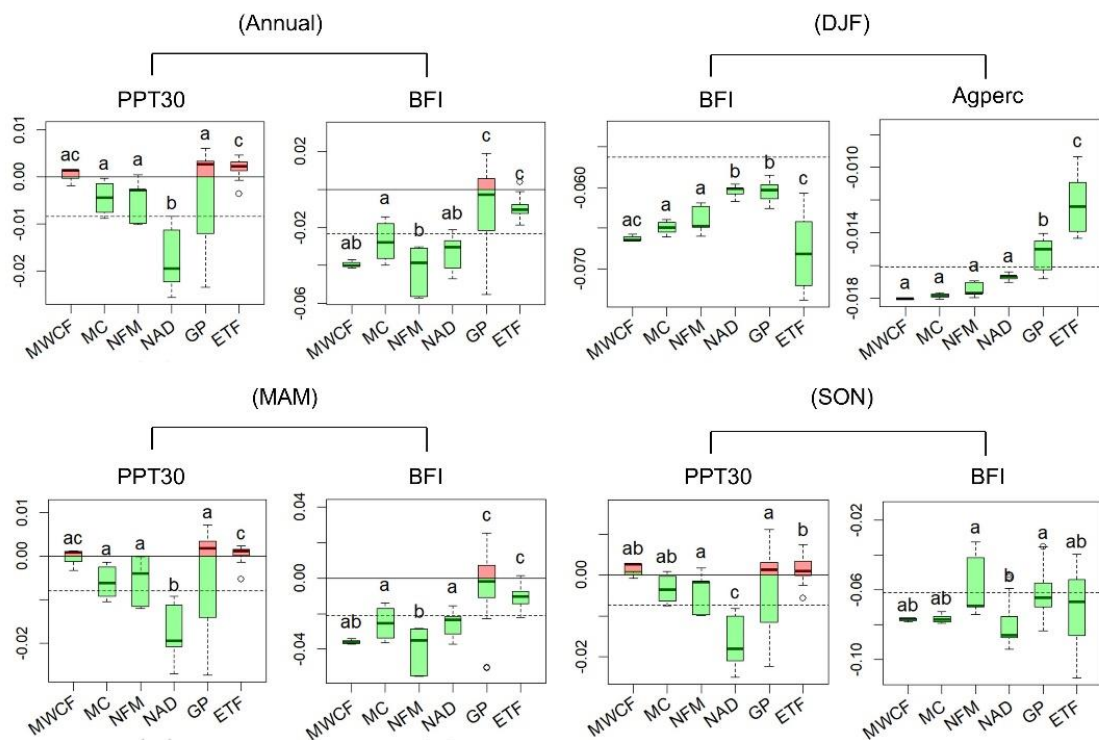
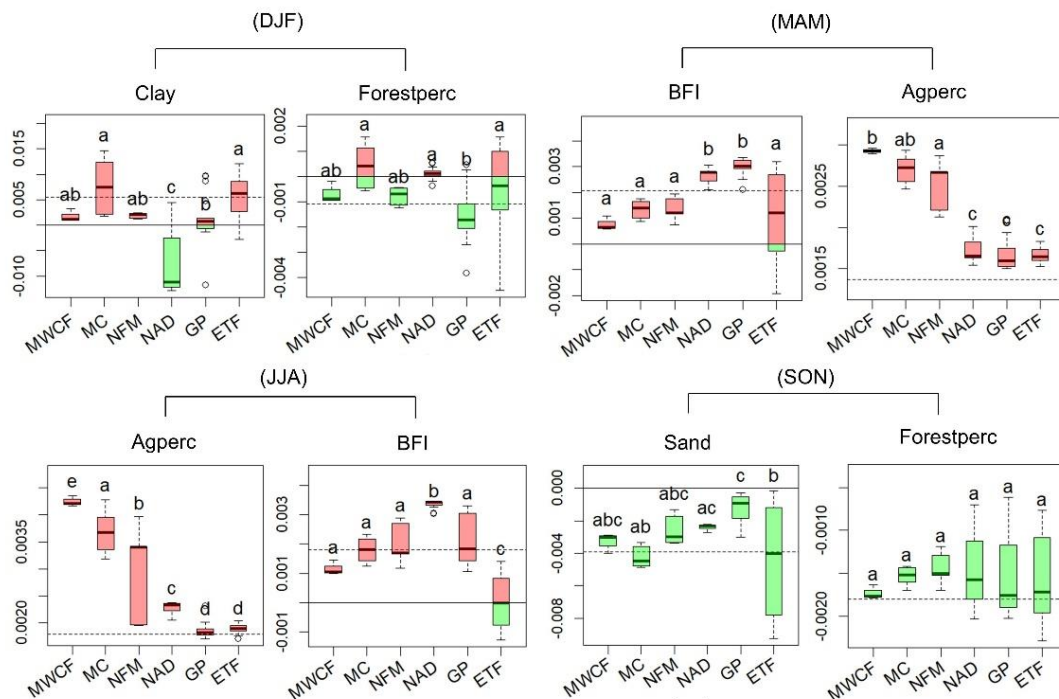


Figure 3-5. GWR coefficients of $R.r$ in different ecoregion (Log10 transformed): PPT30 is mean annual precipitation (1971 ~ 2000, mm). BFI is average baseflow index (%). Agperc is average percentage of agricultural area (%).

For duration of events, a much wider range of predictor variables were identified as having high weighting across the seasonal models than for the other magnitude indicators, including Clay, Forestperc, Agperc, BFI, Sand, and Kfact (Figure 3-6). For the duration of events ($\alpha=0.9$), Forestperc and soil types (Clay or Sand) had the highest weightings in the linear regression variables in autumn (SON) and winter (DJF), whilst Agperc and BFI had the highest weightings in spring (MAM) and summer (JJA). Forestperc was generally negatively associated with duration of longer events in autumn (SON), though there were mixed effects (Positive and negative) in winter (DJF). Clay cover was generally positively associated with duration, whilst sand content was negative. Agperc showed a pattern by ecoregion that was opposite to M95 (DJF), with the highest GWR coefficients in MMCF and lowest in GP and ETF. BFI had a positive unimodal pattern across the ecoregions, with the highest positive contribution to the duration of long events in NAD and GP. Duration of events ($\alpha=0.6$) were more

related with Forestperc and K-factor. Significant differences by ecoregion were only noted for summer (JJA), when Forestperc and K-factor were negatively associated with duration of shorter events, with significantly lower GWR coefficients in MWCF and NFM than ETF, and GP for K-factor.

(a) $\alpha = 0.9$



(b) $\alpha = 0.6$

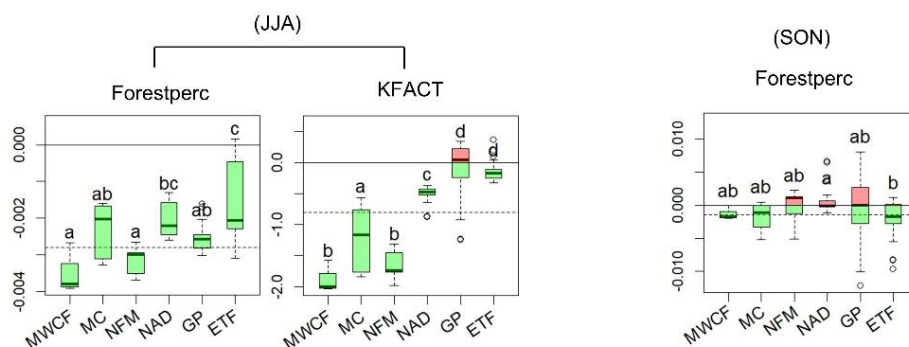
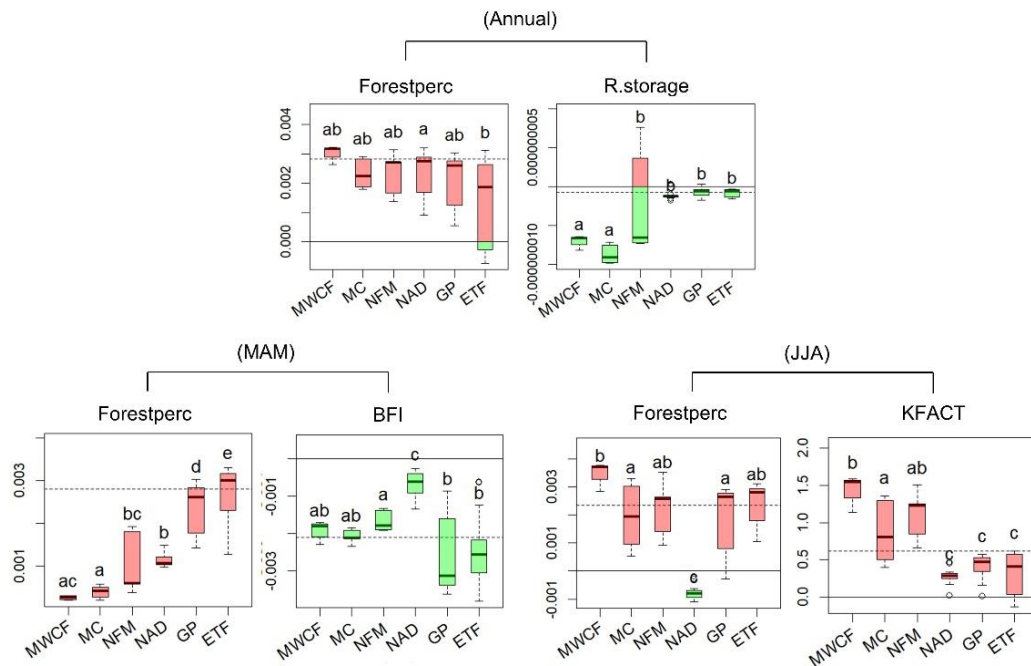


Figure 3-6. GWR coefficients of duration of events (a, $\alpha=0.9$ and b, $\alpha=0.6$) (Log10 transformed): α from Lyne & Hollick filter that larger value yielded longer duration of event. Forestperc is average percentage of forest cover. Sand is average percentage of sand. KFACT is average K-factor for upper most soil horizon.

For the count of events ($\alpha=0.9$ and 0.6), Forestperc was identified as a high weighted predictor variable in all models, annual and seasonal, along with K-factor, BFI, Sand and R.storage. (Table 3-3 and Figure 3-7). It was generally positively associated with count of events with strong spatial variations in some seasons, i.e. lower in the west and higher in the east in the spring (MAM) for longer duration events ($\alpha=0.9$). The association became negative for count of shorter events ($\alpha=0.6$) in the western MWCF, MC and NFM ecoregions in winter (DJF). K-factor had a strongly declining impact from west to east, with GWR coefficients highest in MWCF and lowest in NAD, GP and ETF, turning negative for the short duration events ($\alpha=0.6$). Sand content in the soil was generally negatively associated with the duration of shorter events ($\alpha=0.6$, SON), except in NAD and ETF ecoregions. Finally, both BFI and R.storage were negatively associated with the duration of longer SSC events ($\alpha=0.9$).

(a) $\alpha = 0.9$



(b) $\alpha = 0.6$

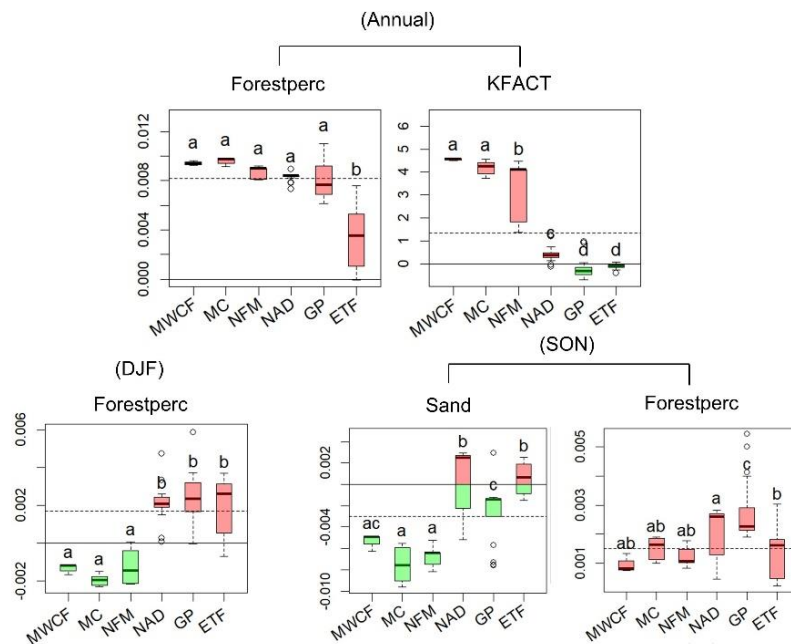
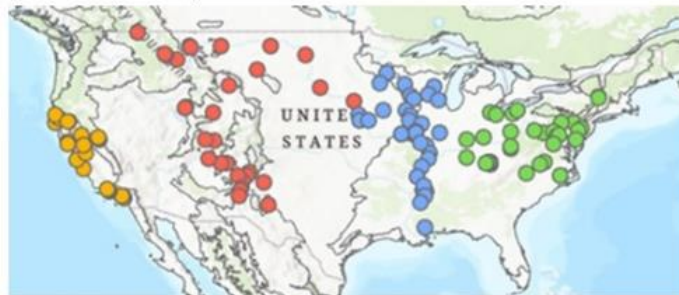
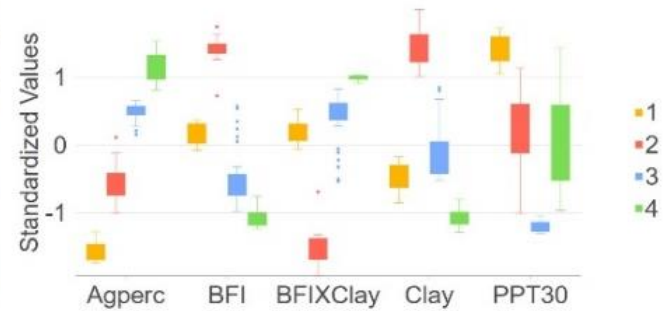


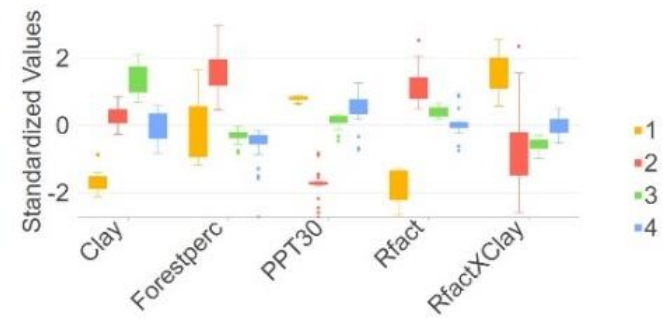
Figure 3-7. GWR coefficients of Count of events in different ecoregion (Log10 transformed): Urbanperc is percentage of urban land (%). Forestperc is percentage of forest land (%). PPT30 is mean annual precipitation (1971 ~ 2000, cm)

The results of the K-means clustering analysis identify clear groups of sites with similar GWR coefficient assemblages, suggesting regional characteristics underlying SSC dynamics (Figure 3-8). K-means and side-by-side boxplots allow further identification of spatially and temporally varying relationships between the indicators and climatic and LULC factors.

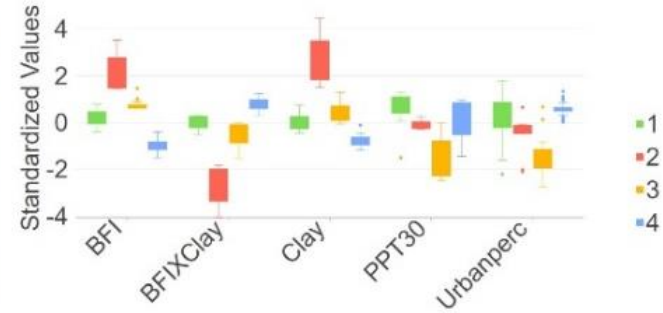
a) M95 (DJF)



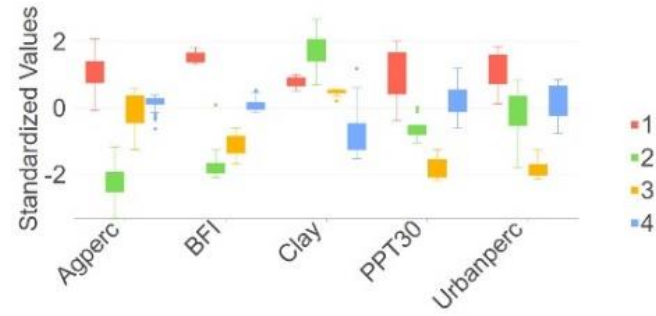
b) M95 (JJA)



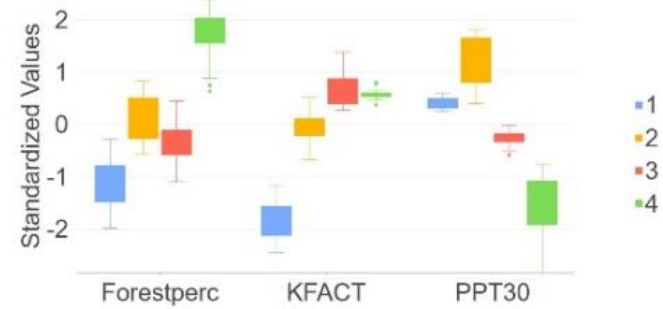
c) M50 (DJF)



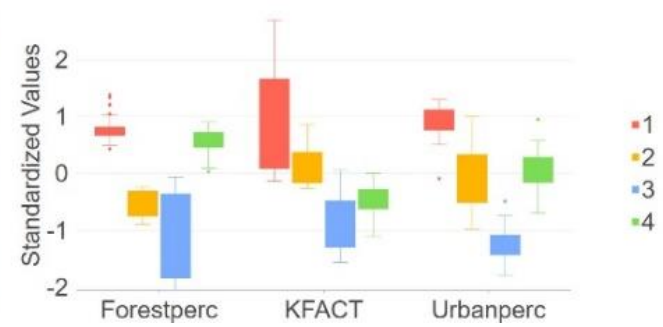
d) M50 (MAM)



e) Duration of event ($\alpha = 0.6$) (JJA)



f) Count of event ($\alpha = 0.9$) (JJA)



g) Count of event ($\alpha = 0.6$) (Annual)

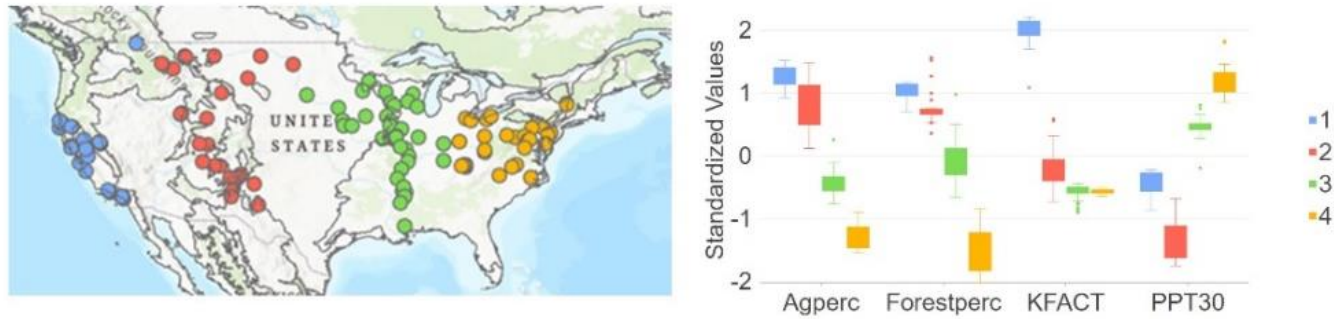


Figure 3-8. A part of K-means clustering results (Magnitude & Frequency) on GWR coefficients from predictor variables in available distinctive seasons: Four distinctive patterns were identified with the variables including BFI x Clay.

Sites located in the western U.S. (e.g. California) grouped together consistently, where M95 and M50 were more strongly associated with PPT30, duration of event ($\alpha = 0.6$) was less strongly associated with Forestperc and K-fact, and count of event was more associated with Agperc and K-fact, relative to the coefficient mean. Sites in the Rocky Mountain region grouped together, except for sites in Montana (Figure 3-8c,d,e,f). BFI and Clay had a stronger relationship with M95 in this region in winter (DJF), relative to the coefficient mean. Forestperc with Rfact had a stronger relationship with M95 in summer (JJA). Count of event ($\alpha=0.6$) was also affected by Forestperc and Agperc in this region. Sites in the Rocky Mountain and the North American Deserts region grouped together for many of the indicators and seasons, especially M95 and the frequency indicators (Figure 3-8a,e,f,g). Southern sites group separately in spring, when M50 is associated with Agperc (Figure 3-8d), and again in the autumn when Urbanperc has a greater influence on M95 (Figure A3-17). Sites in the Great Plains, Midwest and Mississippi River regions group together for most of the indicators, especially duration of event ($\alpha = 0.6$) and count of event ($\alpha = 0.9$), which were closely associated with K-fact. The regions grouped separated for some of the magnitude indicators. For example, clay content was more closely associated with M95 (JJA) in the Midwest than lower Mississippi. Model coefficients are generally closer to the average than for sites in the western US. Sites (M95) on the Mississippi cluster together all year, except in summer (JJA) (Figure 3-8b). Similarly, the Mid Atlantic and Midwest sites group together, except duration and count of events. For example, in the GWR models for count of events ($\alpha=0.6$), the Mid Atlantic has lower coefficient values for Agperc and Forestperc, in comparison to sites located further west (Figure 3-8g). The sites in New England and Mid Atlantic always grouped together for SSC indicators without relatively significant influences from catchment characteristics, except M95 (Agperc and BFI x Clay), event duration ($\alpha=0.6$, Forestperc) and event count ($\alpha=0.6$, PPT30).

3.6 Discussion

In this section, we discuss the results of the OLS regression models and how the geographical variations in model coefficients generated by the GWR models

provide insight into the interplay of catchment and climate factors that are associated with sediment transport processes (i.e., fine sediment generation, transport and storage overland, and transport in river systems) (Table 3-4). Indicators of SS dynamics were affected by climate and catchment characteristics with additional spatial and seasonal variations that are indicative of further regional controls that were not captured in the predictor variables despite the data preprocessing taken (Figure A3-27). These additional controls could relate to climate, physiographic setting, and anthropogenic activities, which influence the annual and seasonal models.

Table 3-4. Summary of the key findings of the study, showing the dominant relationships (▲ – positive, ▼ – negative) between catchment and climate factors and indicators of SS transport dynamics. MWCF - Marine West Coast Forest, MC - Mediterranean California, NFM - Northwestern Forested Mountains, NAD - North American Deserts, GP - Great Plains, and ETF - Eastern Temperate Forest.

Factors		Key Findings
LULC	Agperc	▼ M95 overall, but ▲ M95 in NAD in spring and in MWCF, MC and NFM in autumn (Figs. 3-3, 3-5, A3-10) ▲ M50 in MWCF in spring (Fig A3-11) ▲ Duration of long events overall, especially in MWCF, MC and NAD in spring and summer (Fig. 3-6) ▲ Count of short events in all ecoregions, except ETF (Fig. A3-16)
	Forestperc	▼ Duration of events (long and short), except in MC in winter (Fig. 3-6) ▲ Count of long events (Fig. 3-7a) and in short events, except in MWCF, MC and NFM in winter (Fig. 3-7b) ▲ M95 in summer (Fig A3-10)
	Urbanperc	▲ M95 for MWCF, MC and NFM (Fig. A3-10) ▲ M50 in MWCF in winter and spring (Fig. A3-11) ▲ Count of long events in spring and summer (Fig. A3-15)
Soil and hydrogeology	K-factor	▼ Duration of short events, especially MWCF and NFM, but not GP (Fig. 3-6) ▲ Count of long events for all ecoregions in summer, but only NAD, GP and ETF in spring (Fig. A3-15) ▲ Count of short events in MWCF, MC and NFM (Fig. 3-6)
	Clay	▲ M95 for all ecoregions in spring, summer and autumn, but ▼ M95 in winter (Figs. 3-3 & A3-10) ▲ M50 in all ecoregions in spring (Fig. 3-4) ▲ Rising rate in spring, especially in NAD and GP, but ▼ Rising rate in winter (Fig. A3-12) ▲ Duration of long events in all ecoregions except NAD in winter (Fig. 3-6a)
	BFI	▼ M95 and M50, especially in winter (Figs. 3-3 & 3-4) ▲ M50 in MWCF and MC in spring (Fig. A3-11) ▼ Rising rate, except in some sites in GP (Fig. 3-5) ▲ Duration of long events in all ecoregions and seasons (Figs 3-6 & A3-13)
Climate	PPT30	▼ M95 and M50 in all ecoregions and seasons, except M95 in MWCF, especially in spring and autumn (Figs. 3-3, 3-4, A3-10) ▼ Rising rate in most ecoregions, except ETF and, in autumn, MWCF and ETF (Fig. 3-5)
	Rfact	▲ M95 in NAD, GP and ETF in summer (Fig. A3-10)

Land use / land cover impacts on SS transport

LULC was the most common type of predictor variable affecting the SSC dynamics indicators. In the OLS models, at least one of the three LULC classes was included in each model for every indicator. However, the direction and strength of the association varied between indicators and seasons (Table 3-3 and Figures 3-3~3-8).

The magnitude indicators (M95 and M50) were negatively associated with Urbanperc, but the frequency indicators (C.of.e.0.9) were dominated by positive coefficients (Table 3-3). Therefore, in general, higher cover of urban development was associated with lower extreme and average SSC, but a higher frequency of events (Figure 3-8f). From the GWR model, though, the negative association between Urbanperc and SSC magnitude is largely confined to the driest ecoregion (Figure A3-10 & A3-11). For the rest of the USA, there is either no association (GP and ETF) or it is positive (MWCF, MC and NFM). SS is a major contaminant in stormwater runoff from urban areas (Yin and Li, 2008; Borris *et al.*, 2016), which tends to be more problematic in winter-spring than summer (Westerlund *et al.*, 2003; Ciupa *et al.*, 2021; Gong *et al.*, 2021). Increased connectivity due to storm water drains, which carry material washed from impervious surfaces in urban areas (Gellis *et al.*, 2020), and channel incision and scouring due to urban storm water could possibly explain the positive association with M95 and M50 in western regions (Zeiger and Hubbard, 2016). The increased flashiness of urban environment explains the increasing number of events. However, the reduction in the magnitude can relate with street cleaning and storm water management. Seasonal differences by ecoregion are likely affected by intra-annual variations in rainfall and discharge (Figures A3-10,11,15).

Agperc was associated negatively with magnitude indicators (M95, M50 and rising rate), but positively with the duration of long SSC events (MAM and JJA; $\alpha=0.9$) and the count of short duration events (DJF and SON; $\alpha=0.6$) (Tables 3-3 & 4). However, there are some important variations by ecoregion, including a positive association with duration of events (Figure 3-6,a, MAM), and seasonally, such as a negative association with M95 in winter (DJF; Figure 3-3). In addition, an increasing pattern from west to east (i.e. fewer negative values) was observed for rising rate. This pattern was most pronounced in DJF (Figure 3-5) but was also observed in MAM and SON

(Figure A3-12). A similar west-east pattern was also identified for M95, but only for DJF, the pattern was opposite in SON (Figure A3-10). Similarly, this opposite pattern (decreasing positive values, west-east) was also identified in the duration of event ($\alpha=0.9$; Figure A3-13) and count of events ($\alpha=0.6$; Figure A3-16). These results suggest that Agperc affects seasonal variations in the supply of sediment to rivers, which may be related to the timing of agricultural practices or bare soil, which would vary regionally due to the presence of different crops, irrigation, and soil erodibility that affect soil erosion and delivery, often with time lags (Cooper, 2009; Darama *et al.*, 2021; Haddadchi and Hicks, 2021). The agricultural lands consist of NLCD classes 81 (Pasture/Hay) and 82 (Cultivated crops) (Falcone *et al.*, 2010), which are LULC types known to contribute suspended sediment to rivers (Tiecher *et al.*, 2017). However, the generally negative GWR coefficients from agricultural lands are not supported by previous research on soil erosion and delivery to channels but could be explained by confounding factors, such as the spatial distribution of LULC (e.g. farms not in the close proximity to river networks) and erosion mitigation measures such as buffer strips and local policies for maintaining soil resources retention (Tiecher *et al.*, 2017; Shi *et al.*, 2021).

Forestperc was positively associated with the count of long SSC events and negatively associated with the duration of events (long and short) (Table 3-3). Spatially, the positive association with count varies depending on the seasons but was highest for the count of longer duration events in JJA in MWCF and lowest in the driest region (NAD; Figure 3-7a). The GWR clusters suggest that Forestperc in the Rocky Mountains area experience higher pulses of sediment (M95, Figures 3-8b & A3-10) and count of events in summer ($\alpha=0.9$ in Figure A3-15) and autumn ($\alpha=0.6$ in Figure A3-16). Whilst Forestperc was mostly negatively associated with duration, which could relate to higher runoff in managed forests, some sites in MC and ETF had a positive association for longer duration ($\alpha=0.9$; i.e. seasonal) events. These variable results are related to the impacts of forests on hydrological pathways and soil erosion processes on forest rich areas (Riitters *et al.*, 2004; Zimmermann *et al.*, 2012), complicated by potential covariations between forest cover, slope steepness, management practices, and climate.

Soil and hydrogeology impacts on SS transport indicators

Soil and hydrogeological properties (K-factor, clay content, and BFI) have significant relationships with SSC indicators. Soil clay content and BFI were identified in models for magnitude (M95, M50 and rising rate) and duration, while K-factor, and to a lesser degree sand content, featured in models for frequency (count of events).

In general, K-factor is positively associated with the number of SSC events (Figures 3-7, A3-15 & A3-16), thus areas with more erodible soils have a greater frequency of high SSC events. The spatial pattern is very pronounced for shorter duration events, showing a decreasing pattern west to east, with high coefficients in MWCF, MC and NFM (Figure 3-7). For longer duration events, the lack of a clear west-east pattern in the annual models is caused by opposing patterns in different seasons; there is an increasing pattern west to east in spring (MAM) but a decreasing one in summer (JJA) (Figure 3-6 & A3-15). These spatial patterns may be due to the timing of high intensity regional rainfall and availability of erodible materials, especially in California and Great Plains (Figure 3-8f). K-factor is associated with soil structure (e.g. particle size distribution and organic matter) and highly variable depending on LULC. The different distribution of K-factor is likely the result of the impacts of both climate and catchment controls (Martínez-Murillo *et al.*, 2020).

Soil clay content had a variable association with SSC dynamics indicator, varying between magnitude indicators and seasonally within an indicator. While it was negatively associated with the annual model for M95 and winter (DJF) model for M50, it was positively associated with these magnitude indicators for other seasons (Table 3-3). The GWR results suggest that clay content may have a greater influence on SSC in some ecoregions, especially NFM, NAD, and GP (Figures 3-3 and 3-4). However, duration of events ($\alpha=0.9$) from the clay cover (Figure 3-6) did not follow the pattern of Figure 3-1 in DJF, which may be due to seasonal differences in flashness of the sedimentograph. In cold regions, snowmelt runoff would cause soil loss in spring (Aygün and Kinnard, 2021), which would be exacerbated where there is a high proportion of precipitation as snow and LULC with bare soil or grass (Tramblay *et al.*, 2010; Huang *et al.*, 2020), and may contribute to sediment availability and delivery to the channel. In addition, ephemeral rivers are correlated with fine grained channels with silt or clay (Li *et al.*, 2021).

BFI was negatively associated with magnitude indicators (M95, M50 and rising rate) and positively associated with duration of longer SSC events ($\alpha=0.9$) (Table 3-3). Significant variation was observed in the GWR coefficients spatially and seasonally, with stronger negative associations in winter (DJF) for M95 and M50. For duration and count of events, GWR coefficients of BFI by ecoregion broadly mirror the spatial pattern for BFI (Figure 3-1), being highest in NFM and NAD, with some evidence of seasonal variations (Figure 3-5, 3-6, A3-10~13). These spatial patterns are likely driven by a combination of climate, geology, soil matrix and groundwater flows (Price, 2011). Baseflow is supported by aquifers fed from ephemeral rivers (Goodrich *et al.*, 2018). As baseflow is affected by ground water and soil structure, the negative coefficients from magnitude indicators could be due to dilution impacts from precipitation, and the positive effects to the duration of events might be caused more by additional environmental factors that also correlate with BFI and topography (e.g. the Rocky Mountains, NFM) (Thomas *et al.*, 2004; Price, 2011).

These additional environmental factors may also underly the interaction terms included in the models. A positive association between BFI x Clay and magnitude indicators was identified in the OLS models (Table 3-3). The GWR model coefficients displayed a west-east variation that mirrored many of the other variables, i.e. highest along the coasts (MWCF & ETF) for M95, M50 and rising rates (Figure A3-10~12). The K-means clustering identified the northern Rocky Mountains, North American Deserts and Great Plains regions grouped together (Figure 3-8a,c), and those are areas where BFI x Clay was strongly positively associated with M95 and M50 (Figure A3-10 & 11). These interactions are likely driven by covariations in baseflow, topography and climate, which affect sediment generation, delivery overland to channel, and transport within the river network. For example, mountainous areas often have greater forest cover and a colder climate with a greater proportion of precipitation as snow, which affect rainfall partitioning, hydrological flow pathways, and baseflow generation through snowmelt (Santhi, 2008; Huang *et al.*, 2021).

Climate impacts on SS transport indicators

GWR coefficients were significantly different by ecoregion (Level-I) and varied seasonally (Figures 3-3~3-7), resulting in large-scale spatial patterns in model coefficients (Figure 3-8), which could be related to climate factors. Many of the GWR

model coefficients were higher in the west coast, lower in the central U.S, and higher in the eastern temperate region, similar to the west-to-east pattern in annual precipitation (PPT30) across the contiguous USA (Figure 3-1). For example, PPT30 is associated positively with M95 in the moist coastal region (MWCF) but switches from positive to negative seasonally in the semi-arid ecoregions and northwest forest (MC and NFM; Figure 3-3). PPT30 is a positive driver of event frequency in ETF (Figure A3-16).

The annual precipitation indices used in this study were generally negatively associated with magnitude indicators of SSC transport dynamics. However, there is evidence of differences by ecoregion that could relate to the timing and intensity of the predictor variable (PPT30). For example, whilst GWR coefficients were generally lowest for M95 in NAD over most of the seasons, they were significantly lower in GP and ETF in DJF (Figure A3-10). In general, the negative relationship between magnitude indicators and PPT30 is likely caused by dilution effects (Kozak *et al.*, 2019), which is moderated regionally by different frequencies and intensities of rainfall that affect the generation and transport of sediment (Hancock, 2012). However, PPT30 is a static representation of 30-year rainfall (1971~2000), which may not capture well the seasonality inherent in the SS delivery system. Rfact is positively associated with M95 in JJA (Table 3-3), with the highest coefficients found in the Rocky Mountains, desert and Northern Great Plains (Figure 3-8b). The Rfact values may represent well the intensity and frequency of rainfall runoff generation cycles at these sites in these months (Figure A3-10). Although larger standard errors (s.e.) in GWR may indicate the effects of local collinearity (Fadliana *et al.*, 2019), climate controls reacted to the catchment characteristics more in wetter seasons e.g. positive impacts of Rfact (M95, Figure 3-3) and PPT30 (D0.6, Figure A3-14) in summer.

Spatial patterns in SSC transport dynamics and predictor variables

This research identified possible climate and catchment controls on SSC dynamics at continental scale using daily SSC and annual average descriptors of potential predictor variables using a regression and spatial analysis approach. Further modelling (e.g. improvement of gap filling techniques for catchment characteristics with finer time intervals, applying AI or machine learning) (Tao *et al.*, 2021) can help to validate these findings to support the prediction of changes in SSC dynamics in the

future with climate change. Whilst this study used a part of GAGES dataset because of the site coverage and suitability of data types, future studies using SSC data from US gauging stations could consider using both GAGES and GAGES-II. These datasets have a greater number of potential explanatory variables, including seasonal precipitation data, which would align more closely with seasonal summaries of SSC dynamics indicators.

The limitation in the study also identifies possible future works as implication of flow weighting process in the daily SS data, uses of nonparametric summary of the indicators and better statistical approach with appropriate uncertainty. With the daily mean data and subsequent calculation of SS dynamics indicators, there is probability of misleading estimation between predictor and response variables e.g., covariance with water. Therefore, interpretation at specific regions should be taken as association with limitation between variables. However, the data preprocessing may have minimized the impact. Furthermore, implementing regression with nonparametric approach may have yielded different values from magnitude indicators e.g., M95 and M50, which is a part of limitation (Washington *et al.*, 2014). Checking elevated final error levels due to Kalman's smoothing may have brought more accurate calculations of the SS dynamics (Daly *et al.*, 2008). Prior to implementing regression, interpretation of PCA may have brought other magnitude indicators to be taken forward, e.g., magnitude of 25th percentile, peak day value, average annual change rates, etc.

The OLS approach assumes that linearity between independent and dependent variables, independence, constant variance and normality (Currit, 2002). The limitation of the OLS approach is that data may not meet the assumption of normality and relatively poor fitting. Despite the limitation of poor fitting from OLS, the results well covered the association between significant processes and SS dynamics indicators. The OLS approach assumes that annual time series are normally distributed. Taking this parametric approach also has beneficial impact on controllability of overfitting (Gautam and Singh, 2020). The assumption of a linear relationship between significant processes as an input and suspended sediment dynamic indicators as output is reasonable considering number of predictor variables taken (Table 3-1) as a part of hydrological cycles (Robertson and Saad, 2019). Maximum likelihood or generalized method, instead of OLS was not implemented due to the limitation of not being able to

easily solving non-convex optimization problems and needs for additional iterative methods of obtaining optimized parameters (Jain and Tewari, 2015; Ikbali *et al.*, 2022). Nonlinear regression was not implemented as of the complexity in fitting the relationships between SS transport and triggering impacts from various processes e.g., correction processes of autocorrelation and heteroscedasticity of errors (Nicodème and P, 2022).

The spatial dimension of each catchment was represented as points, but actual catchments are nested, which implies any interpretation in association with spatial positions in the maps need to consider actual catchment areas (Levi *et al.*, 2018). Another limitation from GWR is unrealistic reflection of real spatial influences. NWM GWR (Network Weighted Matrix Geographically Weighted Regression) with improved kernel function may have provided better reflection of significant processes to the SS dynamics indicators (He *et al.*, 2023). Although K-means compensated nonlinearity from the GWR coefficients, it holds uncertainty from the linear modelling approach given the nonlinear responses between climate and SS transport (X. Wu *et al.*, 2023). Interpretation of side by side box plots also holds limitation as those use standardized values. Furthermore, the interpretation based on K-means clustering can be subjective to the number of clustering chosen. Time series K-means can be a future work despite difficulties of retrieving time dimension from LULC for interpretation (Xiaohui Huang *et al.*, 2016). Above all, K-means is the most popular, and the known drawback from choosing number of clusters was minimized by finding right clustering numbers (Wade, 2023). K-means assumes that clusters are spherical, which may not be the true reflection of the SS transport system (Chen *et al.*, 2019). Each cluster also exhibits approximately equal variance, but this approach may always not be applicable (Miraftabzadeh *et al.*, 2023).

3.7 Conclusions

The research applied recently developed suspended sediment dynamics indicators to investigate how catchment and climate factors influence spatial and seasonal variations in SSC. Regression models were developed for seven SS transport dynamic indicators for 120 SSC monitoring sites on rivers across the US at annual and seasonal timescales. The models included a range of statistically significant predictor variables, of which LULC, PPT30, baseflow index, and soil properties, like clay content, were the

most common across the SS transport dynamics indicators. When additional spatial modelling was conducted to remove spatial autocorrelation (GWR), significant differences in coefficients were identified by ecoregion, suggesting regional influences from catchment and climatic factors. Key results are:

- Agricultural percent cover is positively associated with longer duration SSC events and more frequent short events, and seasonally with SSC magnitude, likely due to effects on soil hydrology and sediment supply.
- Forest percent cover is positively associated with shorter and more frequent SSC events, and extreme high magnitude SSC in summer months, which might be related to the impacts of forest management on hydrological processes or covariations with topography and climate.
- Urban percent cover was the least common LULC variable in the models. It is positively associated with the frequency of long SSC events, especially in spring and summer, and with extreme high SSC magnitude in the western US.
- Soil erodibility (K-factor) is positively associated with the frequency of SSC events, but negatively with the duration of short events, especially in the west coast and forested mountain regions. Thus, more erodible soils yield more frequent and short-lasting high SSC events, though climate and catchment variables likely have strong influences.
- Soil clay content is positively associated with average SSC in all ecoregions over most seasons (spring, summer and autumn) and with the duration of long SSC events, especially in winter. Clay content may relate to the availability of fine sediment, but there are spatial covariations with topography and climate that suggest an influence of snowmelt in mountainous regions and ephemeral rivers in dry regions.
- Baseflow index is positively associated with the duration of long SSC events and slow rates of SSC increase, but negatively associated with average and extremely high SSC, which likely related to reduced overland flow and more stable flow regimes that reduce sediment erosion and transport.
- Annual precipitation is negatively associated with SSC magnitude and rates of SSC increase overall, likely due to dilution effects. However, there are important spatial variations with positive associations in moist forested regions (MWCF and ETF).

- The rainfall and runoff factor is positively associated with extreme high SSC in desert, Great Plains and Eastern Temperate Forest regions in summer, possible related to intense seasonal storms.

This study is one of the first to investigate the short-term dynamics (days to months) of suspended sediment transport in rivers at continental scale and the underlying catchment and climatic variables that control spatial and seasonal variations. It provides new understanding of the varying influence of land use and land cover on the magnitude and frequency of high suspended sediment concentrations caused by climate and catchment factors. Further research should be conducted on the impact of climate on suspended sediment transport dynamics to inform future monitoring, modelling and mitigation related to the climate change.

4 Climate Oscillation Effects on Intra and Inter Annual Suspended Sediment Concentrations in Rivers and Identification of Important Processes

4.1 Introduction

Climate change is affecting the water cycle on Earth and is predicted to impact precipitation amount, timing and intensity (Sohoulande and Singh, 2016; Tabari, 2020). Precipitation is the main driver of soil erosion and suspended sediment generation, which affects hydrological processes (Hancock, 2012; Wang *et al.*, 2014; Ampomah *et al.*, 2020; Cui *et al.*, 2020; Fortesa *et al.*, 2021; Ryberg & Chanut, 2022). Water quality degradation including suspended sediment generation is largely human impact and difficult to resolve (Ahmadisharaf *et al.*, 2020). It is due to the changes in land use and land cover, which creates challenges in identifying trends of sediment generation for decades (Kulimushi *et al.*, 2021). Thus, it is worthwhile to implement investigation of SS response systems to natural variations in climate (Argaman *et al.*, 2020). Climate oscillations were used to understand the nonstationary nature of small shifts in weather (He *et al.*, 2020).

Large scale climate oscillations (large scale atmospheric circulations) can be linked with climate variability (Schillerberg & Tian, 2020). Those are the evidence, driven by the whole system of ocean atmosphere that such variation and phase changes with ecological indicators can be a proxy to manage water resources (Ham *et al.*, 2017). These multiscale relationships are observed in regional and global scales, especially with hydrological components (Labat, 2008; Tamaddun *et al.*, 2017). Climate oscillations cause variations in precipitation (Ouyang *et al.*, 2014; Tian and Quiring, 2017; Rezaei and Saatsaz, 2021). Climate oscillations are also found to affect precipitation and stream flows in North America (Nalley *et al.*, 2019) e.g., Pacific Decadal Oscillations (PDO), El Niño Southern Oscillation (ENSO) and North Atlantic Oscillation (NAO), despite the well-known uncertainties, existing in rainfall runoff simulation (Zahmatkesh *et al.*, 2015).

Application of multi annual climate oscillations to SS drivers and dynamics is possible given the examples in analysing periodic characteristics between climate oscillations and precipitation in particular seasons e.g., winter or summer (Jiang *et al.*, 2014;

Ebrahimi *et al.*, 2021; Fan *et al.*, 2021). Many applications of wavelet analyses used mostly sediment loads (Camilo & Restrepo, 2017; Al-Ghorani *et al.*, 2021; Wang *et al.*, 2022). Positive and negative phase changes of climate oscillations were also correlated with precipitation events (Zhang *et al.*, 2019). The differences in climate over the North America is distinctive between West and East, providing benefit of understanding multiple catchments in a wider spatial extent (Polade *et al.*, 2013; Tamaddun *et al.*, 2019). In the Northeast coast of the US, winter precipitation received negative correlation with NAO (Chartrand and Pausata, 2020), represented as clear periodic signals (Nalley *et al.*, 2016). Negative phases of ENSO and NAO were related with wetter weather over the continental North America (Nalley *et al.*, 2019). Positive phases of PDO linked with more precipitation events in California (Guirguis *et al.*, 2019). Furthermore, low frequency variability of PDO was known to have reacted with streamflow at some watersheds in North America. In the meantime, PDO is known to be effectively influencing surface climate and hydrology in Western North America (Whitfield *et al.*, 2013; Chesnokova *et al.*, 2020). There also are well known contribution of AO to summer rainfall over the central US (Hu and Feng, 2010).

The hydrological changes caused by climate oscillations may alter the flux of suspended sediment in rivers. Rainfall is the dominant driver of soil erosion and overland transport of fine sediment, whilst river discharge is the main driver of bank and bed erosion and sediment transport (Murphy, 2020). Over the United States, ENSO impacts on rainfall, temperature and inter annual variability of biosphere vegetation patterns were identified (Li and Kafatos, 2000). Climate oscillations impacts on excessive precipitation and drought were identified throughout the continent e.g., AMO, NAO, ENSO and PDO (Tayler A. Schillerberg and Tian, 2020). Spring and Summer crops were also affected by sub annual ENSO indices (Royce *et al.*, 2011). In North California, PDO is correlated with annual and winter precipitation and temperature (Norman and Taylor, 2003). Those precipitation and vegetation cover are the constituent of the significant processes delivering SS.

Climate oscillations are closely linked with atmospheric pressure variation, thus bringing different climatic impacts e.g., rainfall over various corners of the continent. ENSO and PDO exert extreme climate over the United states including severe drought cases (Polade *et al.*, 2013). The mechanism in ENSO driven rainfall variability is

known for inconsistency (Huang and Xie, 2015). As an example, El Niño phase brings dry air sinks in South East Asia and Central America that creates shifts in global atmospheric circulation followed by sea surface changes i.e., warmer than average across Pacific. However, La Niña is opposite to El Niño that dry and sinking air occurs over Africa and Pacific that creates sea surface temperature cooler than average. The regions other than the dry sinking areas receive rainfall for each different phase of ENSO (NOAA, 2024). PDO also is affected by ocean temperature, the mechanism shares with ENSO (NOAA, 2024). From Arctic oscillation, the air pressure change is affected, thus exerting strong influences on climate and weather, especially in winter (Ambaum et al., 2001). NAO is created from sea surface level changes and further links with North Atlantic jet stream and storm track. During positive NAO, atmospheric pressure is high over the US, and during negative phase, pressure is high in the eastern US (Whan and Zwiers, 2017; NOAA, 2024a).

Studying climate oscillations can help us to better understand the impacts of climate change on suspended sediment dynamics, as they have been done for hydrology (Chu et al., 2018) and water quality studies (Hao and Lu, 2021). Seasonally varying precipitation is an important element from climate change (Jiang et al., 2014; Shao et al., 2016; Jiang et al., 2020; Le et al., 2023). Winter case also receives impact of CC that changes of magnitude, duration and number of events from precipitation and snowfall are occurring (Whitfield and Shook, 2020; Ohba and Sugimoto, 2022). Ground water in mountains also receives the impacts of climate change (Rust et al., 2018; Immerzeel et al., 2020).

The research aims to determine if temperature and precipitation changes caused by climate oscillations affect suspended sediment dynamics in rivers. This research uses dynamics in suspended sediment concentrations (mg/l), without hysteresis between SSC and discharge (Misset et al., 2019). By analysing variation between climatic oscillations and the hydrological components that are associated with mechanism of suspended sediment generation, the analysis results are used to better predict drivers of suspended sediment dynamics in association with climate oscillations. Thus, the research objective is to confirm; 1) Determine if there are multi-annual variations in SSC transport indicators, and 2) If they correlate with occurrence of climate oscillations or their impacts on temperature or precipitation, investigate the relationships. The

study aims were achieved through the analysis of climate oscillations, weather and SSC indicators using continuous and cross-wavelet analysis for 4 catchments in the US.

4.2 Study areas

Catchment selection processes to perform wavelet transform analyses included the optimal spatial distribution of climatic influences and minimal impact of distinctive site attributes to SS dynamics. Relatively small size catchments were selected. Periods of available data were not considered due to the scarcity of the SS dataset. Availability of site attributes were also considered for selection of sites (Falcone *et al.*, 2010). Catchments without major dams were chosen (Jurotich *et al.*, 2021), located in different parts of the country (Nalley *et al.*, 2019) that experience the effects of different climate oscillations. Four catchments (Figure 4-1) were selected considering previous research on periodicities identified between climate oscillations and climate associated factors e.g., precipitation and stream flow in different seasons e.g., JFM, JJA and DJFM (Polade *et al.*, 2013; Veres and Hu, 2013; Nergui *et al.*, 2016).

Catchment descriptions

The selected catchments have contrasting climate and site attributes that generate suspended sediment. The site attributes e.g., percentage of land cover were derived in 2001, and climate data e.g., PPT30 represents the 30 year time frame of 1997~2000 (Falcone *et al.*, 2010). Notable differences were identified from the site attributes associated with climate e.g., PPT30 and Rfact (Figure 4-1, a). The climate and site attributes were distinctively different between West and East without specific patterns from LULC between the selected catchments (Figure 4-1, a,b). To appropriately amplify the relationships between the SS drivers e.g., precipitation and exerting climate oscillations, seasonally subset oscillation data were selected for each catchment.

Site A is located in relatively flat area towards the east coast in Mid Atlantic region. The catchment area is 4,713 km². PPT30 is 121.12 cm. Urban land cover is 83.8 % and rest of them are forest cover. Most dominant soil type is silt. The site has the 3rd highest mean watershed slope of with a value of 10. The catchment also possesses the widest extent of clay cover and agricultural areas. As it is located in Northern

Piedmont, the catchment receives the most amount precipitation throughout a year in all seasons, compared to other catchments. The catchment also possesses a reservoir in a tributary. Dominant geology is Gneiss (69.49%). The permeability in the region is 2.97 inches/hour (Falcone *et al.*, 2010). Existing impact of NAO in winter to precipitation in the eastern USA has allowed subset of NAO into DJFM (Chartrand and Pausata, 2020).

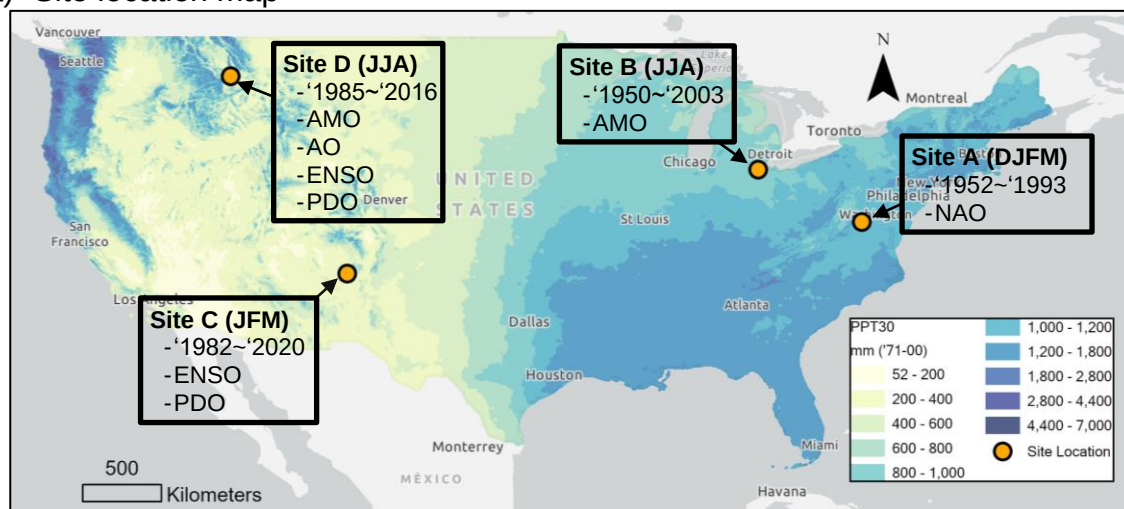
Site B is covered with forest and receives the larger amount of precipitation than West (Site C and D). The catchment area is the largest between the selected sites (16,409.4 km²). PPT30 is 91.87 cm. Agricultural area is the most dominant land cover (78.8 %). Clay and silt covers are 36.5 % and 47 %, respectively. Mostly cultivated crops are found as it is in Eastern Corn Belt Plains. Wide distribution of anthropogenic activities was found in the catchment, which is reflection of more population distribution than other catchments, having the largest urban coverages. The catchment receives the most runoff in winter. Sedimentary rocks dominate the catchment (84.02 %). The permeability in the region is 1.21 inches/hour (Falcone *et al.*, 2010). The distribution of mean precipitation and AMO forced simulations of JJA enabled subset of climate oscillations into JJA (Veres and Hu, 2013).

Site C is in the driest region of Arizona/New Mexico Plateau. PPT30 is 41 cm. The catchment (1,088 km²) receives the least amount of precipitation and rainfall runoff factor (Rfactor) throughout a year. The catchment also has the most precipitation seasonality index (Imteaz and Hossain, 2023). Forest cover takes 30 % of land cover. Clay and sand covers are 26.07 % and 36.92 %, respectively. It is mostly covered with Shrubland. The stream density and Horton overland flow are also the highest between the selected sites. Sedimentary rock is 59.95%. The permeability in the region is 2.62 inches/hour (Falcone *et al.*, 2010). Season of JFM was chosen due to its aligning impact of precipitation with JFM average teleconnections (Polade *et al.*, 2013).

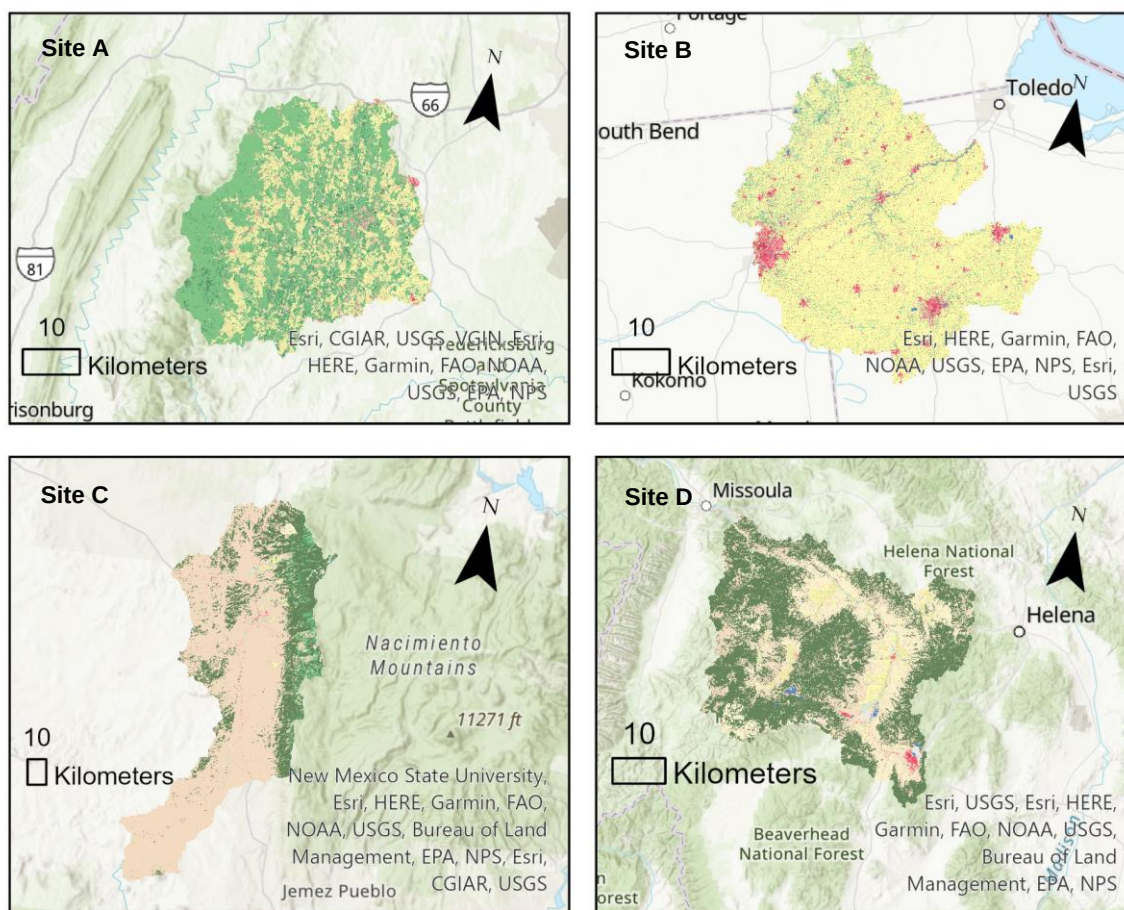
Site D is in the far Northwest (Pacific Northwest Region) where has the most known impacts of climate oscillations (AMO, AO, ENSO and PDO). The catchment area is 9,520 km². PPT30 is 43.3 cm. Urban and forest covers are both 30.7 %. Sand and silt covers are 56.08 % and 34.5 %, respectively. The catchment generates the most runoff in summer. The region is mostly covered with evergreen forest. The highest permeability is observed in the catchment (30.2 inches/hour). As the catchment is in

the mountainous region (Middle Rockies), the site has the largest value of base flow index (BFI). Dominant geology is Gneiss (63.46%) (Falcone *et al.*, 2010). Like Site B, the catchment subset the climate oscillations as of its dominance in JJA (Veres and Hu, 2013).

a) Site location map



b) LULC maps



NLCD Land Cover '2001



c) Topography

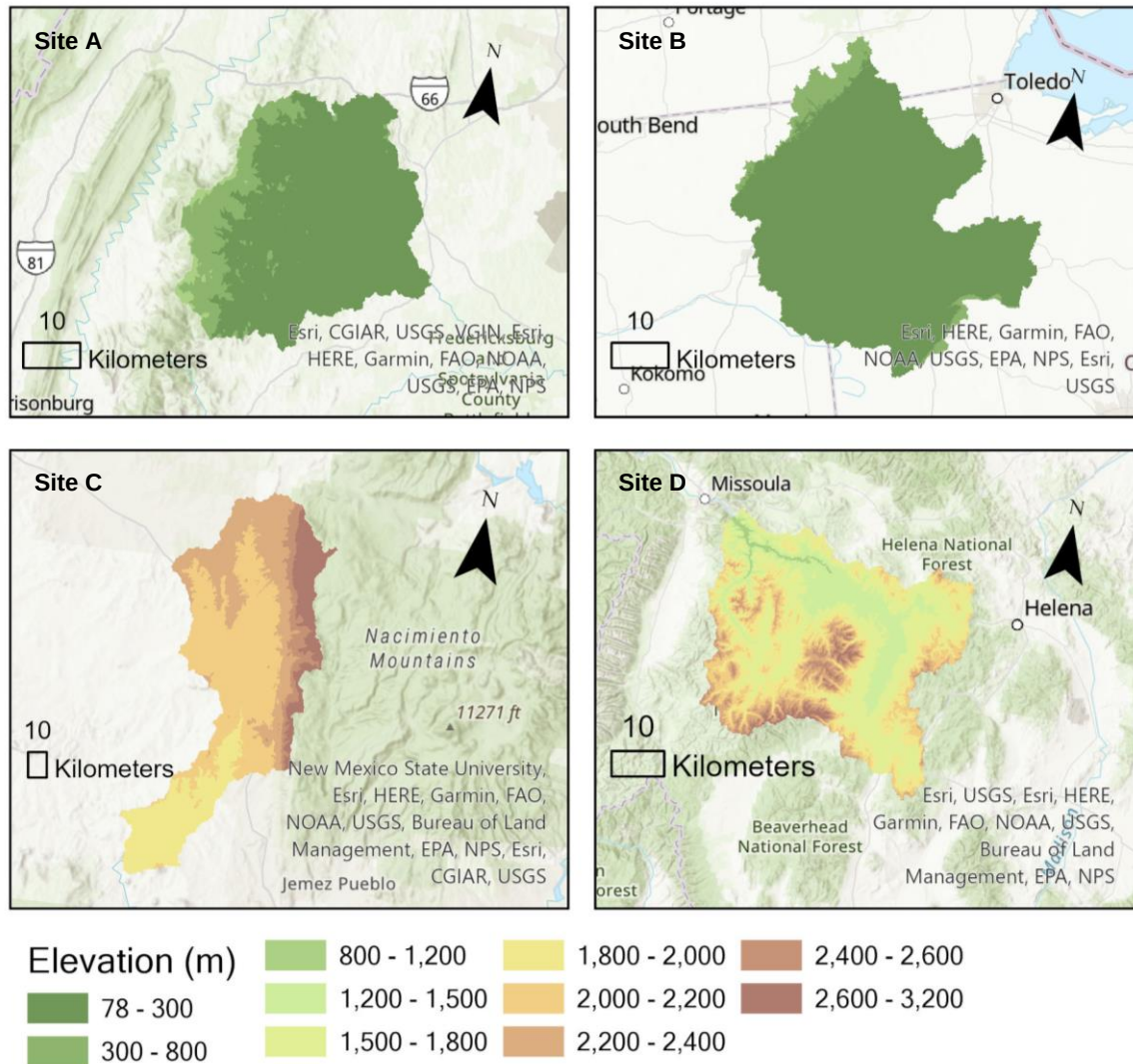


Figure 4-1. Maps of catchment locations, LULC and topographical information, with no major dams including a list of influential climate oscillations: (a) Site A (USGS: 01664000, Rappahannock River at Remington), Site B (USGS: 04193500, Maumee River at Waterville), Site C (USGS: 08334000, Rio Puerco Abv Arroyo Chico NR Guadalupe) and Site D (USGS: 12334550, Clark Fork at Turah Bridge nr Bonner) were selected considering contrasting hydrological environment, regional climate influences and impact of climate oscillations including data quality. Years represent availability of SS daily time series. Literature review results of seasons in association with climate oscillations are written in each box. The map of PPT30 from 1971 to 2000 was obtained from '<https://prism.oregonstate.edu/normals/>'. (b) National Land Cover Database (NLCD) layer of 2001 (Wickham *et al.*, 2010) was used to create LULC maps. (c) Topographic elevations were retrieved from Elevation Derivatives for National Applications (EDNA) (USGS, 2005).

4.3 Materials and Methods

Suspended sediment transport dynamics were quantified using indicators by season. The indicators and climate oscillations were analysed with continuous wavelet and wavelet coherence analyses to determine periodicities and phase changes with climate oscillations, precipitation and streamflow. Interpretation of phase differences in wavelet coherence analyses establish relationships between climate oscillation and climatic elements, which is also another benefit of identifying periodicities from climate oscillations (Cui & Li, 2019).

4.3.1 Data

Daily suspended sediment data (mg/l) and site selection

The site selection was to ensure that evenly distributed impacts were identified from the selected catchments considering the coverage of differing climatic impact over the continent. The site selection process initially started with 1,667 sites, available in the suspended sediment data (U.S. Geological Survey, 2016). However, due to the unavailability of the site attributes outside the boundary of the continental U.S., 1,543 sites were filtered to choose relevant catchments and further reduced due to the gaps in data. It was assumed that the temporal changes of site attributes were minimum covering the data period available in SSC. Although previous research discussed limitations and uncertainties of the daily SS data (mg/l) from USGS (Sommerfield, 2016) and application of suspended sediment with turbidity data instead (Formazin Nephelometric Unit, FNU) (Wang & Steinschneider, 2022), daily SSC was used in this study as the daily SSC shares similar dynamics with the recent turbidity data (Shin *et al.*, 2023a). In addition, the indicators to be discussed later are seasonal and annual aggregation of the daily values, which was taken as noise removal, masking the limitation from the daily fluctuations (Rust *et al.*, 2021). Most importantly, the data processing ensured that the selected catchments possess SSC time series at least 30 years to account for climatic influences on SS generation environment (WMO, 2018). Another limitation is that the filtering focussed on capturing differing climatic influences, and less strict rules were applied for comparing the differences in LULC and catchment areas.

Data pre-processing

The data preprocessing was to capture inter/intra annual variation of SS generation at the different site locations. After selecting the sites, missing values in the daily time series were interpolated by Kalman's smoothing (Max=3 days) using the Gaussian function to a form of covariance matrices (Aravkin *et al.*, 2021). Then, SS indicators in magnitude and frequency were calculated for each season (e.g., JJA, JFM and DJFM) to create magnitude and frequency indicators of annual time series (Shin *et al.*, 2023). Assumption was taken that possible covariance from discharge weighting in the SS data was minimized by noise removal from the aggregation of seasonal time series. After loading SSC data for the selected sites (R Core Team, 2023), magnitudes e.g., 95th percentile of each subset of the specified season were averaged. The frequency indicators (Duration of events, number of events and peaks per events) were calculated after subsetting time series for each season. This process created annual time series of seasonally calculated dynamics. Then, the gaps in annual time series after data pre-processing were filled with Autoregressive integrated moving average (ARIMA) (Prasad *et al.*, 2020). If ARIMA creates significant anomalies in the gaps, maximum likelihood fitting was used instead (Benavides *et al.*, 2023). Then, time series were standardized before implementing wavelet analyses (Nalley *et al.*, 2019).

Precipitation data

Precipitation data were downloaded from NOAA (National Oceanic and Atmospheric Administration, 2023a) to perform continuous and cross wavelet analyses and match identified periodicities with SS dynamics. Daily precipitation data were downloaded from each available period of suspended sediment from gauging stations located within catchments for Site B, C and D (Figure 4-1). Site A used a county level monthly data only for DJFM due to the gaps in the daily time series from station data (Washington 3 SSW, VA). Site B used a station data (Lima station WWTP, OH) to generate an average annual time series of JJA (Veres and Hu, 2013). For Site C, a station data (Jemez Springs, NM), located near the catchment boundary was used due to an unavailability of the precipitation data in the basin, then subset into JFM. Site D used daily precipitation time series from a meteorological station (Deer Lodge 3 W, MT) to calculate average annual times series (JJA) (Veres and Hu, 2013).

4.3.2 Methods

Subset of average annual time series from each identified seasons were analysed using: (a) Continuous wavelet analyses, (b) Wavelet Coherence analyses, (c) Interpretation of impact of climate and site attributes between precipitation and associated SS dynamics in magnitude and frequency and (d) Find associated processes in terms of phase changes of climate oscillations (Schillerberg & Tian, 2020).

Application of new indicators of SS dynamics and conceptualization of its application

Precipitation is taken as the primary driver of SS dynamics in other climatic elements as temperature constitute in occurrence of precipitation in various intervals (Wasko *et al.*, 2015). SS dynamics indicators (Shin *et al.*, 2023) were used to reflect the SS transport mechanism in magnitude and frequency for relevant seasons e.g., winter or summer (Polade *et al.*, 2013; Fuentes-Franco *et al.*, 2016). The frequency indicators (Event duration and Count of events) used the alpha value of 0.2 considering rainfall durations in the US (Gootman and Hubbart, 2021; Wilson *et al.*, 2021) to identify periodic variation in SS dynamics considering the nature of SS dynamic behaviours in association with rainfall events. However, number of peaks per event (P.p.e) used the alpha values of 0.6 and 0.2 to check variability in periodicities existing in longer duration rainfall events.

Climate oscillations in different seasons

Several climate oscillations were identified from literature, especially over North America. ENSO and PDO were correlated with the stream flows in western US (Polade *et al.*, 2013). AMO affected precipitation over eastern US (Veres and Hu, 2013). Arctic oscillation (AO) correlated with precipitation in the central US (Hu and Feng, 2010). To align with the seasonal impacts of climate oscillations to SS drivers (Jiang *et al.*, 2014), Climate oscillations were also seasonally subset e.g., JFM (Polade *et al.*, 2013), JJA (Veres and Hu, 2013) and DJFM (Chartrand and Pausata, 2020). The seasonal time series of the climate oscillations for this research is shown in Figure 4-2. ENSO of JFM was downloaded from NOAA (National Oceanic and Atmospheric Administration, 2023b). PDO and NAO were downloaded from NOAA to calculate the

same periodic values as defined in SSC dynamics calculations. AO was also downloaded from NOAA (National Oceanic and Atmospheric Administration, 2023c).

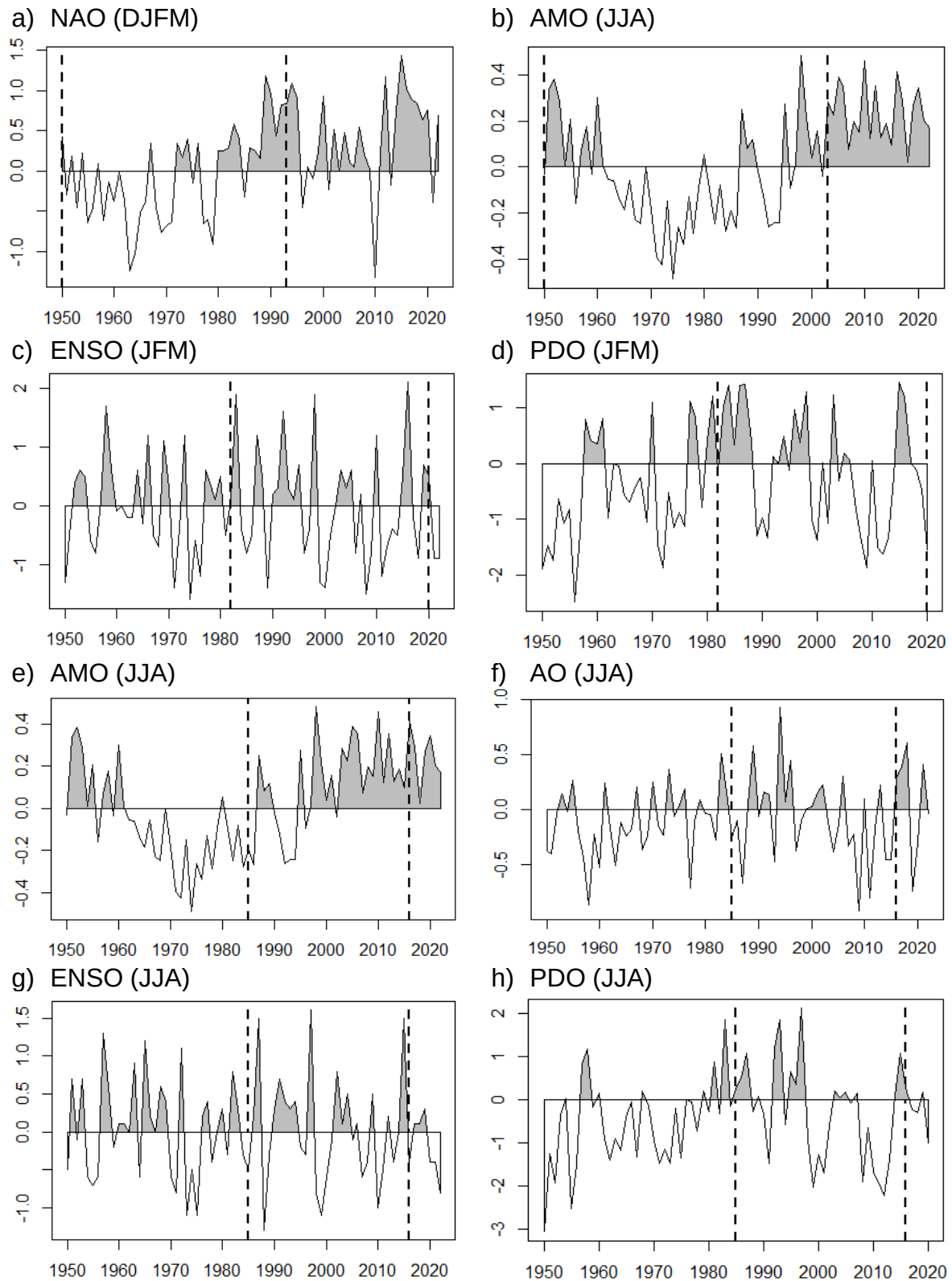


Figure 4-2. Plots of seasonally subset climate oscillations used in the research: Climate oscillations for each selected seasons show different positive and negative sections

from 1950 to 2020 (Site A-a, Site B-b, Site C-c,d, Site D-e,f,g,h). The periods between dotted lines are the periods with SS data availability.

Wavelet transforms

Continuous and cross wavelet analyses were used to capture periodic signals existing between climate oscillations and the indicators developed (Nalley *et al.*, 2019). The continuous wavelet analysis is to find periodicities to support the conceptualization from the research that rainfall impacts on SS, discharge and SS dynamic indicators are in line with the periodicities existing in literature. Wavelet coherence analysis is to understand characteristics between phase changes for different catchments (Jean *et al.*, 2014). Package 'WaveletComp' of Morlet wavelet (Equation 1), available in R was used to perform the wavelet analyses (Mount *et al.*, 2013; Rösch *et al.*, 2018; Su and Miao, 2019);

$$\Psi_0(\eta) = \pi^{-\frac{1}{4}} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2} \quad \text{Eq. 4-1}$$

Where, dimensionless frequency and time are ω_0 and η , respectively.

Morlet wavelet, a commonly used wavelet in hydrological studies was chosen as of its ability to describe shape of hydrological type data (Nalley *et al.*, 2019) and provide good balance between time and frequency (Zhang *et al.*, 2014). Morlet also has benefit of detecting peaks from complex symmetric function (Nalley *et al.*, 2016). An alternative for detecting patch and gap events is Mexican Hat wavelet. However, Morlet for detection of scale of events is more appropriate (Mi *et al.*, 2005). Another alternative to using Morlet wavelet for sediment study is Daubechies, which is a type of Haar wavelet for detecting time localization information (Ateeq-Ur-Rehman *et al.*, 2018). As Daubechies wavelet finds high frequency jumps by running averages, it may not be suitable to detect inter annual shifts, which vary seasonally (Mohammadi *et al.*, 2020). Limitation of CWT is that the interpretation can be subjective by observing the result figures.

Considering the nature of research using environmental variables including SS triggering factors and application of AR(1) to a water quality study with 95% confidence level, the research used the red noise to determine the significance levels for both continuous and cross wavelet analyses (Vasseur & Yodzis, 2004; Keener *et al.*, 2010).

The Loess (Locally weighted scatterplot smoothing) value of 0.75 was applied as a detrending coefficient (Rösch *et al.*, 2018). Number of simulations was set to 100 considering number of values in average annual time series from each catchment.

Wavelet coherence transforms

Wavelet coherence transform (Cross wavelet) was implemented between the climate oscillations and SS indicator time series to analyse causality and phase changes including seasonally subset precipitation (Keener *et al.*, 2010; Jean *et al.*, 2014). Assumption of this approach is that implementing the wavelet coherence analyses can identify leading cases of climate to SS generation processes. Catchment characteristics were checked whether those periodicities and phase changes were affected by anthropogenic activities. Cross wavelet is defined as (Keener *et al.*, 2010),

$$R_n^2(s) = \frac{|S(s^{-1}W_n^{XY}(s))|^2}{S(s^{-1}|S(W_n^X(s))|^2) \cdot S(s^{-1}|S(W_n^Y(s))|^2)} \quad \text{Eq. 4-2}$$

Where, S is a smoothing operator from wavelet type.

Phase differences were observed using the cross wavelet, and lag times were measured to find relationships with processes of the catchments. Results having less significance ($p > 0.05$) in average power curves were removed in the end. Unlike other studies about precipitation and streamflow using multiple wavelet coherence (MWC) (Nalley *et al.*, 2019), the research solely used continuous and wavelet coherence due to spatially and temporally irregular mechanism of SS generation, also considering imposing doubling uncertainties, driven in SS generation e.g., LULC, climate and anthropogenic activities.

4.4 Results

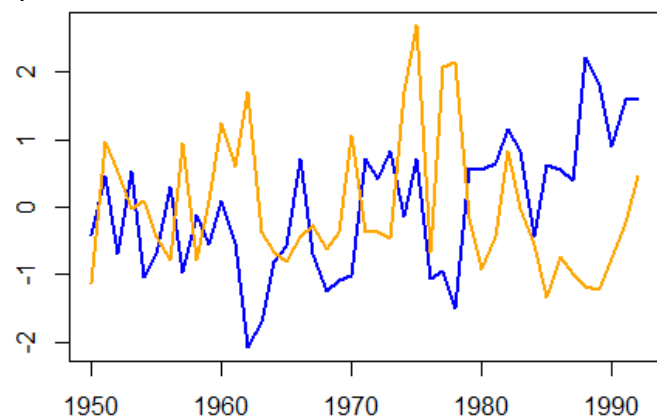
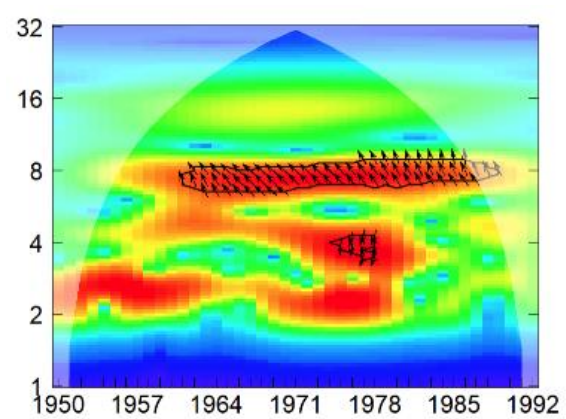
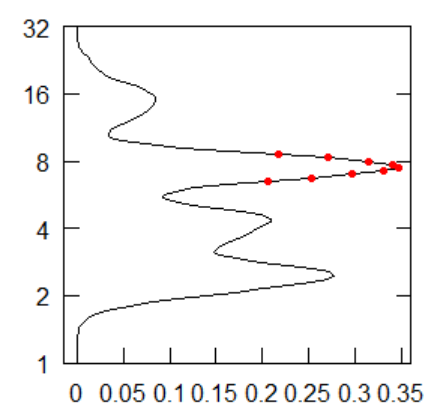
The continuous wavelet transform and wavelet coherence analyses show significant periods of temporally different correlation between each site (A,B,C,D) in different seasons e.g., summer (JJA) and winter (JFM and DJFM). The continuous wavelet analysis (Figure A4-1) shows that there are overlapped periodicities between precipitation, streamflow and SSC at Site A. Those are in conjunction with the mechanism of conceptualization of SS transport, which supports justification of analysing relationships between climate oscillations, precipitation and SS dynamics.

Thus, cross wavelet analyses were performed to identify spatially and temporally varying connection between climate oscillations and hydrological environment. Climate oscillations (AMO, PDO and NAO) were reflected in the drivers of SS transport dynamics (i.e., as a part of rainfall and runoff generation cycles), and those were linked with significant hydrological processes in each catchment.

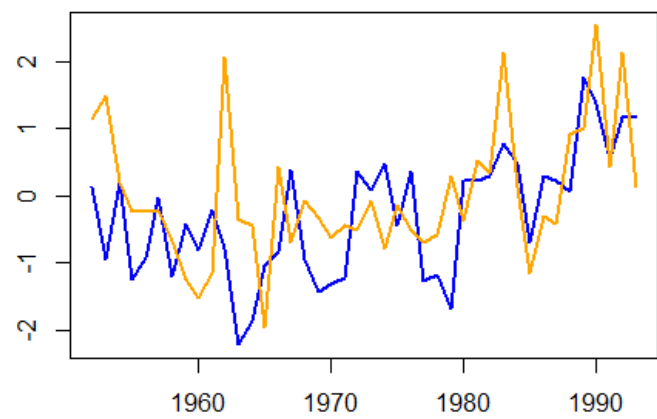
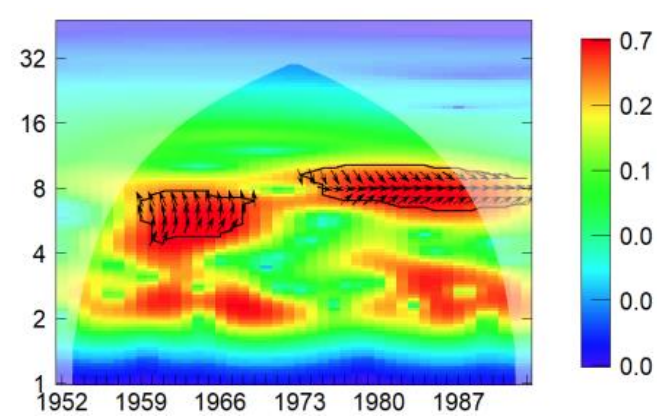
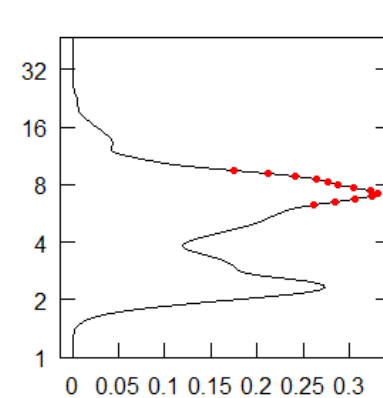
Site A

SS dynamics and NAO at Site A had a strong 8 year periodicity (Figure 4-3) with varying phase changes. However, there were no statistically significant periodicities between precipitation and NAO. M95 had mostly out of phase relationships (M95 leading) with NAO (Figure 4-3, a). However, D0.2 had 6~9 year in-phase relationships, mostly positively led by NAO (Figure 4-3, b). In a similar period, Cofe0.2 had an 8 year out of phase relationship (Cofe0.2 leading) with NAO across the 1970s and 1990s (Figure 4-3, c). Out of phase relationships with 8 year periodicity was identified from P.p.e0.6. P.p.e0.6 leading was identified in early 1960s, but NAO leading was identified in 70s (Figure 4-3, d). However, from P.p.e0.2, NAO leading (out of phase) was identified in 1960s, but P.p.e0.2 leading (in phase) was identified in 1980s (Figure 4-3, e) with the similar 8 year periodicity.

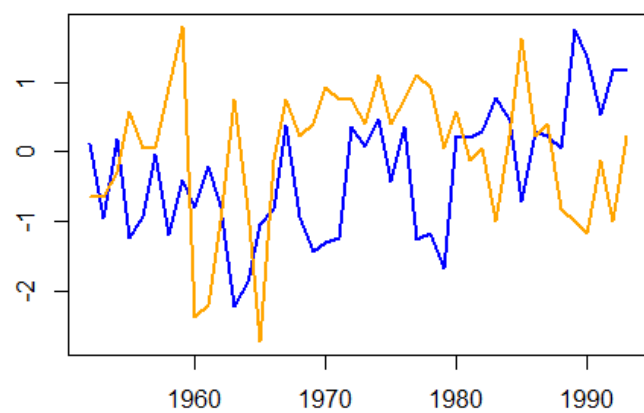
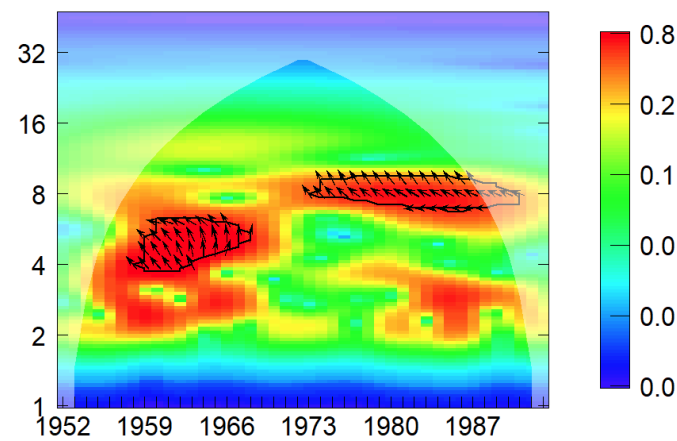
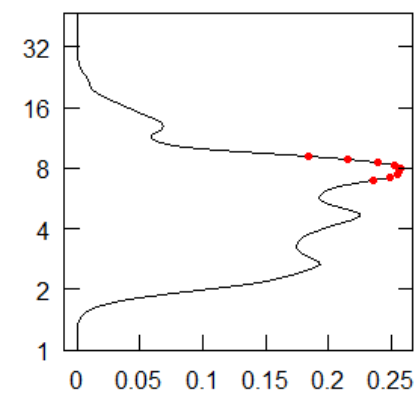
a) M95



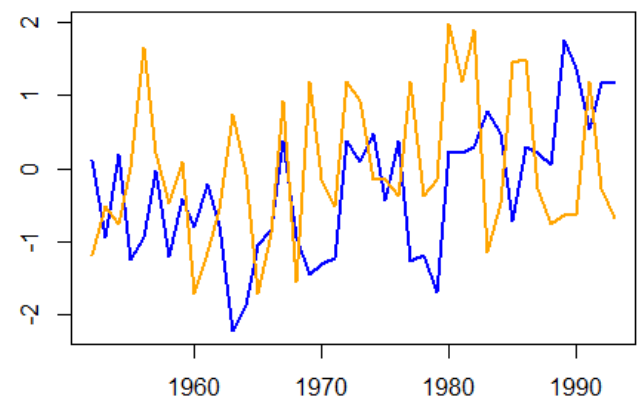
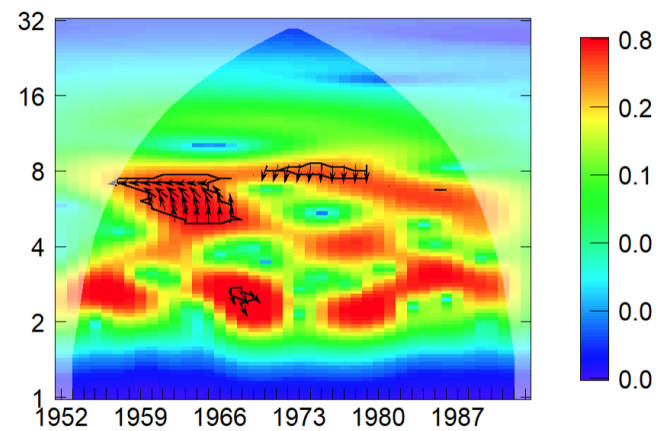
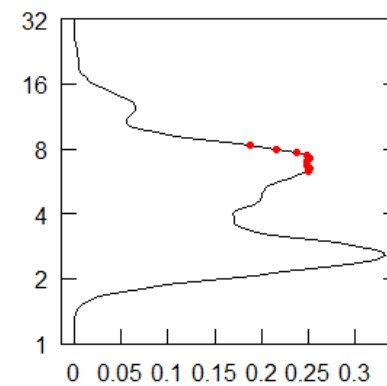
b) D0.2



c) Cofe0.2



d) P.p.e0.6



e) P.p.e0.2

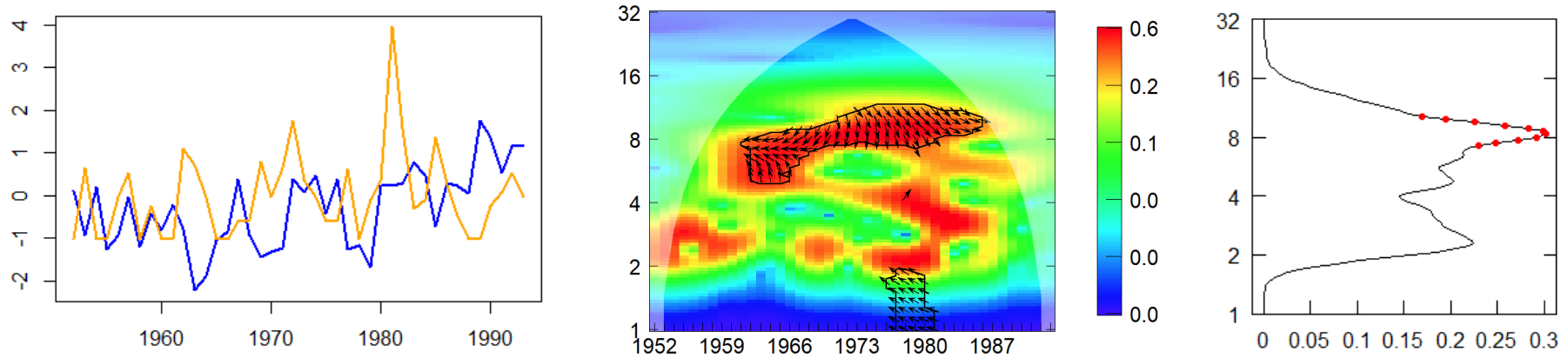
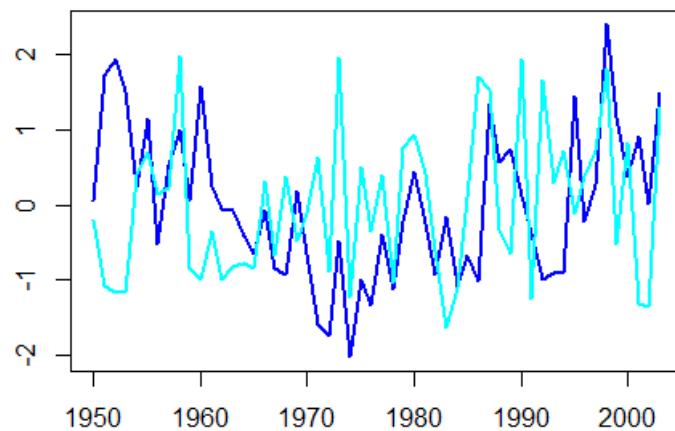
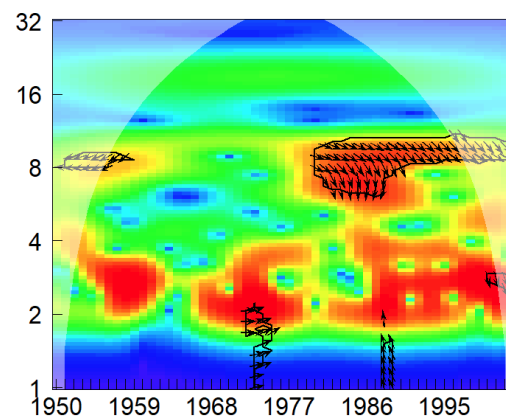
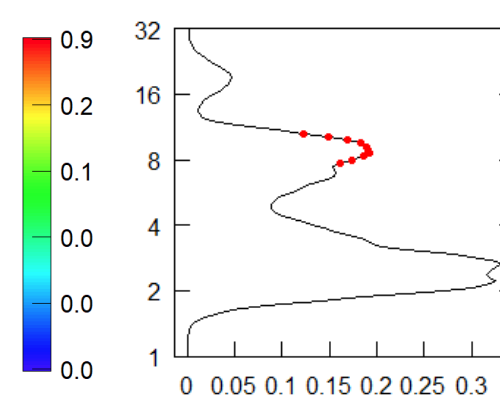


Figure 4-3. Plots of standardized annual time series and wavelet coherence analyses using standardized values of NAO and SS dynamic indicators (Site A, DJFM): The thick black lines in the wavelet coherence result (Mid) shows periodicities with statistical significance ($<.05$). The red dots from the average power curves (Right) shows p values ($<.05$).

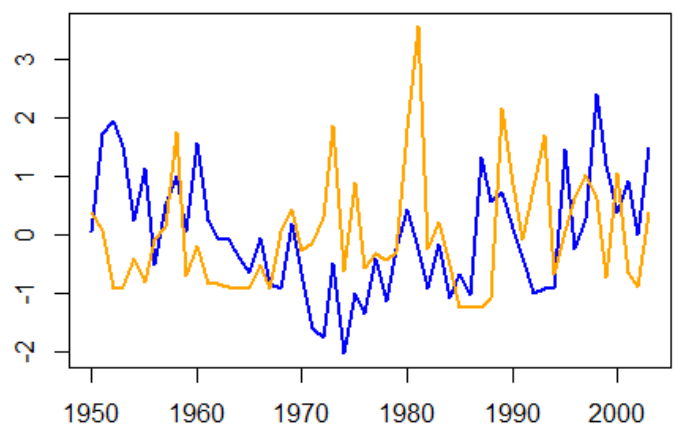
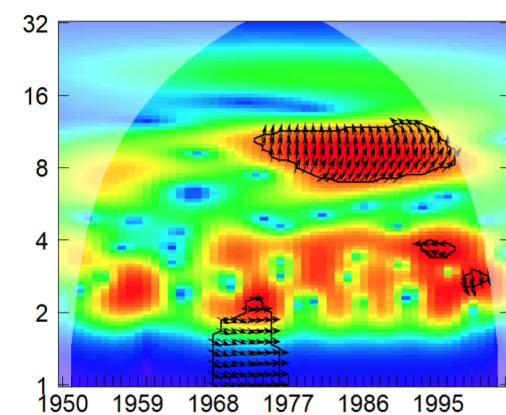
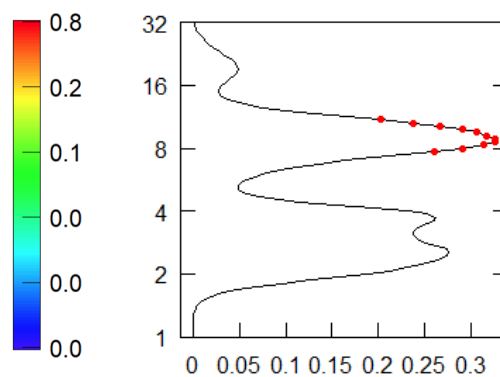
Site B

The wavelet coherence analyses between AMO, precipitation and SS dynamic indicators mostly show strong decadal (8~14 year) periodicities (Figure 4-4). The 8 year periodicity between AMO and precipitation from 1980s to 1990s were in-phase correlation (led by precipitation, Figure 4-4, a), but M95 showed AMO leading relationships (Figure 4-4, b). Cofe0.2 (leading by 90°) had comparatively less wavelet power than other indicators, and the periodicity identified was 20~25 year across 60s to 80s (Figure 4-4, c). P.p.e0.6 had in-phase AMO leading correlation (Figure 4-4, d) from late 70s and 80s. In case of P.p.e0.2, 7~12 year periodicities were identified, and a transition of phase occurred throughout 70s to 90s from synchronous to P.p.e0.2 leading (Figure 4-4, e).

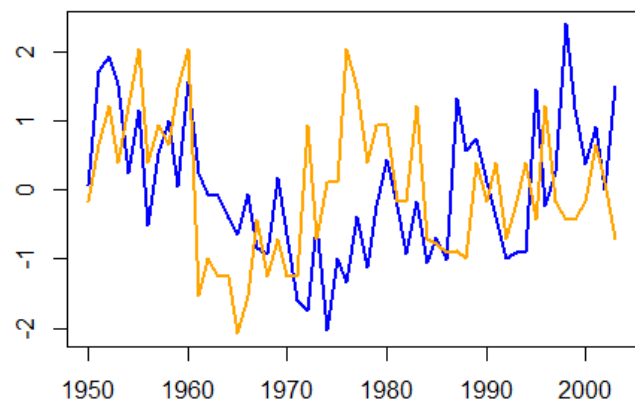
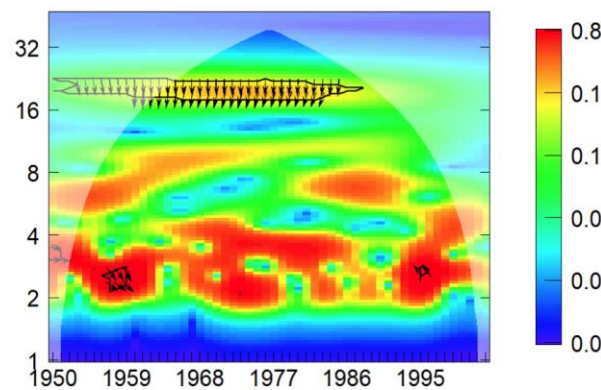
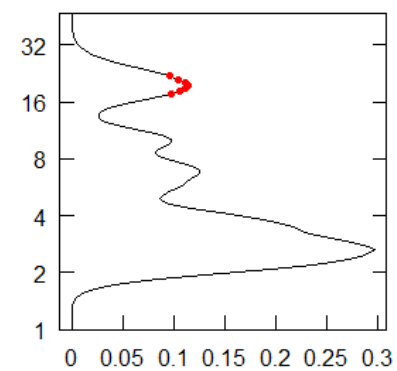
a) Precipitation



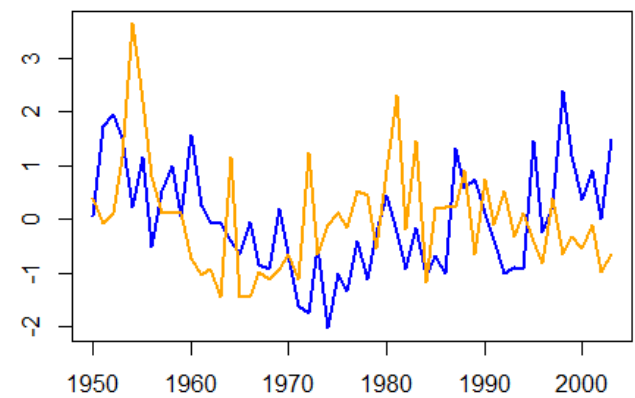
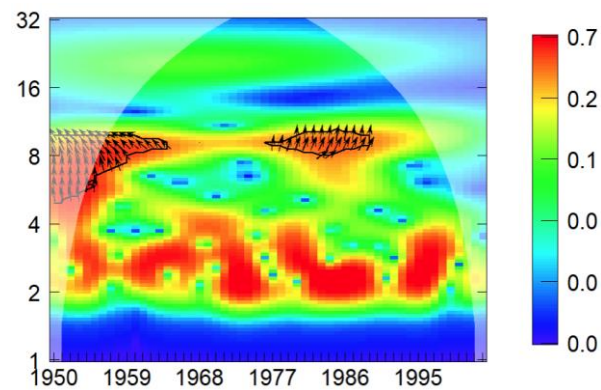
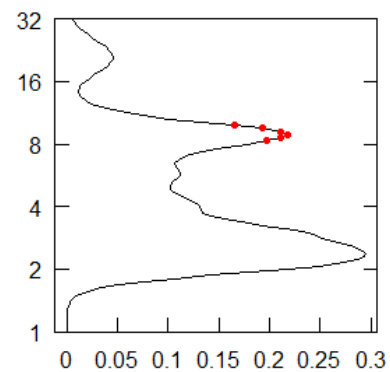
b) M95



c) Cofe0.2



d) P.p.e0.6



e) P.p.e0.2

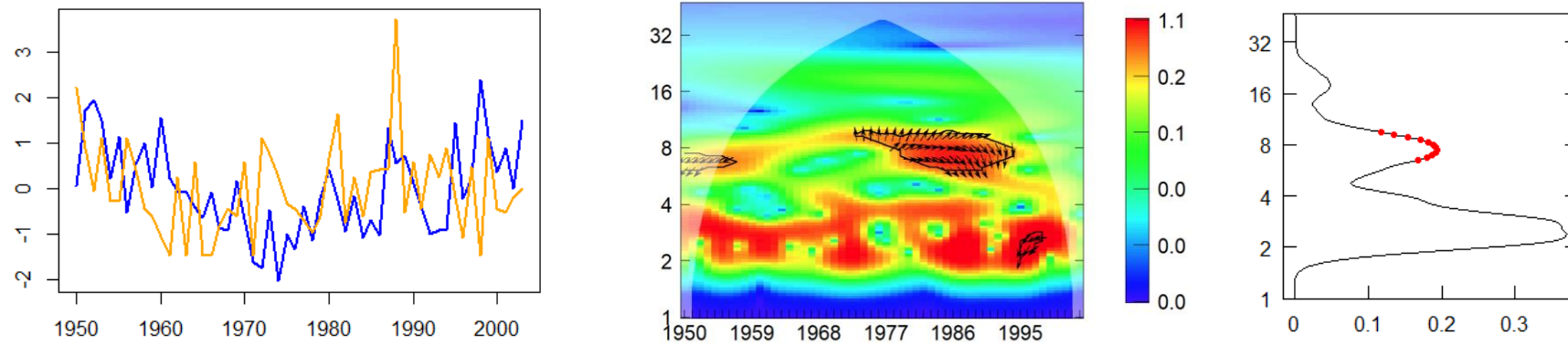
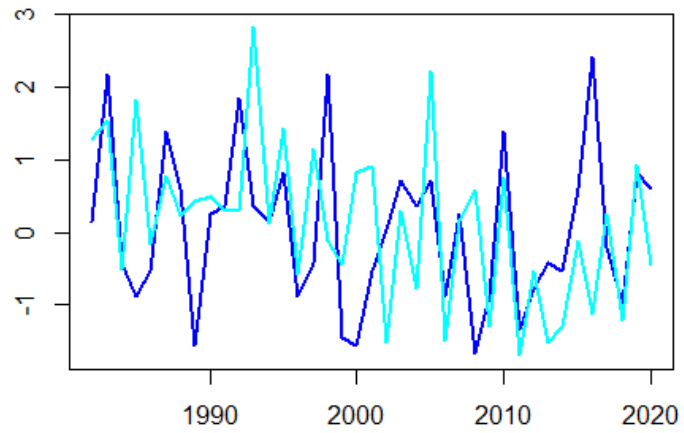
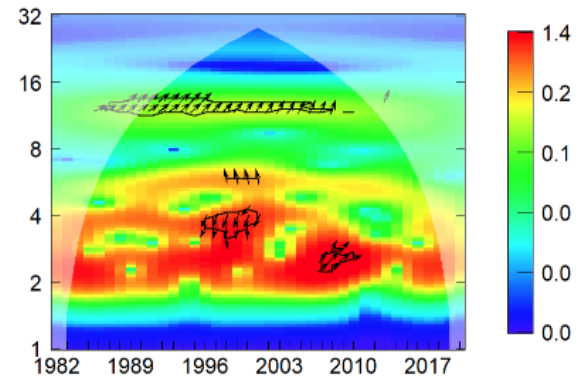
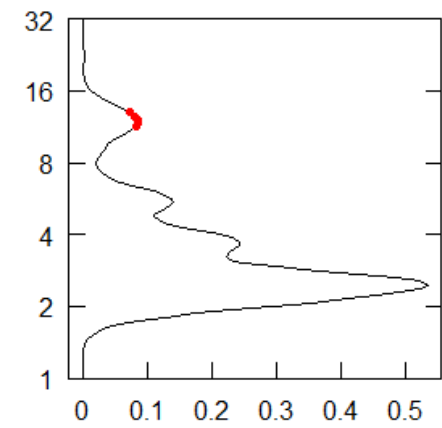


Figure 4-4. Plots of standardized annual time series and wavelet coherence analyses using standardized values of AMO, precipitation and SS dynamic indicators (Site B, JJA): The thick black lines in the wavelet coherence result (Mid) shows periodicities with statistical significance ($<.05$). The red dots from the average power curves (Right) shows p values ($<.05$).

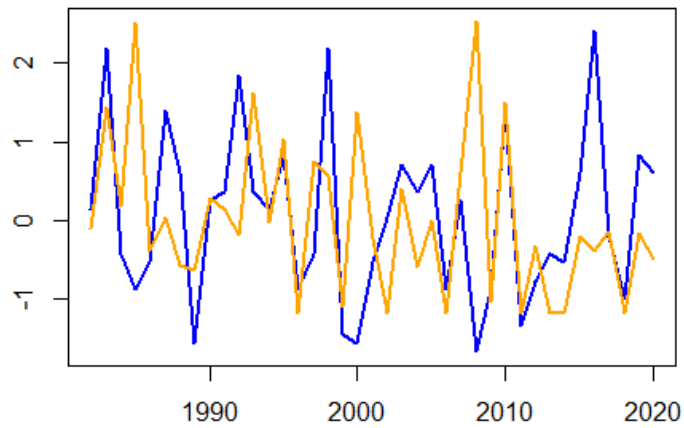
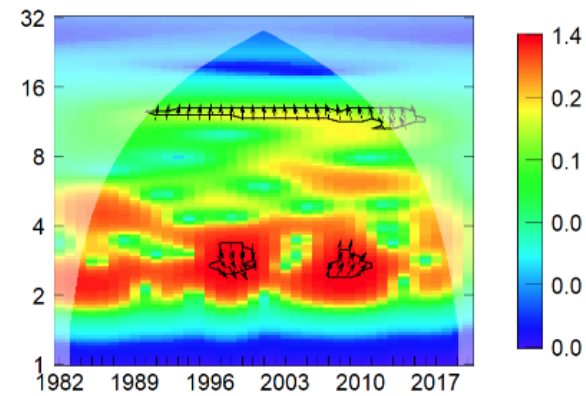
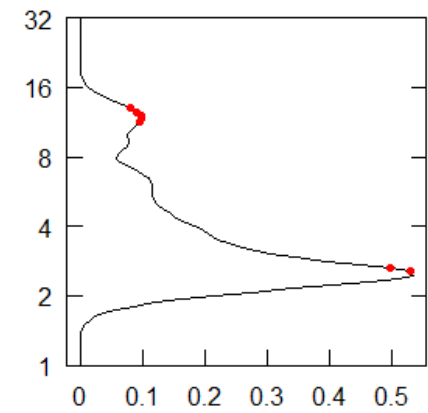
Site C

Site C received different periodicities from magnitude and frequency indicators from ENSO and PDO (Figure 4-5 and 4-6). ENSO imposed 12 year periodicity to M95, D0.2 and P.p.e0.6 (Figure 4-5, b,c,e) (Tamaddun *et al.*, 2017). However, 6~8 year periodicity was identified from Cofe0.2 and P.p.e0.2 (Figure 4-5, d,f). Similar periodicities were identified between precipitation and ENSO in JFM with in-phase correlation (ENSO leading) (Balanzategui and Nordhauß, 2021). M95 leading correlation for 12 year was identified from 1990s to 2010s but with less wavelet power (Figure 4-5, b). However, D0.2 yielded clear in phase correlation with ENSO (D0.2 leading), having 12 year periodicity (Figure 4-5, c). In case of Cofe0.2, 6~7 year periodicity was identified with Cofe0.2 leading status (Figure 4-5, d). Precipitation had in-phase correlation with ENSO (ENSO leading) but P.p.e0.6 had a generally lagging relationship (Figure 4-5, e). However, P.p.e0.2 had a conversion of ENSO leading status ('90s) to P.p.e0.2 leading ('00s) (Figure 4-5, f).

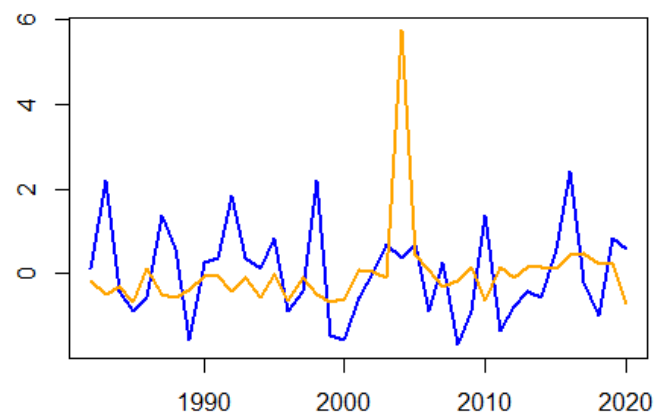
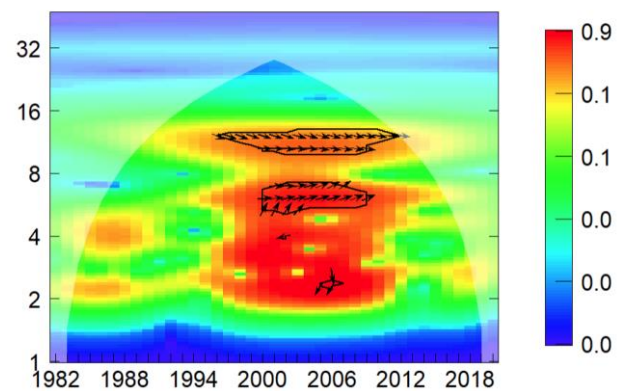
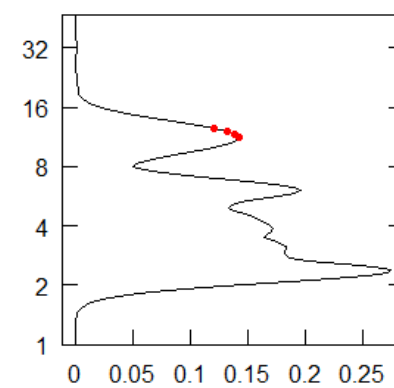
a) Precipitation



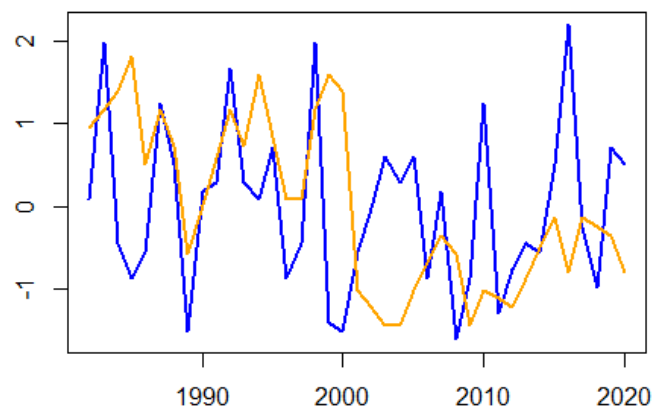
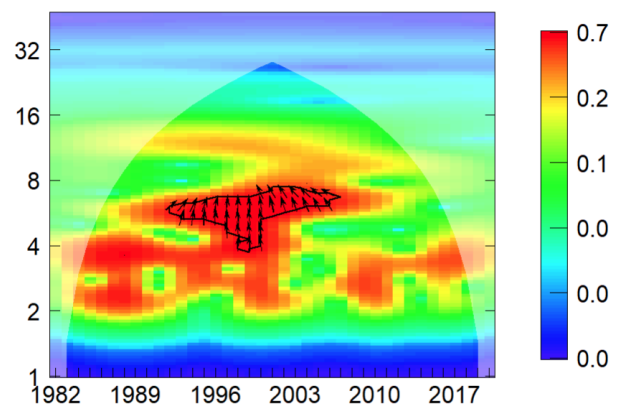
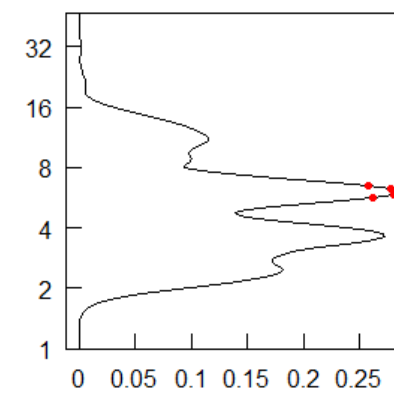
b) M95



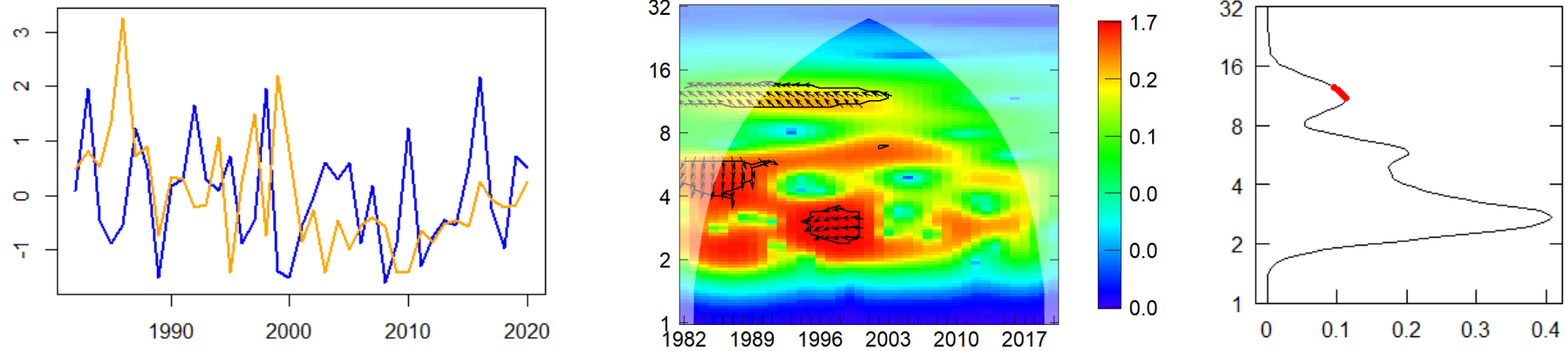
c) D0.2



d) Cofe0.2



e) P.p.e0.6



f) P.p.e0.2

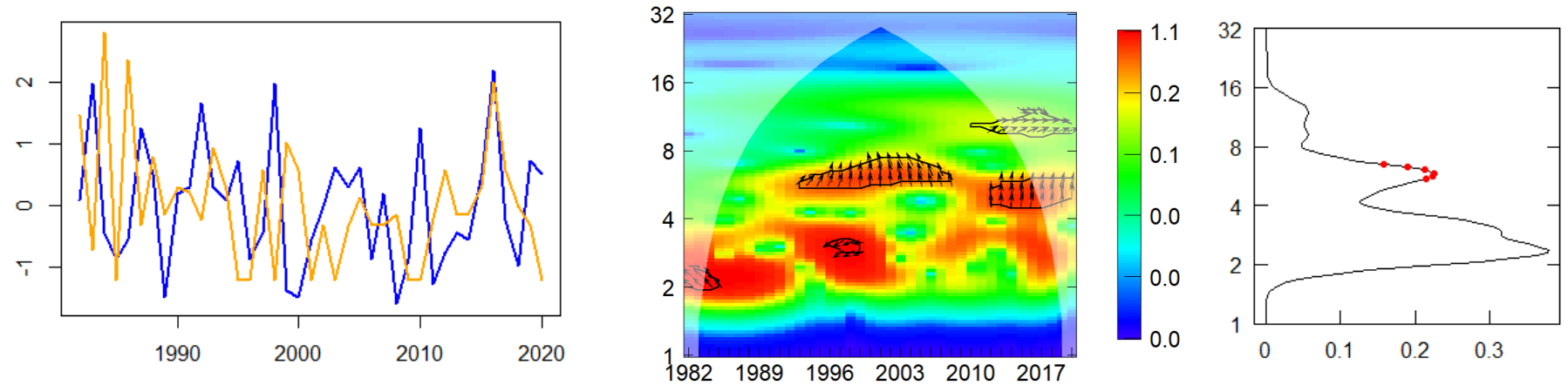
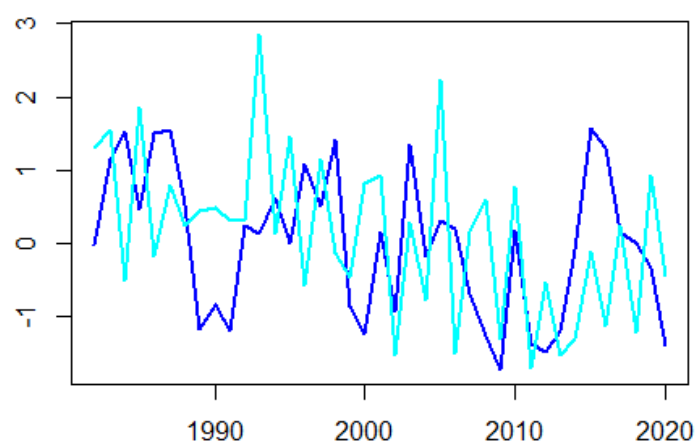
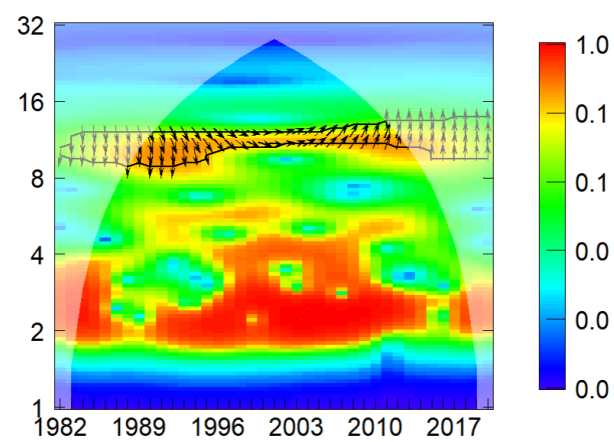
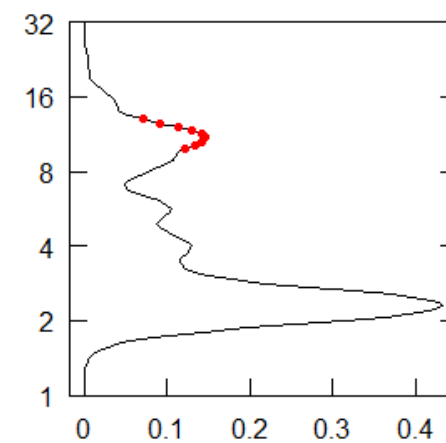


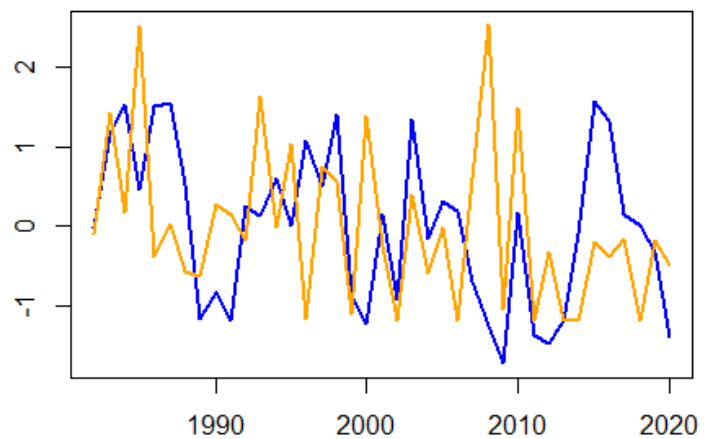
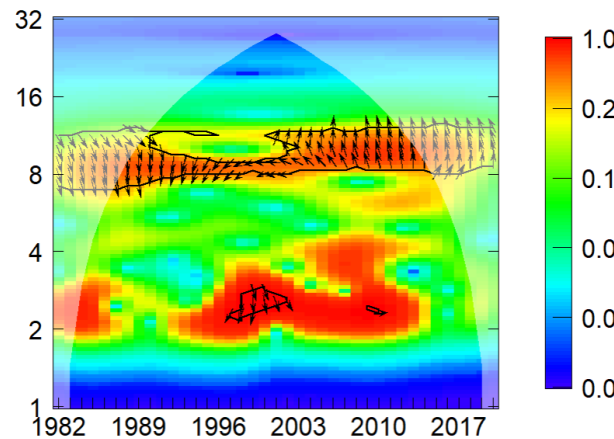
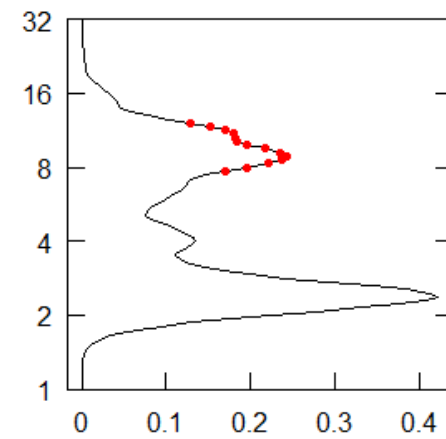
Figure 4-5. Plots of standardized annual time series and wavelet coherence analyses using standardized values of ENSO, precipitation and SS dynamics (Site C, JFM): The thick black lines in the wavelet coherence result (Mid) shows periodicities with statistical significance (<0.05). The red dots from the average power curves (Right) shows p values (<0.05).

The wavelet coherence analysis results between PDO and SS dynamics indicators at Site C in JFM show a strong 8 to 12 year periodicities (Figure 4-6). Varying periodicities from frequency indicators were identified that 8~12 year periodicity was confirmed from D0.2, led by D0.2 from 1990s to 2000s (Figure 4-6, c). Similar 8~12 year in-phase relationship (PDO leading) was also identified from Cofe0.2 (Figure 4-6, d). P.p.e0.6 also had 8~12 year in-phase (PDO leading) relationships with PDO from late 1990s to mid 00s (Figure 4-6, e). However, P.p.e0.2 had rather a complex 9-year periodicity after mid-90s (Figure 4-6, f). Those periodicities are similar to the periodicities of snowmelt flows identified in Upper Colorado region (Tamaddun *et al.*, 2017).

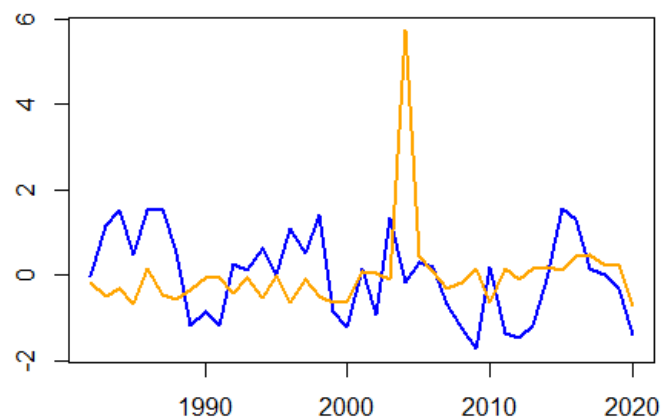
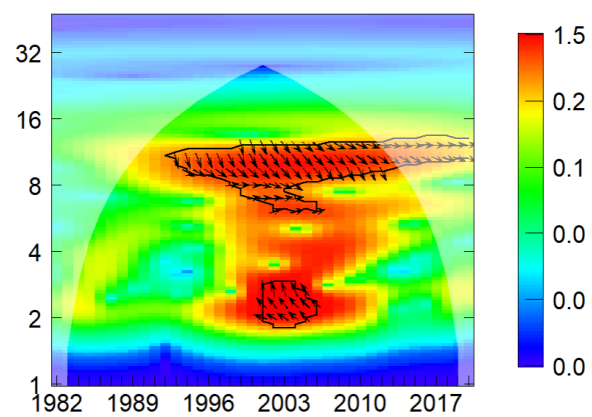
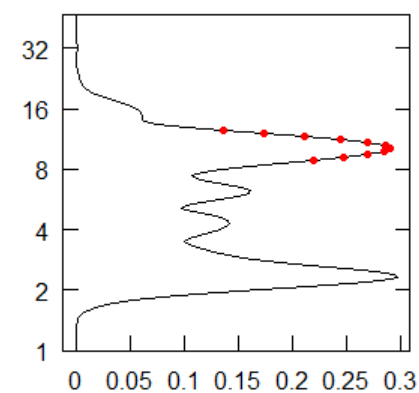
a) Precipitation



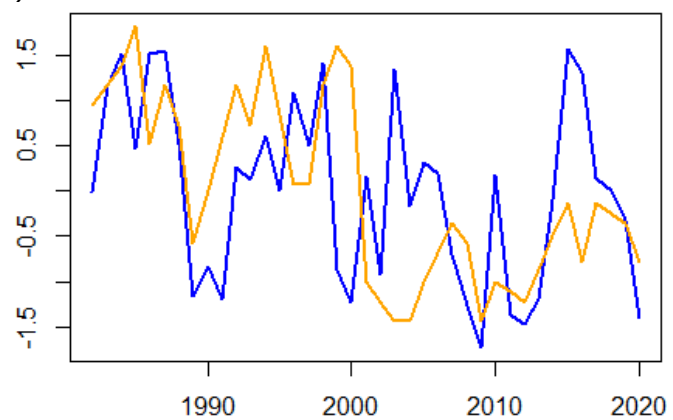
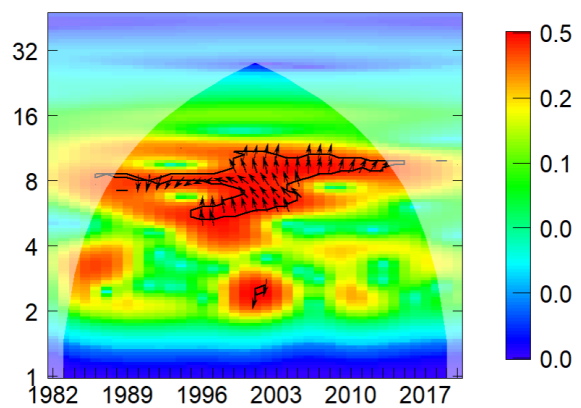
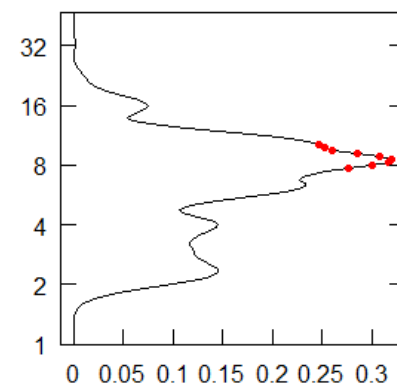
b) M95



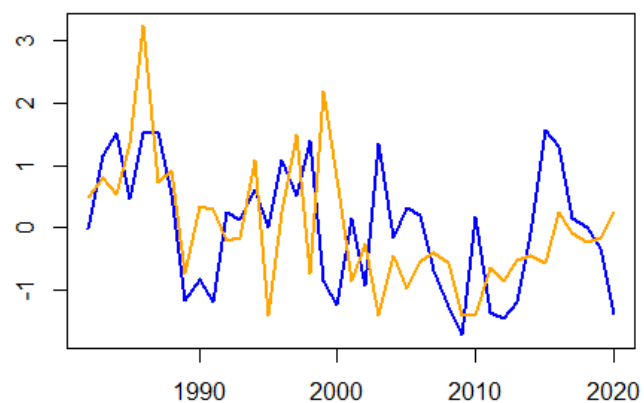
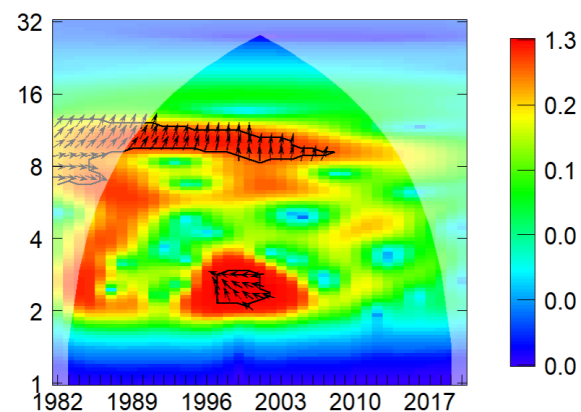
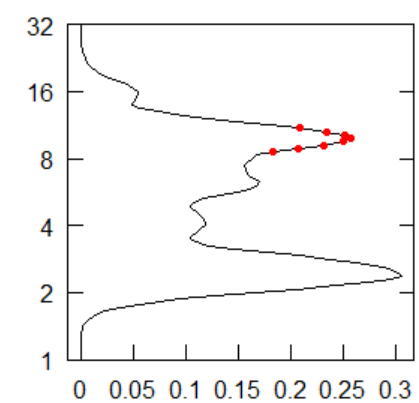
c) D0.2



d) Cofe0.2



e) P.p.e0.6



f) P.p.e0.2

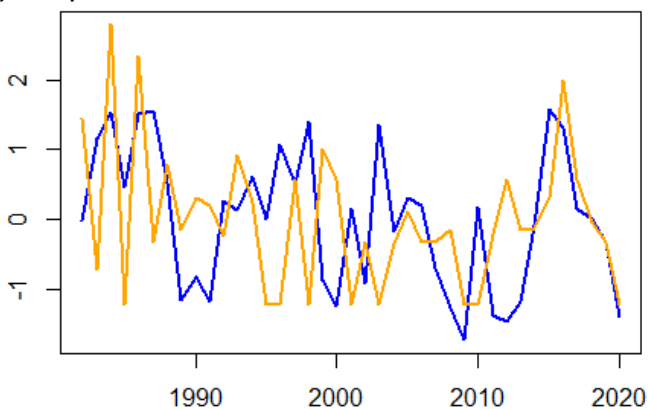
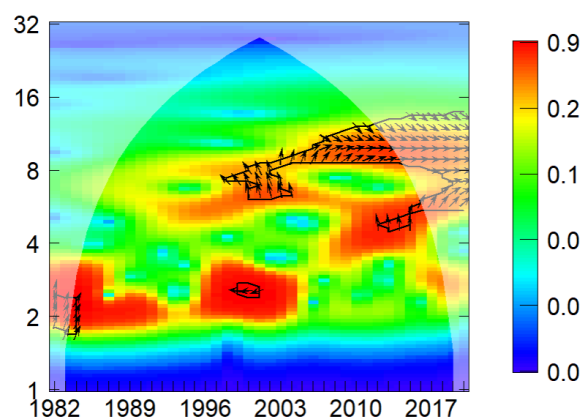
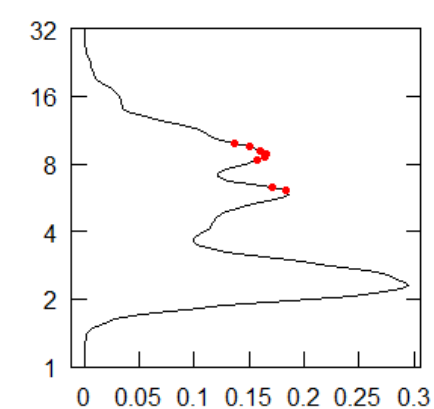
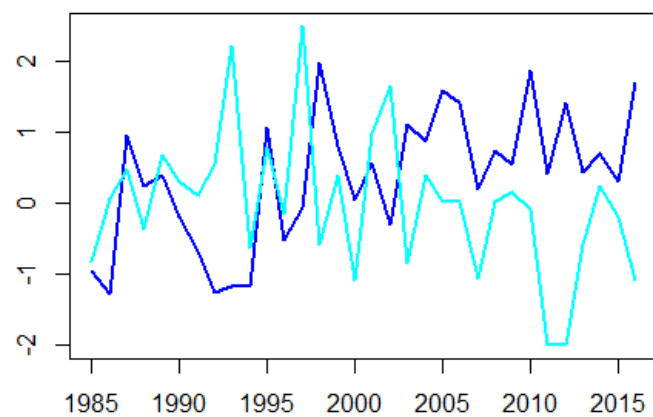
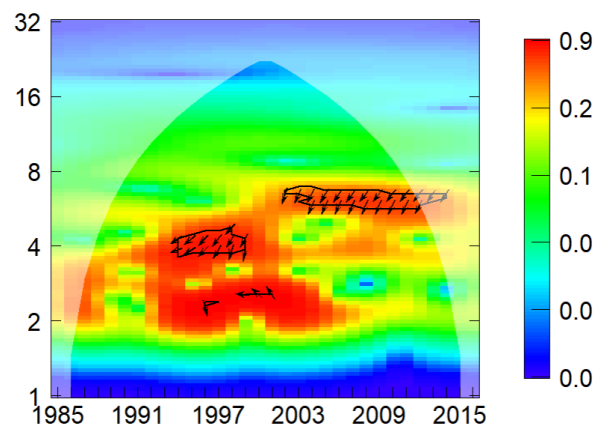
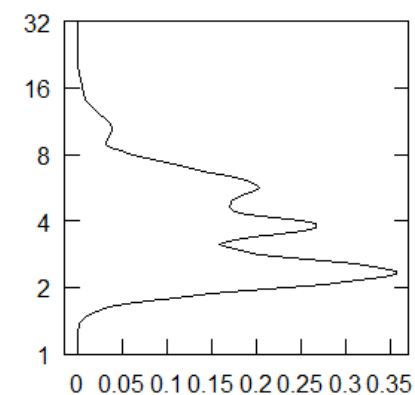


Figure 4-6. Plots of standardized annual time series and wavelet coherence analyses using standardized values of PDO, precipitation and SS dynamic indicators (Site C, JFM): The thick black lines in the wavelet coherence result (Mid) shows periodicities with statistical significance ($<.05$). The red dots from the average power curves (Right) shows p values ($<.05$).

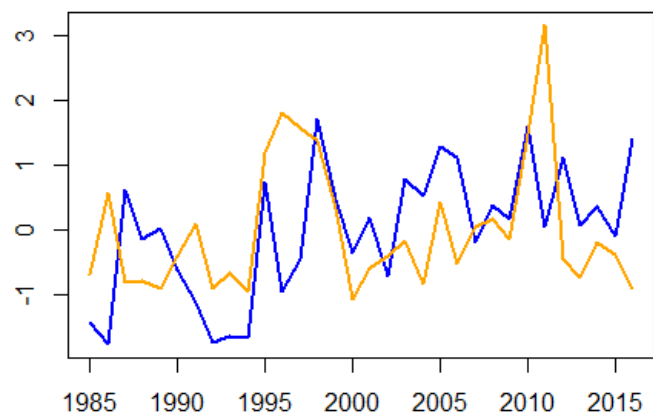
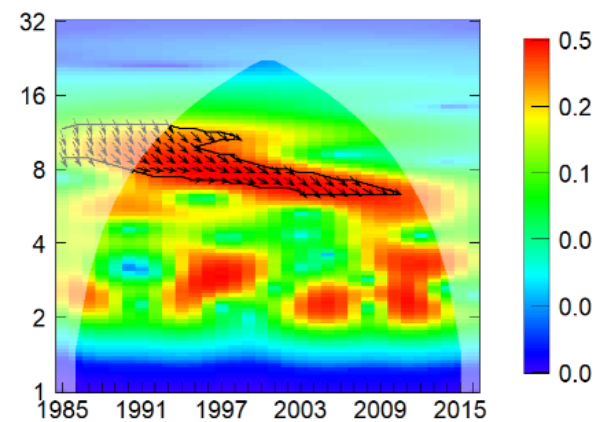
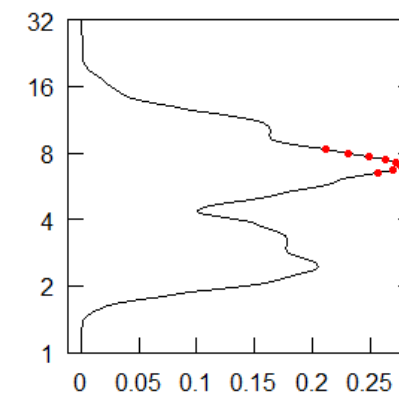
Site D

Site D received different periodicities from magnitude and frequency indicators between AMO, AO, ENSO and PDO (Figure 4-7 ~ 4-10). The cross wavelet analyses results from AMO at Site D show 8 year periodicity from magnitude and frequency indicators (D0.2, Cofe0.2, P.p.e0.6 and P.p.e0.2) as shown in Figure 4-7. There were less likely chance to yield statistically significant result from precipitation and AMO in JJA (Figure 4-7, a). However, the distinctive 8-year periodicity was identified from M95 having in-phase correlation (Figure 4-7, b). The standardized time series (Left) shows similar trends between AMO and SS magnitudes. D0.2 (JJA) shows a lagging relationship with AMO from mid 1990s to early 2000s (Figure 4-7, c). Cofe0.2 showed 8~9 year periodicity in 1990s (Figure 4-7, d). P.p.e0.6 had 9 to 14 year periodicity with a transition from AMO leading to P.p.e0.6 leading (Figure 4-7, e). P.p.e0.2 yielded similar periodicity but, in-phase, P.p.e0.2 leading correlation was identified from late 1980s to early 2000s (Figure 4-7, f).

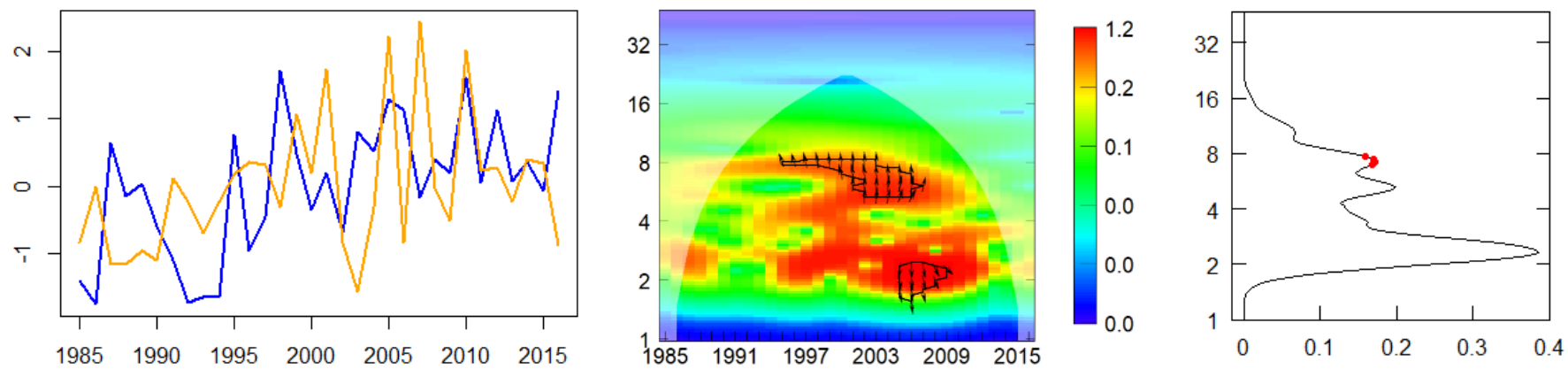
a) Precipitation



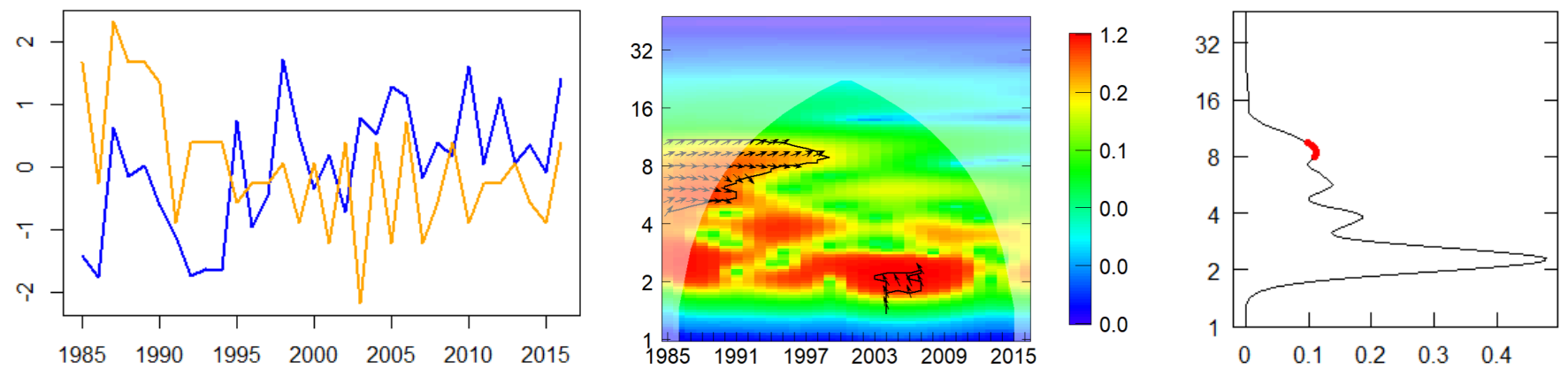
b) M95



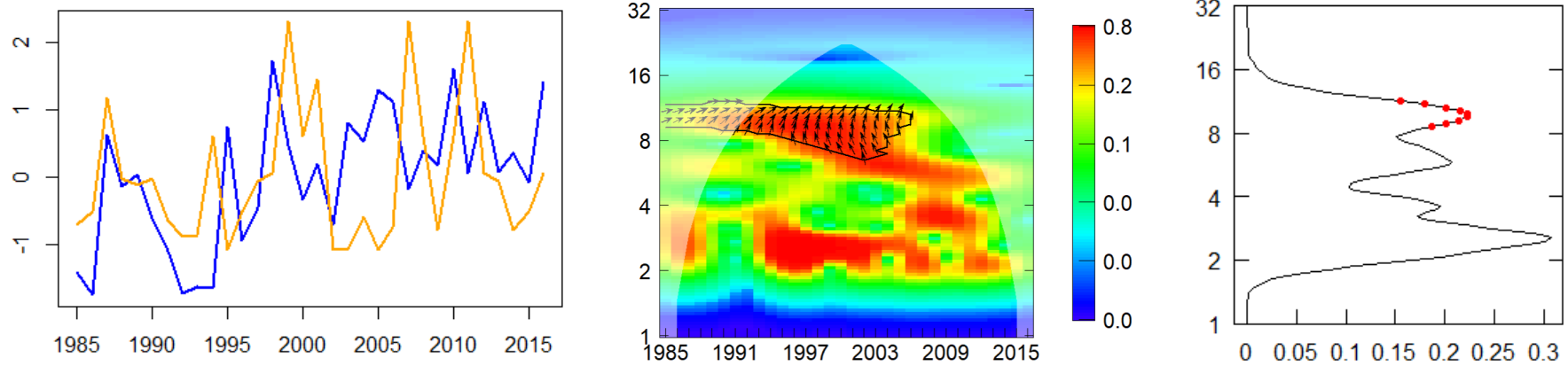
c) D0.2



d) Cofe0.2



e) P.p.e0.6



f) P.p.e0.2

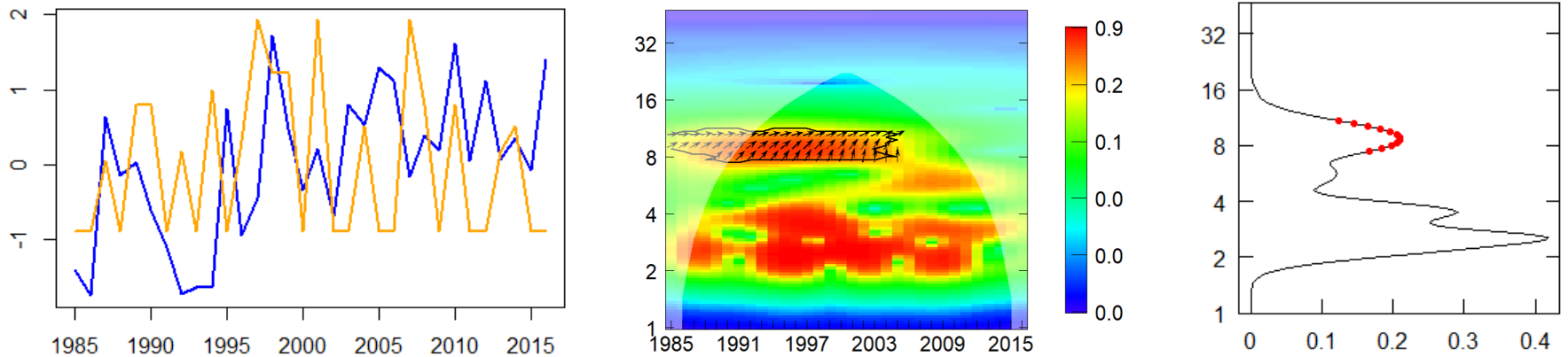
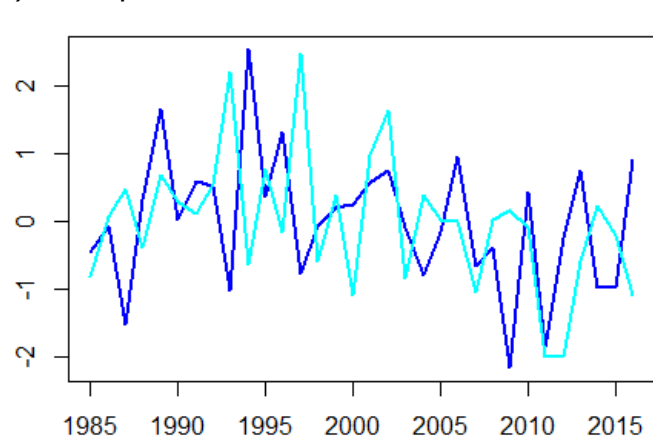
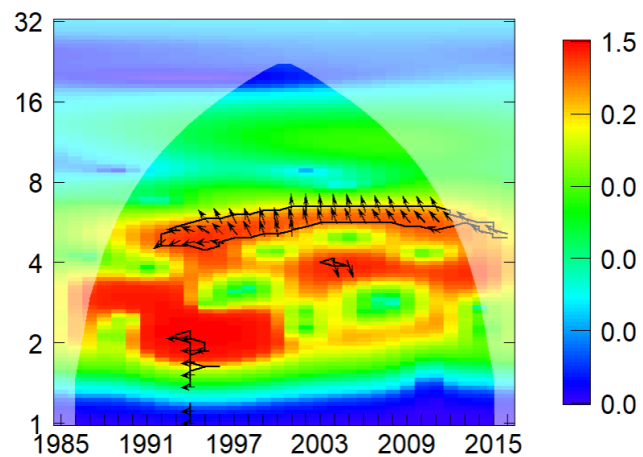
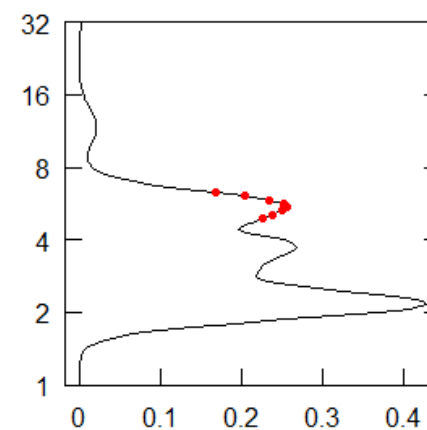


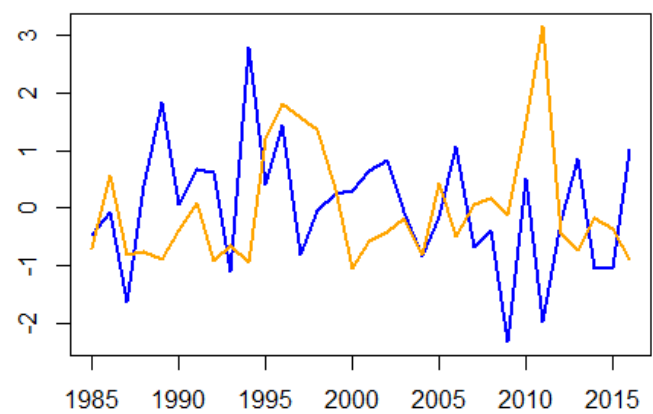
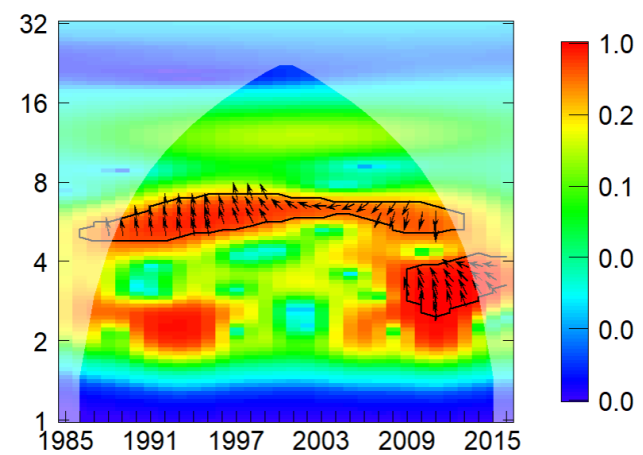
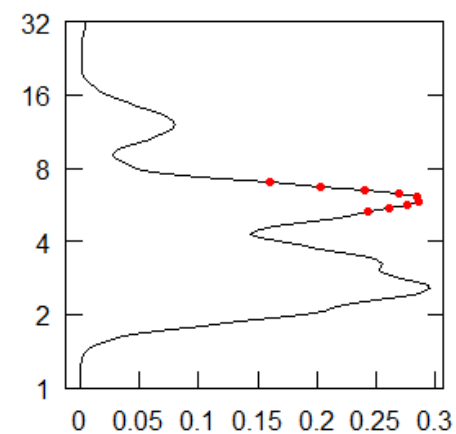
Figure 4-7. Plots of standardized annual time series and wavelet coherence analyses using standardized values of AMO, precipitation and SS dynamics (Site D, JJA): The thick black lines in the wavelet coherence result (Mid) shows periodicities with statistical significance ($<.05$). The red dots from the average power curves (Right) shows p values ($<.05$).

The cross wavelet analyses results between AO (JJA) and SS dynamics in Site D show that 5~6 year periodicity with out of phase correlation between precipitation and AO (JJA), as shown in Figure 4-8. The 5~6 year periodicity (Tamaddun *et al.*, 2019) was also identified from M95 with lagging correlations (Figure 4-8, b). However, D0.2 had in-phase correlation with D0.2 leading (Figure 4-8, c). Similar to the periodicity identified between AO and precipitation in JJA, Cofe0.2 shows 5~6 year periodicity with Cofe0.2 leading correlation in 1990s (Figure 4-8, d). P.p.e0.6 had in phase correlation (P.p.e0.6 leading) with AO from mid 1990s to 2000s (Figure 4-8, e).

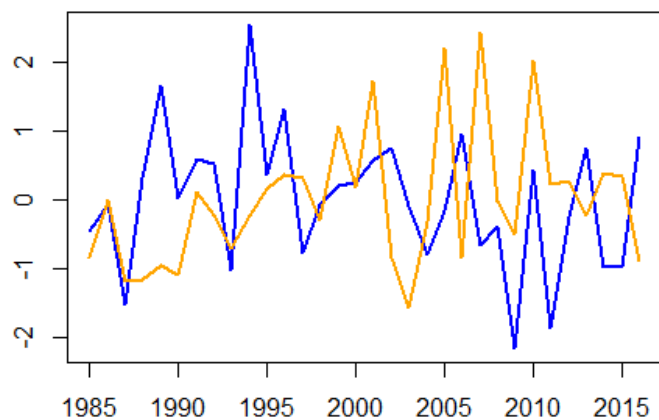
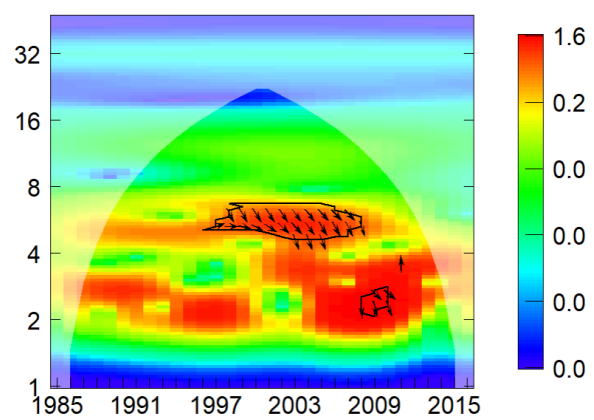
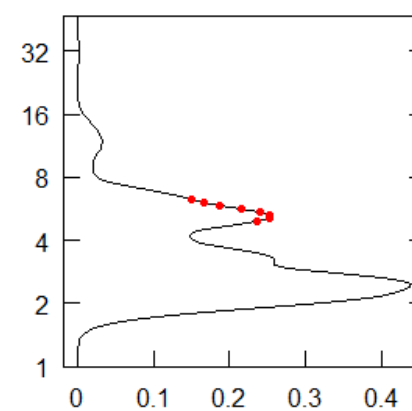
a) Precipitation



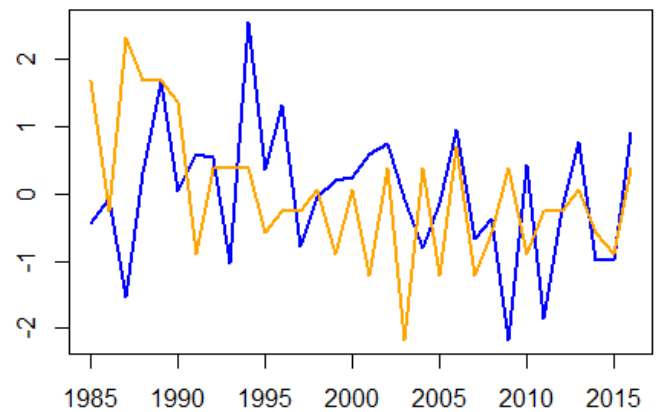
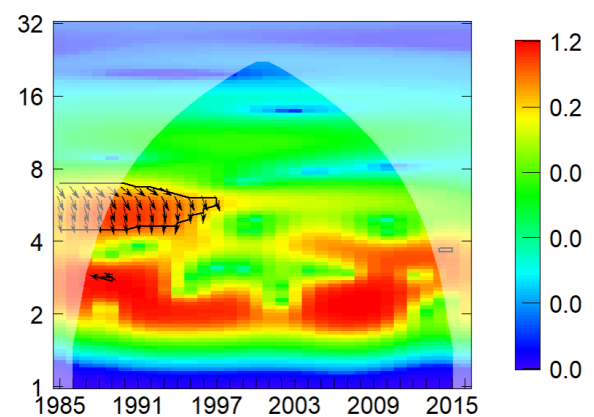
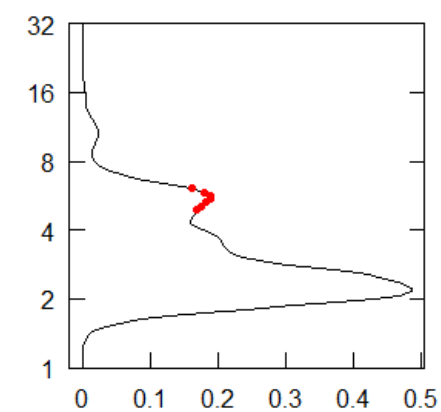
b) M95



c) D0.2



d) Cofe0.2



e) P.p.e0.6

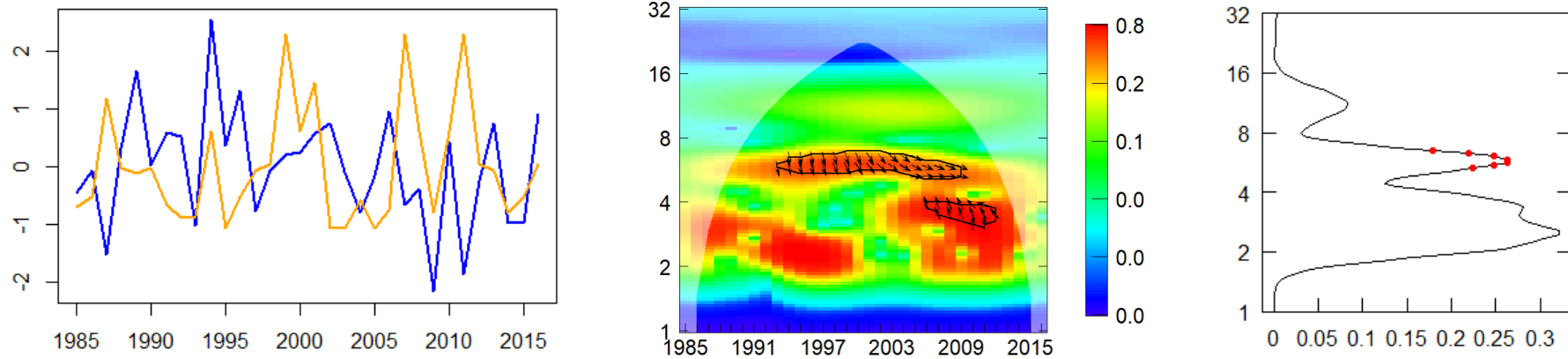
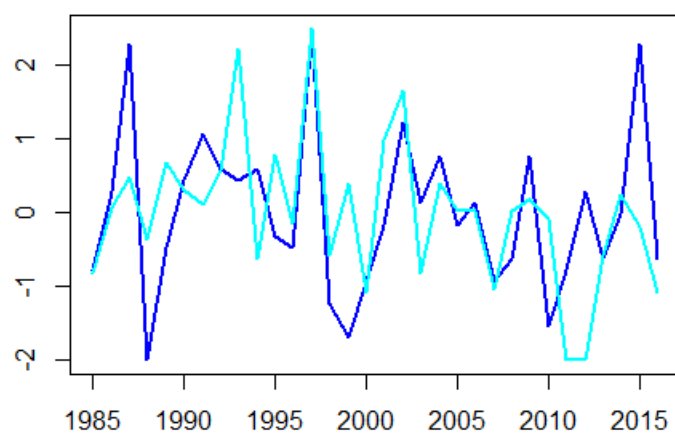
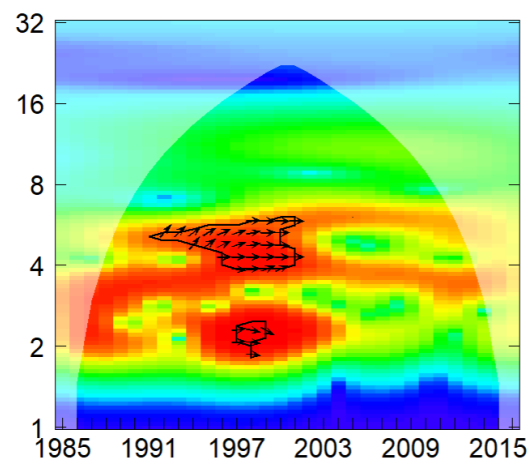
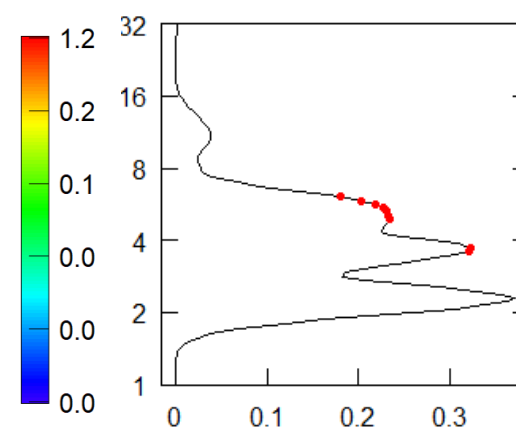


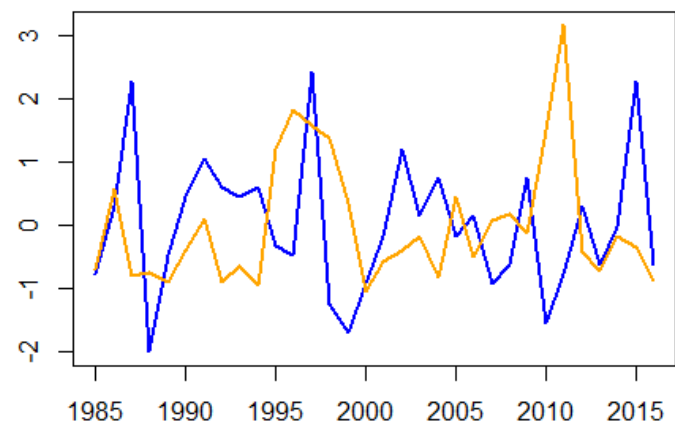
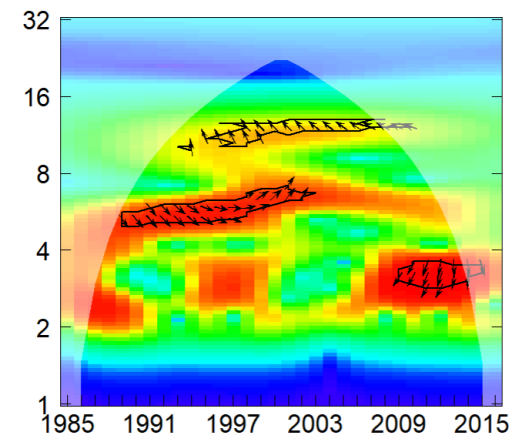
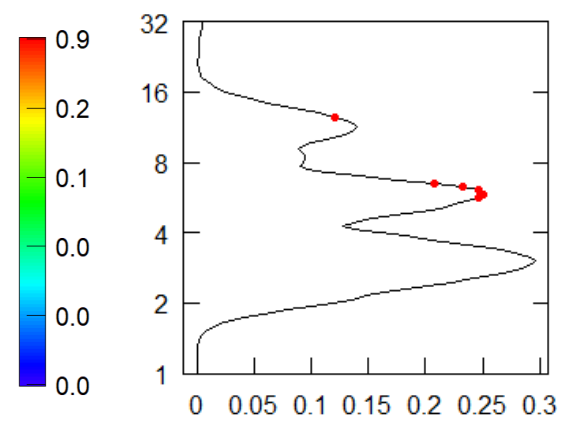
Figure 4-8. Plots of standardized annual time series and wavelet coherence analyses using standardized values of AO, precipitation and SS dynamics (Site D, JJA): The thick black lines in the wavelet coherence result (Mid) shows periodicities with statistical significance ($<.05$). The red dots from the average power curves (Right) shows p values ($<.05$).

The cross wavelet analysis between ENSO and SS dynamics (JJA) shows 5 ~ 6 year periodicities and occasionally 9~14 year periodicities (Figure 4-9). From M95, a transition of leading status was identified between 1980s and 1990s, ENSO was leading M95 in 1980s but an opposite direction was identified from 1990s (Figure 4-9, b). D0.2 received out of phase correlation (led by ENSO) with 5~6 year periodicities from late 1990s to early 2000s (Figure 4-9, c). Cofe0.2 also had the out of phase correlation, but it was led by Cofe0.2 (Figure 4-9, d). P.p.e0.6 and P.p.e0.2 had 9~15 year periodicity with ENSO leading out of phase correlation from 1990s to 2000s but with less wavelet power (Figure 4-9, e,f).

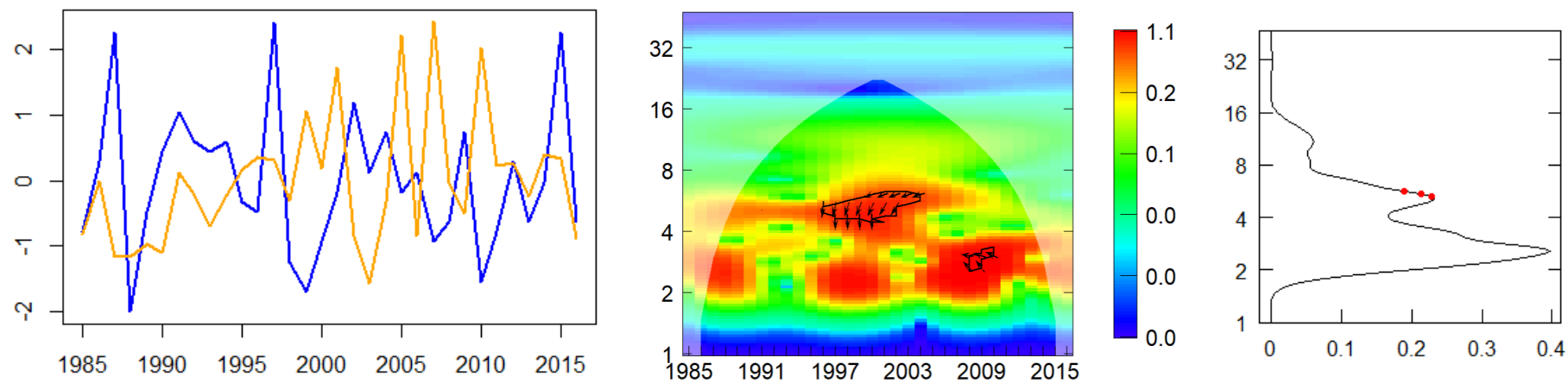
a) Precipitation



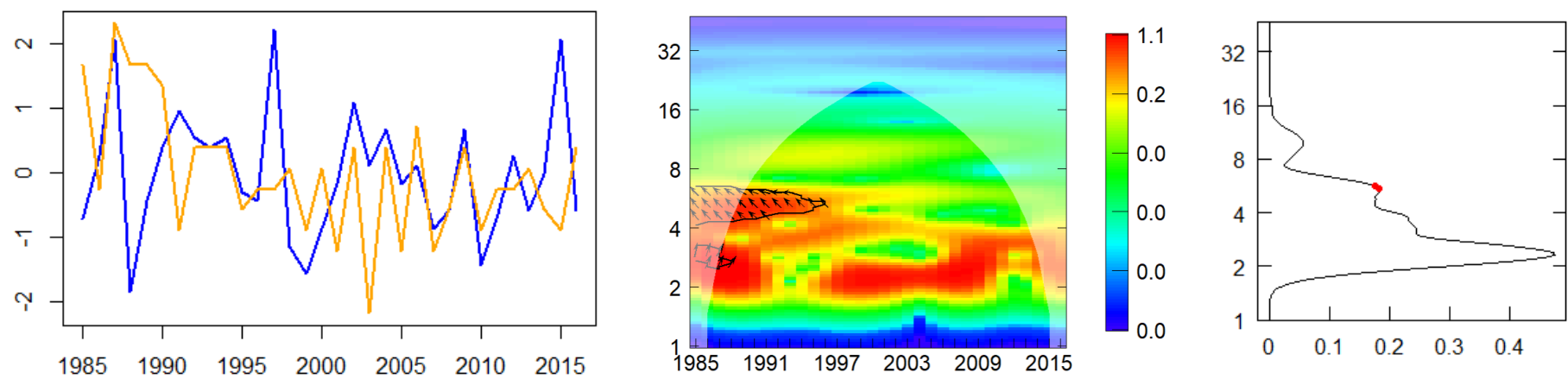
b) M95



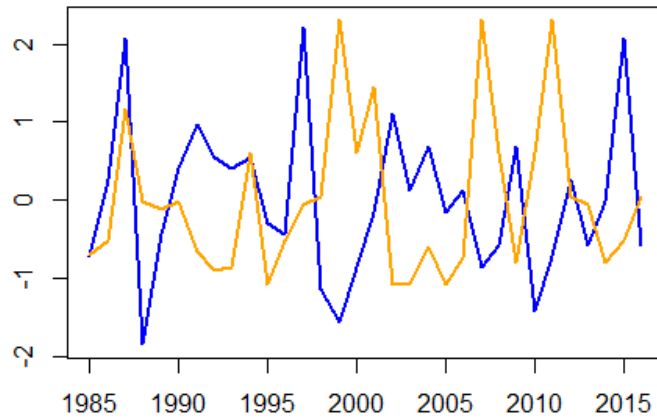
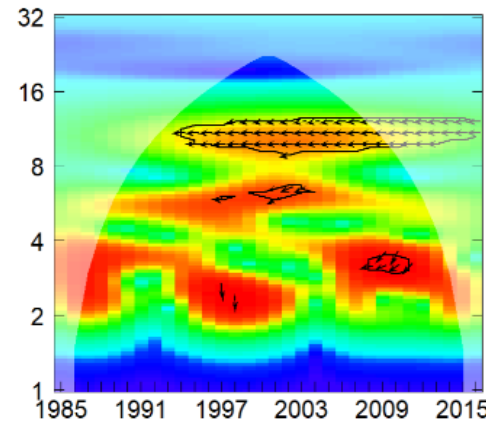
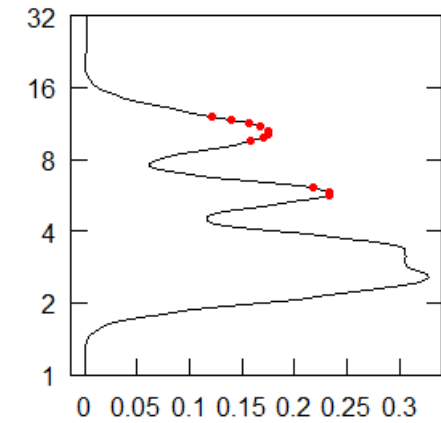
c) D0.2



d) Cofe0.2



e) P.p.e0.6



f) P.p.e0.2

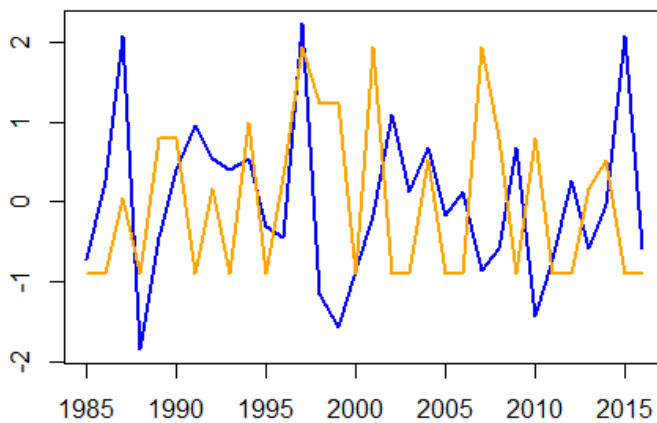
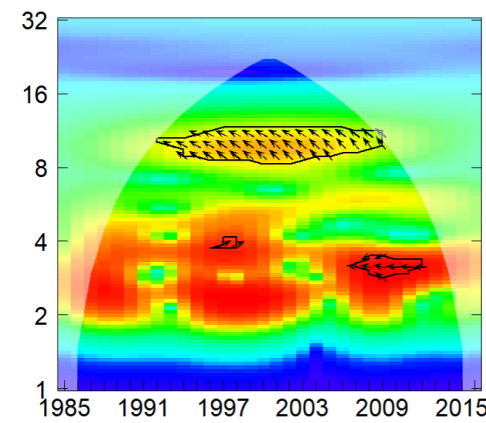
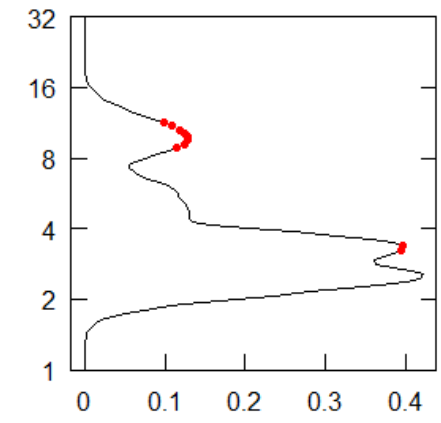
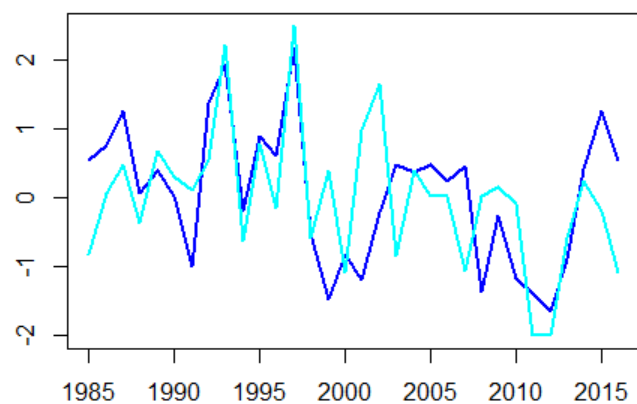
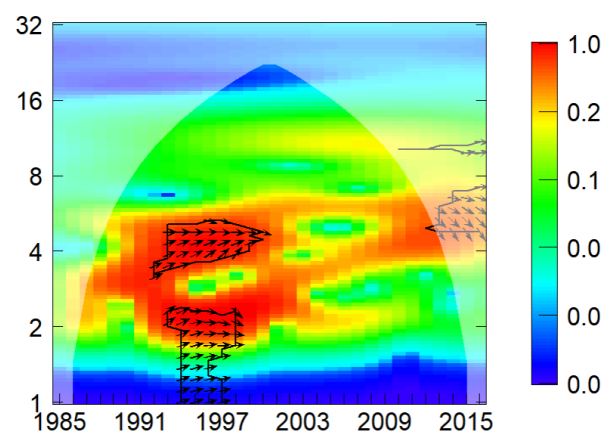
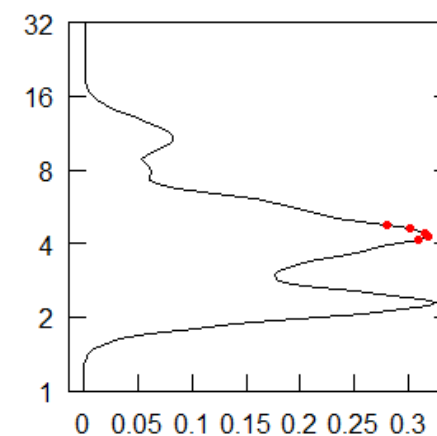


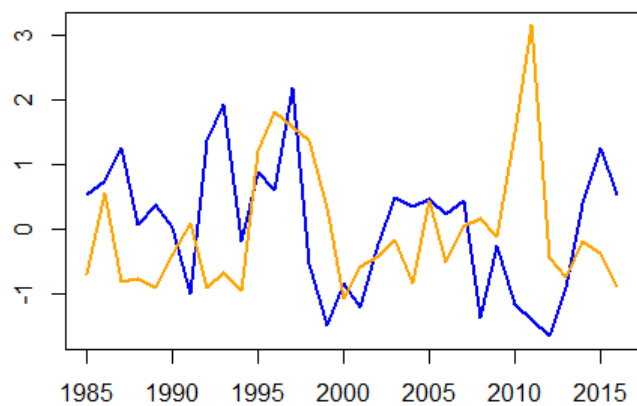
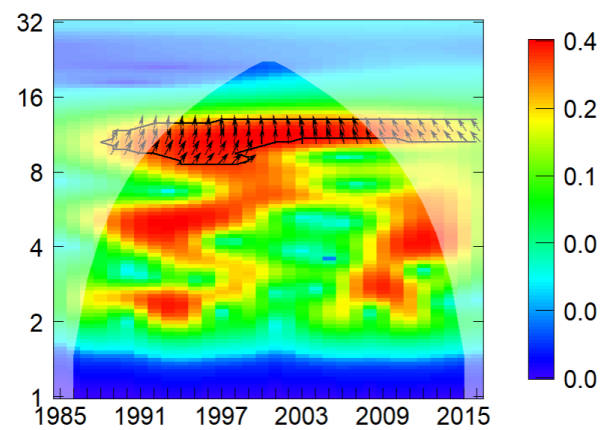
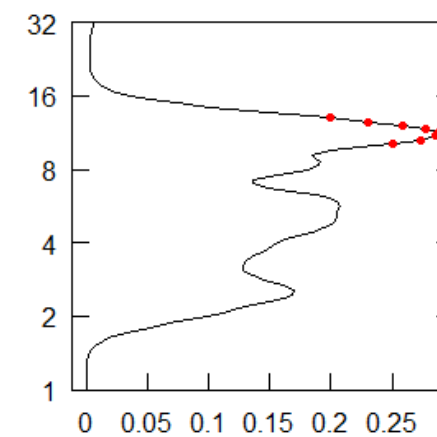
Figure 4-9. Plots of standardized annual time series and wavelet coherence analyses using standardized values of ENSO, precipitation and SS dynamics (Site D, JJA): The thick black lines in the wavelet coherence result (Mid) shows periodicities with statistical significance ($<.05$). The red dots from the average power curves (Right) shows p values ($<.05$).

The correlation with PDO showed 9~15 year periodicities from SS dynamics (Figure 4-10). Precipitation had 5 year in-phase correlation with PDO in 1990s (Figure 4-10, a). 9~15 year periodicity was identified from M95, and a transition of in phase to the out of phase relationship was identified from 1990s to 2000s (Figure 4-10, b). In terms of frequency indicators e.g., D0.2, P.p.e0.6 and 0.2 (Figure 4-10, c,d,e), SS leading relationships were identified.

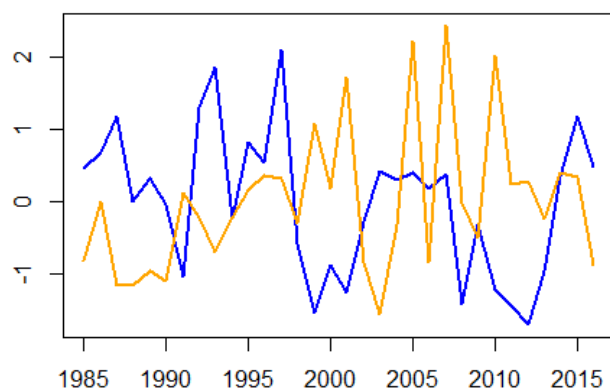
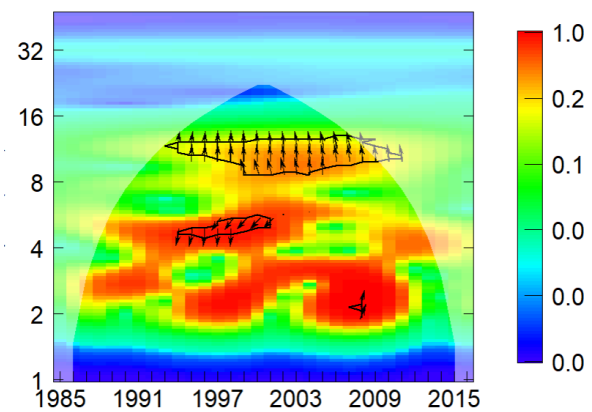
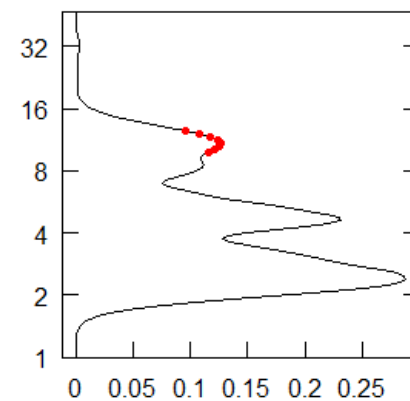
a) Precipitation



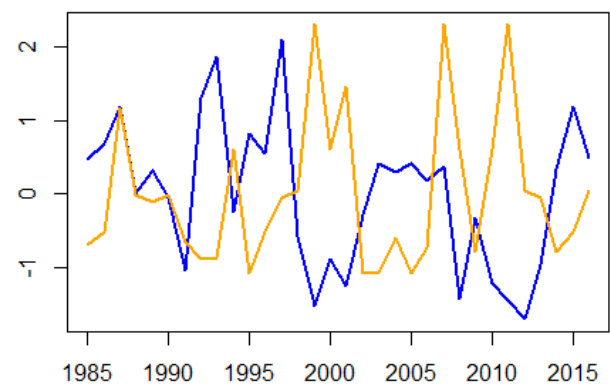
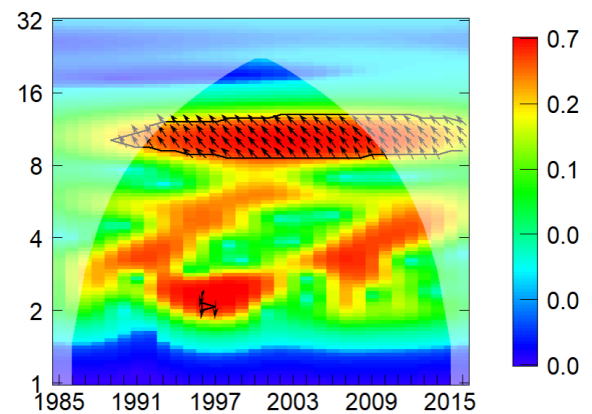
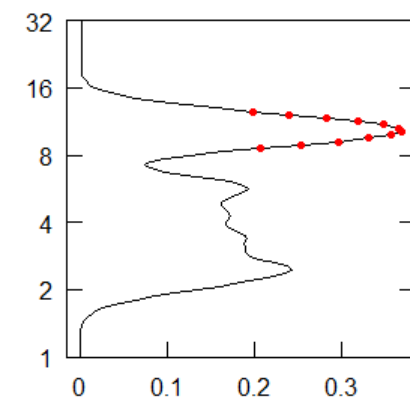
b) M95



c) D0.2



d) P.p.e0.6



e) P.p.e0.2

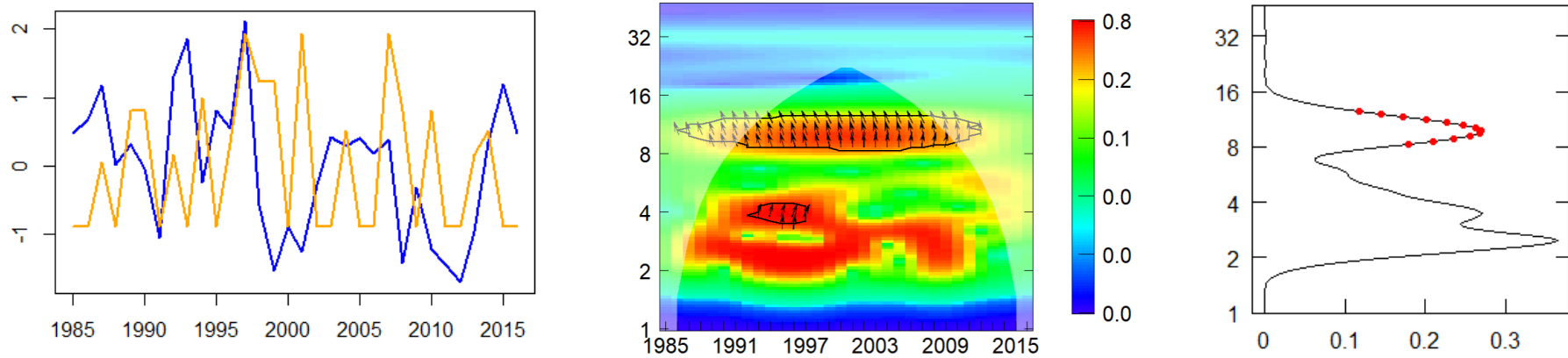


Figure 4-10. Plots of standardized annual time series and wavelet coherence analyses using standardized values of PDO, precipitation and SS dynamic indicators (Site D, JJA): The thick black lines in the wavelet coherence result (Mid) shows periodicities with statistical significance ($<.05$). The red dots from the average power curves (Right) shows p values ($<.05$).

4.5 Discussion

Warm and cold phases of climate oscillations either positively or negatively affected SS dynamics by change of atmospheric pressure (Figure 4-3~4-10). Those incorporate the element of the climatic variability, especially in association with impact of precipitation, which influenced rainfall erodibility. Identifying efficacy of climate oscillations serves as a baseline to link with other elements in climatic cycles. The analyses implemented filtered out impact of climate to SS dynamics in magnitude and frequency from highly complex responses of sensitive LULC. There were a case that the cross wavelet between ENSO and extreme precipitation are correlated (Wang *et al.*, 2022). However, most of comparable periodicities are identified from rainfall erosivity from literature.

Climate oscillations impacts on precipitation and short-term SS dynamics were identified over US continent. North (Summer) and South (Winter) found random periodicities from the selected climate oscillations. In winter cases, NAO yielded overall 8 year periodicities. ENSO and PDO yielded decadal periodicities. In summer cases, AMO yielded decadal to multi decadal periodicities. AO yielded 6 year periodicity. ENSO yielded 5 year periodicities but PDO yielded decadal periodicities. ENSO and PDO yielded more leading cases than other climate oscillations. Especially, summer cases of ENSO in negative phases are strongly influential to SS frequencies (Table 4-1).

Table 4-1. Climate oscillation impact on precipitation and SS dynamics to link with positive / negative phases of climate oscillations: Led by climate oscillation status either positively or negatively provides a proxy for occurrence of SS dynamics in the next year of the same season (Habib *et al.*, 2021). Then, convergence of the leading status into the warm (+) or cold (-) phases of climate oscillations are used to precisely list the impact of the climate oscillations (Xu, 2021).

Site	Climate Oscillations	Precipitation	M95	D0.2	Cofe0.2	P.p.e0.6	P.p.e0.2	Phase change
A (DJFM)	NAO	N/A	<ul style="list-style-type: none"> 8 year M95 leading 	<ul style="list-style-type: none"> 6~9 year NAO leading positively ('60s) to D0.2 leading ('70s~'80s) 	<ul style="list-style-type: none"> 8 year Cofe0.2 leading (70s and 90s) 	<ul style="list-style-type: none"> 8 year P.p.e0.6 leading to NAO leading 	<ul style="list-style-type: none"> 8~9 year NAO leading negatively (Late '60s) to P.p.e0.2 leading ('70s~'80s) 	<ul style="list-style-type: none"> '60s in negative phase
B (JJA)	AMO	<ul style="list-style-type: none"> 8~12 year Precipitation leading 	<ul style="list-style-type: none"> 8 to 14 year AMO leading positively ('70s~'90s) 	N/A	<ul style="list-style-type: none"> 20 to 25 year Cofe0.2 leading by 90 degree but with less wavelet power 	<ul style="list-style-type: none"> 8 year AMO leading positively (Late '70s ~ '80s) 	<ul style="list-style-type: none"> 8 year Synchronous to P.p.e0.2 leading 	<ul style="list-style-type: none"> '70s ~ Early '90s in negative phase
C (JFM)	ENSO	<ul style="list-style-type: none"> 8 year ENSO leading positively (Low wavelet power, '80s~mid '00s) 	<ul style="list-style-type: none"> 12 year ENSO to M95 leading (Low wavelet power) 	<ul style="list-style-type: none"> 12 year D0.2 leading 	<ul style="list-style-type: none"> 8 year Cofe0.2 leading 	<ul style="list-style-type: none"> 12 year P.p.e0.6 leading (Less wavelet power) 	<ul style="list-style-type: none"> 6 year ENSO leading positively ('90s) to P.p.e0.2 leading ('00s) 	<ul style="list-style-type: none"> 3~4 year fluctuation of +/-
	PDO	<ul style="list-style-type: none"> 9~12 year Precipitation leading to PDO leading 	<ul style="list-style-type: none"> 8~13 year PDO leading negatively ('90s) to M95 leading ('00s~'10s) 	<ul style="list-style-type: none"> 8~12 year D0.2 leading 	<ul style="list-style-type: none"> 8~12 year PDO leading positively (Late '90s ~ Early '10s) 	<ul style="list-style-type: none"> 8~12 year PDO leading positively (Late '80s to late '00s) 	<ul style="list-style-type: none"> 6 year P.p.e0.2 leading to PDO leading 8~11 year Both PDO positively (Mid '00s) and P.p.e0.2 leading to synchronous 	<ul style="list-style-type: none"> '90s in positive phase Late '90s ~ Early '10s in negative (Mostly) Mid '00s in positive phase
D (JJA)	AMO	N/A	<ul style="list-style-type: none"> 8 year M95 leading 	<ul style="list-style-type: none"> 8 year D0.2 leading 	<ul style="list-style-type: none"> 8 year Cofe0.2 leading 	<ul style="list-style-type: none"> 8~12 year AMO leading positively ('90s) 	<ul style="list-style-type: none"> 8~12 year AMO leading positively ('90s ~ mid '00s) 	<ul style="list-style-type: none"> Early '90s in negative phase + to – from 90s to mid 00s
	AO	<ul style="list-style-type: none"> 6~7 year AO leading negatively (Early '90s) to Precipitation leading 	<ul style="list-style-type: none"> 5~7 year M95 leading to AO leading 	<ul style="list-style-type: none"> 5~7 year D0.2 leading 	<ul style="list-style-type: none"> 5~7 year Cofe0.2 leading 	<ul style="list-style-type: none"> 6~7 year P.p.e0.6 leading 	N/A	<ul style="list-style-type: none"> Late '80s to mid '90s in positive phase (Mostly)
	ENSO	<ul style="list-style-type: none"> 4 year ENSO leading positively (Mid '90s ~ Early '00s) 5~7 year ENSO leading positively ('90s ~ Early '00s) 	<ul style="list-style-type: none"> 6~7 year M95 leading to ENSO leading positively 12 year M95 leading (less wavelet power) 	<ul style="list-style-type: none"> 6 year ENSO leading negatively (Late '90s) 	<ul style="list-style-type: none"> 6~7 year Cofe0.2 leading negatively (Early '90s ~ Mid '90s) 	<ul style="list-style-type: none"> 6 year ENSO leading negatively (Early '00s) 9~13 year Synchronous 	<ul style="list-style-type: none"> 4 year ENSO leading negatively (Late '90s) 9~12 year P.p.e0.2 leading (less wavelet power) 	<ul style="list-style-type: none"> Mid '90s ~ Early '00s in negative phase Late '90s in negative phase
	PDO	<ul style="list-style-type: none"> 5 year PDO leading positively ('90s) 	<ul style="list-style-type: none"> 9~15 year PDO leading positively ('90s) to M95 leading 	<ul style="list-style-type: none"> 10~13 year D0.2 leading 	N/A	<ul style="list-style-type: none"> 9~15 year P.p.e0.6 leading 	<ul style="list-style-type: none"> 8~15 year P.p.e0.2 leading 	<ul style="list-style-type: none"> '90s in positive phase

8 year periodicity was identified from NAO at Site A (Nalley *et al.*, 2016). NAO-influenced D0.2 and P.p.e0.2 for DJFM. NAO- were positively associated with D0.2 but negatively with P.p.e0.2 due to negative interaction with precipitation. Despite the lack of literature available, a study about wind erosion in China was compared with erosivity. It identified decadal periodicity with NAO, which is close to the periodicity identified from this site (Wang *et al.*, 2022). NAO influences in the northeastern US were prevalent in both summer and winter cases between positive and negative phases (Coleman and Budikova, 2013). However, NAO- in DJFM as identified in 60s in Table 4-1 is not associated with rainfall events in eastern US (Al and Iyyer, 2008; Whan and Zwiers, 2017). Therefore, it might be due to correlation with snowfall (Chartrand and Pausata, 2020) and subsequent eroding power of snow melt runoff over the agricultural lands (Aygün and Kinnard, 2021).

8 year periodicity was identified with positively leading cases of AMO at Site B (JJA). The positive impacts were dominant in M95 and P.p.e0.6 (Table 4-1). Both dynamics indicators received different periodicities. M95 received decadal periodicity (8~14 year). P.p.e0.6 received inter decadal periodicity of 8 year. Both indicators had similar period from 70s to 90s, which is in negative phase of AMO. Thus, AMO- was associated with increasing M95 and P.p.e0.6 at Site B. Those may be consequences of the occurrence of maximum precipitation in summer from Maumee River basin. With evidence that this watershed is known for flashness and large amounts of suspended sediment (Schmidt *et al.*, 2020). However, it may not be solely driven by climate that the site also has more land use consequences, e.g., clay and forest covers, observed after winter months (Stow *et al.*, 2015). There were lack of literature about AMO and sediment transport, but high correlation exist between AMO and AO (Hamouda *et al.*, 2021). Therefore, as an example, AO had 6 year periodicity from rainfall erosivity over China (Zhang *et al.*, 2022), which partially supports the findings from this watershed.

The winter cases uniquely influenced SS dynamics, especially frequencies from PDO and ENSO over Site C (JFM) in Table 4-1. ENSO had near decadal

periodicity. The periodicities, positively led by ENSO were identified in precipitation and P.p.e0.2 in 90s. ENSO without precise division of positive or negative phases (+/-) were positively associated with precipitation (Polade *et al.*, 2013; Nergui *et al.*, 2016; Stahle *et al.*, 2020) and P.p.e0.2 at Site C in winter. A number of decadal relationships between rainfall erosivity and ENSO were identified in different corners on Earth, e.g., 9~10 year in Bangladesh (Reza *et al.*, 2023) and China (Xu *et al.*, 2021; Cui *et al.*, 2021). ENSO in winter is modulated by PDO over North America (Maher *et al.*, 2022). PDO had clear decadal periodicity over the frequency indicators (Cofe0.2, P.p.e0.6 and 0.2). The impact is positive especially in 2000s, and this period is in a negative phase of PDO. Thus, PDO+ was positively associated with P.p.e0.2, and PDO- was also positive to Cofe0.2 and P.p.e0.6 at this watershed. However, PDO+ was negative to M95. It is all part of climate cycles well represented in the streamflows, in conjunction with ENSO and PDO in Western US (Tamaddun *et al.*, 2017). These findings, especially the impact on the frequency indicators are supported by the fact that this region of the arid Colorado region in Southwest receives impact of winter precipitation bias, observed in multi-year scales (Pierce *et al.*, 2022). The increasing relationships were also driven by the fact that there is more erodibility in Arroyo region near Rio Puerco Abv Arroyo Chico NR Guadalupe station (Gellis *et al.*, 2012).

Due to its geographical position, impact from the largest number of climate oscillations were identified at Site D (JJA), but leading cases were mostly dominant with ENSO and AMO (Table 4-1). Inter and intra decadal periodicities were identified at this watershed. From P.p.e0.6 & 0.2, AMO leading cases were visible in 90s, and early 90s of AMO is in a negative phase (Figure 4-2). Regardless of phase changes, AMO was positively associated with P.p.e0.6 and 0.2 (Figure 4-7). A high correlation exists between AMO and AO (Hamouda *et al.*, 2021). AO+ (Figure 4-2) was negative to summer precipitation but not leading to SS dynamics (Figure 4-8 & Table 4-1). AO had decadal periodicity with sediment transport over China despite less significance level (Zhang *et al.*, 2022). The hydrological environment at this region will receive climate change effects

(Chase *et al.*, 2016), and the climate of western US is known to be correlated with AMO (Pathak *et al.*, 2018).

Varying impacts of increasing or decreasing impacts from ENSO and PDO were identified from Site D. ENSO had inter decadal periodicities e.g., 5~6 year. Negatively leading SS frequencies (D0.2, P.p.e 0.6 and 0.2) were identified especially over 90s (Table 4-1). Mid to late 90s is in the negative phase. Thus, positive association between ENSO- and precipitation was identified (Polade *et al.*, 2013; Nergui *et al.*, 2016). However, it was negative to D0.2, P.p.e 0.6 and 0.2. PDO with clear decadal periodicity is a positive leading factor of M95 in 90s. 90s is in a positive phase of PDO. Thus, PDO+ was positively associated with precipitation (Polade *et al.*, 2013) and M95. There are cases that rainfall erosivity had 4~5 year periodicity with ENSO (Xu *et al.*, 2019) and PDO (Liu *et al.*, 2018). PDO also brought a number of similar periodicities from rainfall erosivity; Site D of PDO had 9~15 year periodicity (M95, D0.2, P.p.e0.6&0.2).

ENSO and PDO both were positively associated with SS dynamics. ENSO/PDO impact over North America and their correlation is well known in the literature. Those increased or decreased the prolonged rainfall or drought (Luca *et al.*, 2020). The analyses identified impacts of climate at Site C and D that are likely due to the indirect impacts of precipitation to the distinctive processes in two sites e.g., more frequency of SS dynamics (Cofe0.2, P.p.e0.6 & 0.2). The variation of climate was detected over distinctive processes. Thus, the wavelet coherence analysis results are a combination of site attributes and local climate oscillation, but it is more likely yielded by climate. Those events driven precipitation has increased the availability of eroded material (sediment) from the locally distributed hydrological processes with more frequency (Site C: Clay and forest covers, Site D: Urban areas, forest cover and higher BFI) in winter (Shin *et al.*, 2023a). Contrastingly, summer precipitation was associated with extreme magnitude, especially over Site D, which were influenced by PDO+. Furthermore, locally distributed site attribute (Steeper topography) reacted with the precipitation.

The findings from this research detected variation of climate over distinctive processes using climate oscillations despite the limitations. The variability of climate accelerates water cycles on Earth. Sea surface patterns will also change as Earth will be warmer than now due to increasing greenhouse gas emissions. It is also predicted that anomalies of sea surface temperature including PDO will increase in the future (Oshima and Tanimoto, 2009). Therefore, further longer +/- phases of climate oscillations are expected. Accordingly, SS management requires consideration of shifts in short and long precipitation impacts in the future (Tayşi and Özger, 2022). In addition to the changes of climatic variability, jet stream impacts will be imposed in winter seasons (Site A and C) with more extreme precipitation events (Barbero *et al.*, 2019). There are limitations and uncertainties imposed, especially the number of catchments used in this research. The research used four distinctive sites without major dams. Catchment characteristics should expand more to find further sensitive layers in association with CC. Despite uses of daily SS data with limitation of flow weighting, the data preprocessing undertaken prior to wavelet analyses may have minimized possible covariance with water. The choice of seasonally aggregated SS time series e.g., JJA or DJF from literature also holds uncertainty that shorter or longer temporal scales e.g., JJ, DJFM or Apr may bring different results. Computation of lengths of periodicities from CWT and power would also have provided more accurate interpretation than visual observation including detecting positive or negative phases from climate oscillations (Cazelles *et al.*, 2008). It extends to the wavelet coherence analyses that quantification of arrow directions in accordance with wavelet power can improve accuracy of interpretation (Hairudin and Mohamad, 2024). Impact of more intense storms might need to be studied with higher frequency sub daily SSC e.g., using turbidity loggers. As there will be more turbidity data (FNU) in the future, wavelet analyses using more number of FNU sites will yield more information on periodic changes (Inamdar *et al.*, 2018). Prediction of climate oscillations also can use neural networks and support vector machines (SVMs) (Zha *et al.*, 2022).

4.6 Conclusion

The research identified exclusive climatic impacts on SS dynamics using climate oscillations, providing links with significant processes of SS drivers at four catchments with distinctively different hydrological environment over the continental US. Although there are many climate oscillations, applicable to various catchments, AMO, AO, ENSO, PDO and NAO were exclusively studied to list interpretable findings and respond to the objective of this research, understanding climate oscillations impacts on SS dynamics and tracing significant processes. There were uncertainties and limitations created by the availability of periods in data. However, climate oscillations provided evidence that climate leading cases as indirect impacts were developing than SS dynamics were following over distinctive processes.

Seasonally and locally varying impacts of climate oscillations were identified. In winter, NAO- were positively associated with D0.2 but negatively with P.p.e0.2 at Site A due to impacts of snowmelt. PDO+ was positively associated with P.p.e0.2, but PDO- was positive to Cofe0.2 and P.p.e0.6 at Site C, which is influenced by winter precipitation bias. In summer, AMO- was positively associated with M95 and P.p.e0.6 at Site B due to precipitation impact. AMO was positively associated with P.p.e0.6 and 0.2 at Site D. ENSO- was negative to D0.2, P.p.e0.6 and 0.2. PDO+ was positively associated with M95. PDO and ENSO both were positive to SS dynamics over North America. ENSO is more associated with SS in a broad term without being specified by positive or negative phases. Those associations are also indirectly affected by locally distributed SS prone factors e.g., clay and forest covers (Site C) and urban areas, forest cover and steeper topography (Site D) in Western US.

ENSO will be useful in prediction of future impacts of climate to SS generation. Climate like eastern US can take benefit from analysing NAO- and AMO-. Meanwhile, climate of western US can also use PDO- and AMO. The findings in phase changes also serve as additional baselines for reducing uncertainties, especially with direct impacts on soil erosion, but further longer positive or negative phases of climate oscillations will differentiate following the shifts in

extreme climate. The future trajectory of climate oscillations would also require consideration of longer/shorter rainfall duration due to the impact of climatic variability and jet stream influences on the continental US. The research outcomes were used in identifying regional and climatological influences from SS dynamics using the evidence provided by climate oscillations.

5 Overall Discussion

This research has increased the understanding of climate perturbations and their impacts on water cycles in association with suspended sediment transport dynamics in rivers (Ryberg and Chanut, 2022). The whole system approach with newly developed MFT indicators of SS dynamics (Roman *et al.*, 2012), despite the possible covariance existing in the SS transport systems, efficiently identified spatial and temporal boundaries of greater soil erodibility (e.g., Agri, forest and clay) and rainfall induced erosion over urban surface deposition, especially in spring and summer (Table 3-4). The identified spatio-temporal distribution of the significant processes (Figure 3-3~3-8) provides guidance on practical activities for gathering information about input parameters of models. It also draws attention to necessity of producing MFT time series at appropriate intervals due to the correlation with available processes. Creating the time series of MFT at a designated area possesses potential to link between the processes identified and SS transport dynamics in complex geographical and ecological settings for exploitation of appropriate indicators of climatic impacts. Recurring climate patterns (Climate oscillations) enabled sieving elements of climate from the time series of SS and the inherent catchment driven impact of LULC and raised possibility of linking with predictable patterns (i.e., phase changes) in the climatic oscillations (Chapter 4). The wavelet coherence analysis results were the proxy to link with the indirect impacts of SS transport as informed in the findings of Chapter 2 and 3. However, the climate oscillations may change in the future affecting SS dynamics and require better links for prediction of SS dynamics under the changing climate (Gil-alana, 2017). To ultimately discuss the research questions, the study found effective layers of significant processes, delivering SS dynamics in magnitude and frequency. Those layers are not only visible in the magnitude indicators but also frequency indicators, which can contribute to better sampling approaches, governed by spatio-temporal aspect and subsequently varying modelling approach. It is worthwhile to apply the relationships between SS dynamics and significant processes to improve SS modelling. Influences of water cycles on earth are not spatially limited to land surfaces. Despite unidentified drawbacks, efficiency and utility of MFT time series provide good

insight into improving predictability of SS transport. The overall discussion finds efficacy of the SS transport dynamics indicators for improving SS modelling accuracy. The assumption of this approach is that the patterns inherent in the climate oscillations provide baselines that are utilized to estimate future climatic influences on SS transport dynamics, which can match with the evidence listed in the preceding chapters. Climate variability from wavelet analyses were used rather than scenario based climate change impact assessment, which requires additional assumption with limitations e.g., building resilient scenarios incorporating unpredictable temperature rising rates (Baum, 2019), antecedent sea temperature rising (J. Wei *et al.*, 2016; Gonzalez *et al.*, 2022) and unpredictable ecological changes in marine environment (Walther *et al.*, 2002; Gao and Shi, 2016).

5.1 Effectiveness and utility of MFT indicators for monitoring temporal changes of SS dynamics due to non-stationary climate over the world

The SS dynamics indicators in MFT unlocked the potential of revealing complex interactions between processes and rainfall impacts (Zhou *et al.*, 2017). The MFT indicators demonstrated proven efficacy in identifying influential parameters, allowing better understandings of varying interaction between hydrological processes and SS dynamics. The identified spatio-temporal distribution of SS dynamics supports its efficacy and improved knowledge of the non-stationary impact of the climate (Figure 3-3 ~ 3-8). The knowledge from this research as a summary of SS generation environment connects with fundamental aspect about SS sources and processes from the MFT indicators in which other SS studies and methods can take benefit.

Producing seasonal time series of MFT indicators (or Monitoring) has beneficial effects on SS modelling results, especially in conjunction with identifying relevant processes. As an example, physical modelling approaches require input parameters that are spatially and seasonally varying (Pandey *et al.*, 2016), matching MFT time series and seasonal LULC changes within catchment can derive more agile modelling results e.g., intra annual fluctuation of SSC

magnitude in summer season. Such findings especially from frequency indicators can lead to subdivisions from more alpha values between α values of 0.975, 0.9, 0.6 and 0.2 despite the adequate determination of the intervals using Lyne and Hollick filtering (Figure 2-5). It further draws necessity of defining right time frames after checking sensitivity of alpha values e.g., using multi-output support vector regression (M-SVR) (Cheng *et al.*, 2019). Choosing suitable alpha values and MFT indicators can also benefit from each type of SS issues e.g., water quality, ecological or damage to infrastructure by finding relevant parameters of each unique SS generation system e.g., critical shear stress, flood event (Haddadchi and Rose, 2022), reservoir operation and peaks (Zhang *et al.*, 2022a), storage and residence/transit time (Muñoz-Arcos *et al.*, 2022) and flood and non-flood seasons (Yanjun *et al.*, 2016).

Other SS modelling types and ways to better understand SS dynamics can take benefit from the MFT time series, although mostly loads were used in modelling. Physical (Lepesqueur *et al.*, 2018) and statistical models (Ampomah *et al.*, 2020; Yermolaev, 2023) can use new insight from MFT time series, taking into account of existing non-linearity between SS and relevant processes. Delivering further accurate spatially dependant information in different timings using MFT time series can contribute to better prediction of SS after choosing right α values and relevant MFT indicators.

5.2 Climate change impacts on suspended sediment dynamics

Climate perturbations will influence SS dynamics, requiring a useful insight into better prediction (e.g., using climate oscillations). Impact of climate (e.g., precipitation) is often one of major input data for SS modelling (Mahdian *et al.*, 2023). There are significant interrelationships between LULC and CC impacts (Akbar *et al.*, 2023). Shifts in precipitation and its impacts on physical processes is the dominant impact on SS generation (Figure 5-1) (Basher *et al.*, 2020). Temperature and precipitation were closely linked indices in surface water quality study (Ryberg and Chanat, 2022). Relative humidity was used in SS studies in association with land use and hydrology (Boithias *et al.*, 2021). Thus, there will

be increasing impacts of intensity, frequency and duration of disturbances due to CC e.g., hydrological, temperature and forest fire events. These impacts of CC reach whole fluvial systems (Lacroix *et al.*, 2020). CC will impact SS generation, delivery to channels and transport in river networks. There are direct impacts e.g., rainfall intensity (Martel *et al.*, 2021) and indirect impacts e.g., vegetation growth and change (Sun *et al.*, 2022), dieback (Castellaneta *et al.*, 2022) and forest fire (Lacroix *et al.*, 2020). The separation of climate impacts (Figure 4-3 ~ 4-10) is more useful for better understanding of the direct impacts from precipitation. However, the indirect impacts on the land covers are not negligible. Above all complexity, phase changes of climate oscillations are useful for linking with climate induced changes of land covers (Schillerberg & Tian, 2020).

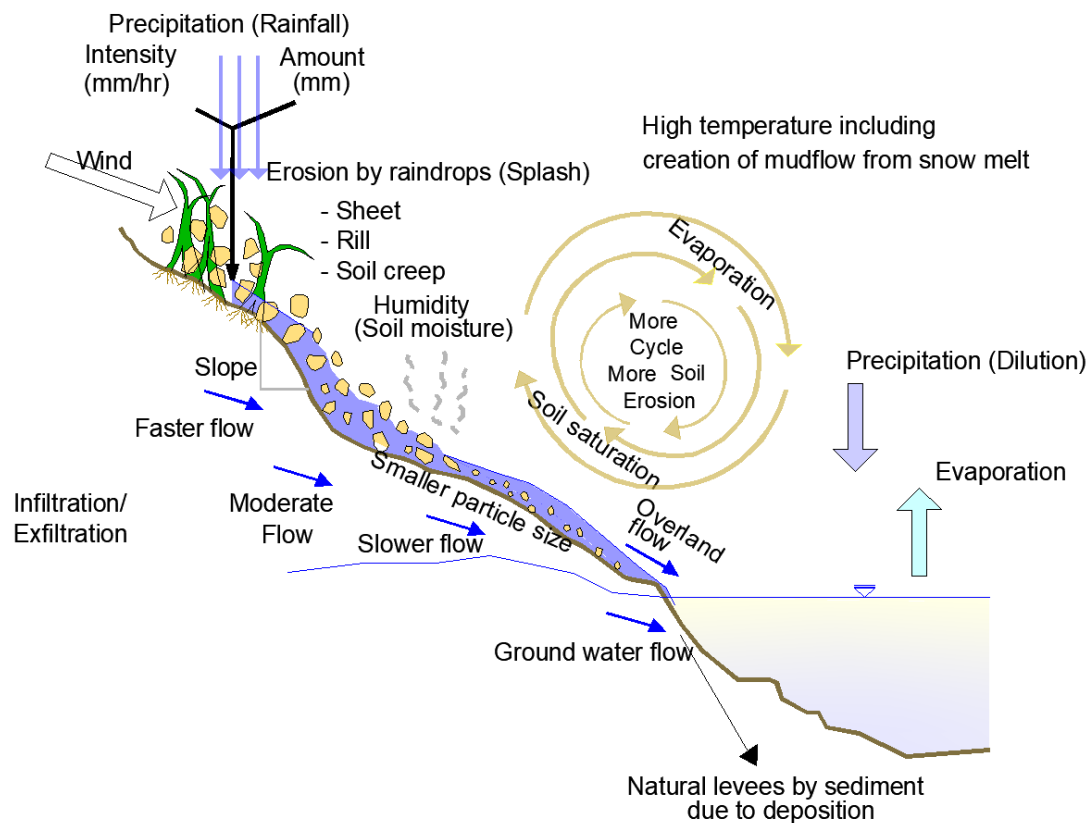


Figure 5-1. SS generation processes and sequential impact of climate: Precipitation triggered soil erosion was taken as the major mechanism of SS generation over various LULC and transportation within catchments.

Climate oscillations will be affected by climate change, thus there are likely to be shifts in phase changes of climate oscillations e.g., shifts of ENSO under global

warming (Beverley *et al.*, 2021). The global warming is due to the anthropogenic activities causing the unprecedented increases in Earth temperature within the short period (Steffen *et al.*, 2015; Baum, 2019). It induces more extreme climatic events, stimulating soil erosion and transport of suspended sediment from significant processes (Konisky *et al.*, 2016; Basher *et al.*, 2020). Thus, it will influence predictability of SS dynamics from phase changes of climate oscillations. There is evidence that stronger linear relationships between PDO and ENSO may modulate SS dynamics in the future (Kwon *et al.*, 2013). Regional variation exists though, ENSO of DJF will further experience amplification and dampening from 2081 to 2100 (McGregor *et al.*, 2022). Not only climate change will impact on the sources of sediment but also catchment connectivity is an important factor to affect SS delivery (Fryirs, 2013; Mahoney *et al.*, 2018; Mahoney *et al.*, 2020). Therefore, it emphasizes wider application of climate oscillations and SS dynamics for efficient extraction of climatic impacts in a wider scale.

Wavelet coherence analysis identified strong links between SS dynamics and climate oscillations at the selected catchments (Figure 4-3~10). Leading cases from climate oscillations were mostly identified from ENSO and NAO especially exerted on precipitation and P.p.e (Table 4-1). The findings from P.p.e in association with climate oscillations is from event based dynamics, which creates difficulties in comparing with other literature. Past sediment studies in rivers largely used sediment loads or concentrations, primarily focussed on magnitudes or trends (Mount and Abrahart, 2011; Dethier *et al.*, 2022; Guan *et al.*, 2022; Vaheddoost *et al.*, 2022; Gardner *et al.*, 2023). In recognition of global impacts from climate oscillations, climate oscillations affected SS in many regions. Despite the wider extent studies available, a variety of methods of identifying correlation between climate oscillations and magnitude of suspended sediment poses a challenge of comparing temporal variation. Well known effects of ENSO were associated with SS behaviour in western US (Andrews *et al.*, 2004; Gray *et al.*, 2015). ENSO correlated with SS in Southeast Asia (Ha *et al.*, 2018; Lund-Hansen *et al.*, 2018). PDO impacts on SS were identified through statistical correlation in South America (Reis *et al.*, 2022). Through rainfall erosivity

modelling using cross wavelet analysis, PDO impacts on SS were detected in rainy seasons over China (Cao *et al.*, 2023). It showed similar decadal periodicities over 1990s and 2000s as discovered at Site C and D (Figure 4-6 and 4-10). PDO and ENSO both influenced SS over western US identified by analysing monthly fluctuation (Naik and Jay, 2011) and age model of core photograph (Hendy *et al.*, 2015). NAO impacts on sediment exists in Greece by identifying relevant hydrological processes (Maas and Macklin, 2002). NAO also correlated with SS in Spain (Liquete *et al.*, 2005). By comparing temporal variation of processes, NAO impact on SS were identified in Southern Iceland (Lawler *et al.*, 2003). Linear correlation between NAO and processes of sediment loss from agricultural land were identified in Northern Europe (Koivusalo *et al.*, 2017). Influences of ENSO, PDO and AMO were also detected in South East Asia by correlation analysis with rainfall anomalies (Perez *et al.*, 2021).

Similarly, studies about rainfall erosion (RE) provided links with ENSO from various methods including wavelet analyses. RE is an important attribute of sediment delivery under climate change (Burt *et al.*, 2016). Influences of ENSO to RE were identified in various regions. ENSO influences on RE were found in China with strong decadal influences (Xu *et al.*, 2019). M95 and D0.2 at Site C received a similar decadal periodicity from ENSO (Figure 4-5). Site D also had decadal relationships e.g., M95, P.p.e0.6 & 0.2 (Figure 4-9). Strong inter decadal relationships were also identified in China (Jia *et al.*, 2022; Zhang *et al.*, 2022; Zhao *et al.*, 2023) and south east Asia (Cui *et al.*, 2021). It is similar to the findings at Site C that Cofe0.2 and P.p.e0.2 had inter decadal relationships (Figure 4-5). Site D also received inter decadal relationships with ENSO that the confounding factors e.g., precipitation, D0.2 and Cofe0.2 had 5~6 year relationships (Figure 4-9). Further linkages with RE and ENSO were identified using various methods over China (Zhu *et al.*, 2019). Other regions were also confirmed that there were relationships with ENSO e.g., Mexico (Maass *et al.*, 2018), Western Columbia (Pablo *et al.*, 2021), Northern Peru (Romero and Baigorria, 2007; Schwab, 2009) and Australia (Webb *et al.*, 2006). ENSO is also generally influential to gully erosion (Anderson *et al.*, 2021).

PDO had decadal relationships with the factors influential to soil erosion in China. PDO influences on RE were identified during rainy seasons (Cao *et al.*, 2023). It also influenced seasonal precipitation in soil erosion prone regions (Wang *et al.*, 2019). In the continental US, the decadal relationships with PDO were identified from Site C, e.g., the decadal relationships from precipitation, M95, P.p.e0.6 & 0.2 (Figure 4-6). Site D had slightly different decadal relationships from SS dynamics e.g., M95, D0.2, P.p.e 0.6 & 0.2 (Figure 4-10). It might be due to the different catchment characteristics i.e., difference in response time from more ground water (Figure 3-1).

Though there is a lack of literature about wavelet coherence analyses with AO and NAO, several cases of influences from climate oscillations were identified over China and Europe. There is a high correlation between AO and NAO, especially in the warm climate projection (Hamouda *et al.*, 2021). ENSO-AO control increased erodible material and impacts from RE over China (Zhang *et al.*, 2022). Quantitative approach was taken with NAO over Central Europe (Mici *et al.*, 2021), and differences between atmospheric circulation indices were used for North East of Spain (Angulo-martínez and Beguería, 2012). AO also influences RE over China with inter decadal (Annual, spring and summer) and decadal (Autumn and winter) relationships (Xu *et al.*, 2021; Wei *et al.*, 2022). In the continental US, west-east differences were identified. The summer cases of AO had inter-decadal relationships with SS dynamics at Site D in Northwest (Figure 4-8). However, NAO in winter were associated with a decadal period relationship with P.p.e0.2 at Site A in the east coast (Figure 4-3).

Based on above literature, ENSO is widely known as most influential to SS transport along with other climate oscillations. Relevant dynamics of ENSO were identified as dynamics that were closely associated with the shorter-term dynamics of precipitation impact e.g., D0.2 and P.p.e0.2. PDO impacts were also not negligible that distinctive impacts were identified from frequency indicators (Cofe0.2, P.p.e0.6 & 0.2) (Table 4-1). There is an increasing number of studies about relationships between sea surface temperature and mean sea level pressure (Islek and Yuksel, 2023). However, it is predicted that sea surface

temperature will be increasing (Olonscheck, 2020; Salarieh *et al.*, 2023). Therefore, it is recommended that impact of SSTs on the anomalies from climate oscillations used is analysed depending on cold/warm phases of SSTs. It then can link with the results from Chapter 4 e.g., longer warm or cold phases of SSTs due to rising temperature.

Regionally differently evolving sea level pressure (e.g., NAO and AO) is anticipated in the future. The sea level pressure has an inverse relationship with sea surface temperature at regions where NAO and AO are measured as warmer temperature creates low pressure fields (Islek and Yuksel, 2023). NAO- in 60s were positive to D0.2 in the eastern US (Table 4-1), which lacks coherence, but it may or may not be more frequent in the future. A doubling impact is spatially and temporally differently influencing marine heat wave (Gentemann *et al.*, 2016). Therefore, understanding reducing impacts of sea level pressure is mandatory.

The proxy for prediction of SS dynamics based on climate oscillations are likely to evolve as time being. As heat absorbed by ocean differentiates SSTs, higher SSTs will alter water cycles over lands (Wei *et al.*, 2016) and altering sea level pressure. There are several measures to improve accuracy of SS modelling in the future e.g., defining boundaries of ocean impacts on water cycles, modelling SSTs in each cold and warm phases and improving SSTs and marine heat waves.

5.3 Linkage with SS modelling using MFT time series

Current physical models for prediction of SS can predict magnitudes (Yields) of SS using various governing equations and input parameters (Pandey *et al.*, 2016). Due to the large amount of input parameters that each physical model requires, modelling magnitudes are not entirely reliable. Thus, producing short term dynamics in SS can be useful to better link with relevant processes i.e., frequency and timing indicators.

Widely used physical models based on soil erosion include SWAT, RUSLE, InVEST, WEPP, AGNPS, ANSWERS and SHETRAN. SWAT and RUSLE use Modified Universal Soil Loss Equation (MUSLE) and Revised Universal Soil Loss Equation (RUSLE), respectively (Pandey *et al.*, 2016). Importantly, those models

have limitations on applying parameters e.g., SS resuspension, which is useful for climate change prediction (Ryberg and Chanut, 2022). InVEST uses sediment delivery ratio (SDR) (Matomela *et al.*, 2022). WEPP, AGNPS and ANSWERS use Foster equation with detachment rate and capacity, especially over hill slopes. SHETRAN uses Wicks equation with raindrop impact and ground properties for hillslopes and Engelund and Hansen equation for transport in channels (Pandey *et al.*, 2016).

Output of SS models should expand to frequency and timings as the vast amount of uncertainty still exist in modelling magnitude. Modelling of magnitude has not solved significant amount of spatio-temporal gaps in SS, and the fundamental issues arise from the complex and nonlinear nature of the processes influencing SS dynamics (Meshram, 2020; Tao *et al.*, 2021). Thus, implementing modelling of only magnitude is not sufficient for choosing right input parameters for prediction of SS. Creation of seasonal time series of MFT will benefit from identifying locally suitable input parameters to realize further accurate modelling.

Creating MFT time series for each magnitude, frequency and timing in various intervals e.g., weekly, monthly and seasonal will produce more agile input parameters for SS models. It will enable weekly, monthly or seasonal regression approaches. Therefore, generation of various layers influenced by processes are possible. It then will be able to identify temporally finer processes that increases sediment in the catchment, transported to watercourses affecting SS dynamics, enabling SS management spatially and temporally in a better efficiency. The localized parameters from the significant processes can be input into various SS modelling in different timings for prediction of magnitude. Frequency time series can be modelled to detect further accurate relationships of input parameters in different timings (e.g., clay covers were identified as significant in spring and Rfact was identified as significant in summer as shown in Figure 3-3, which can create seasonal time series of significant processes). It will yield different relationships between processes and the frequency time series. Further lower alpha values for more number of events will better capture SS resuspension for SWAT and RUSLE models. Timing time series also will yield new relationships

from processes available. To reassure, the MFT time series also can be compared with the relationships with climate oscillations (Table 4-1). By combining the MFT time series and phase changes of the climate oscillations, new relationships appeared in modelling input parameters will boost its accuracy by applying their temporal evolution e.g., Spring had combined impacts of PPT30 and BFI for R.r (Figure 3-5), and autumn had an only impact by forest cover for D0.6 (Figure 3-7), which were not exposed in the magnitude indicator (M50). Prediction of those input parameters can use AI (Gupta *et al.*, 2021; Luu *et al.*, 2023).

Generation of MFT time series will yield combination of significant processes for intended time frame. It provides bases for optimizing input parameters of various SS models for each season. As SS is affected by human and earth systems, creation of MFT time series in precipitation, suspended sediment (Turbidity, FNU) and discharge are highly recommended, which allows comparison of the significant processes. There are possibilities of developing more properly suited indicators of suspended sediment dynamics including monitoring MFT time series.

5.4 Future Work

SS modelling is a challenging task because one major reason is that climatic impacts are not spatially limited to catchments over land surfaces. Purpose of developing better models is to precisely measure climatic impacts on SS delivery from fluvial environment. However, it is inevitable to link predicting SS to adaptation of evolution of earth system patterns (Huntingford *et al.*, 2019). The MFT concept should be tested to various geographical settings over the world to enable further development (Jing *et al.*, 2022).

In this thesis, analyses used water quality data maintained by USGS, which has benefit of using the longest SS data available. The research delivers the findings from the period of the most relevant data availability. However, there are limitations e.g., patchy distribution, short timespans and substantial amount of gaps (Figure 2-1 and Figure A2-1,a). For future studies about SS, it is recommended using turbidity although it may not fully capture the chemical component in SS (Rickson, 2014; Fu *et al.*, 2023). Analyses should also extend

to other countries with different variables and indicators from various climate factors e.g., wind, tornado, typhoon (Li & Li, 2016), soil moisture content (Dowdeswell-Downey *et al.*, 2023) and soil surface roughness (Bahddou *et al.*, 2023). As the climate is connected to ocean evaporation, indicators from marine biology might have been useful for better understanding the impact of climate (Clay *et al.*, 2020). The wavelet analyses in Chapter 4 were also done with only four catchments to ensure no major dams within the catchments after data pre-processing. Linking the results of Chapter 4 with significant hydrological processes is worthwhile that GWR needs to incorporate alpha values 0.2 (Chapter 3).

The use of daily SSC data using flow weighting has implication on the results presented in each chapter. The limitations of not fully in compliance with normality assumption from the indicators also influence magnitudes and event based dynamics e.g., especially subsequently yielding different values in magnitude indicators in case of using non parametric approaches (M95 and M50). Calibration by forward and backward pass filters to find optimal filtering curve is necessary (Nagy *et al.*, 2024). However, the characterization of the data (Chapter 2) were based on clustering analysis, which yielded consistent results and interpretations were based on standardized values (He *et al.*, 2019). Assuming the advantage of linear regression, the regression approach (Chapter 3) also was based on log transformed SS transport dynamics indicators. Therefore, the impact of the unknown methodological limitations from data and violation of normal distribution may have been diminished. Furthermore, the chapter 4 can additionally implement trend analysis (Sommerfield, 2016) to identify whether those selected catchments have sudden jumps in its time series. These limitations also affect developing scenario based SS transport modelling, which has limitation of numerically quantifying direct impacts on modelling results. The research tested the new indicators to daily SS data.

The thesis project developed SS dynamics indicators, which identified variability of correlation between indicators and LULC. Precipitation has been revealed as a negative factor to SS magnitudes due to dilution effects on water bodies (Table

3-3). However, it is inevitable to link precipitation impacts to LULC (Zhou *et al.*, 2017), preferably according to temperature changes under RCP scenarios (Gou *et al.*, 2020). The sensitivity between processes might evolve following the different impacts of precipitation (Duration and frequency). Finding stronger influences between precipitation impacts and LULC, especially catchments having the significant processes identified from this research (e.g., clay covers in association with snowmelt flow and ephemeral rivers, forest managed regions and urban areas with high frequency of long SSC events) will provide more detailed knowledge by generating more precise layers of LULC. Extraction of more precise LULC information e.g., landsat classification (Song *et al.*, 2021; Yu *et al.*, 2019) will be able to extract further sites having more relevant data for wavelet analyses. Using newly accumulated FNU can yield results from right periods of climate studies including sub daily models upon availability of data.

Applying new concepts and different ways of data curation will open further opportunities including finding better gap filling techniques for SS indicators. Firstly, additional effort to find right indicators in various timings or seasons will be worthwhile. Secondly, integration of abnormal SST changes e.g., Indian ocean temperature in 2019 (Shi & Wang, 2021) into the whole system modelling. Obtaining right data of sea surface temperature, specifically relevant to intended catchment can find meaningful insights. Thirdly, full scale alpha values can be used to extract different layers from MFT modelling by means of sensitivity analysis. Developing scripts to run full scale alpha values in 0.1 interval may deliver unknown layers of processes associated with SS dynamics. Fourth, it should apply adjusted input parameters in association with MFT time series for better accuracy of SS magnitude. Using the conventional physical modelling equations, input parameters can vary according to MFT time series. It can create more refined time series of SS magnitudes. Lastly, integrated approach to maintain healthy rivers and oceans at the same time (Yang *et al.*, 2022) is urgently required using not only magnitude but also frequency and timings. High ocean temperature create larger clouds than flooding will differentiate processes over the land (Wei *et al.*, 2016). Once integrated modelling of earth system

sciences and more accurate definition of right indicators are possible, SS modelling can achieve better accuracy under the changing climate.

In a broad term, SS modelling should consider integration of ocean boundary for more precise MFT indicators that are all within water cycle. Integrating full MFT indicators from onshore and offshore will enable right adjustment of input parameters for future SS modelling. Exploitation of essential indications hidden from climate cycles over Earth surfaces and marine biology may lead to better predictability and management of suspended sediment transport in rivers in wider spatial scales in the future. Running scripts for further fractionizing alpha values may find interesting layers of hydrological processes, providing new insights.

Developing indicators of SS dynamics receiving distinctive impacts of climate in the future

New empirical models will require considering approaches in association with the changing status of climate (Batista *et al.*, 2019; Jensen *et al.*, 2019). SS generation might be more frequent as time being, although there was no direct correlation with precipitation and magnitudes (Table 3-3). Furthermore, the gap filling techniques can evolve along the way for better prediction, which will enable applying more precise SS dynamics in the future given the nature of data scarcity.

6 Conclusions

The research aim was to better understand the impact of climate change on intra-annual variations in SSC in rivers. The novelty of the research is that SS dynamic indicators were newly developed to quantify the magnitude, frequency and timing of high SSC events across different spatial and temporal scales, and analysed using multivariate statistics, spatial statistics and wavelet analyses to identify better spatially and temporally varying relationships with significant processes.

First, the novel MFT indicators were calculated from daily SSC at 1,425 sites in the US to quantify the similarity in spatial patterns of SS transport dynamics. The contribution of knowledge is that magnitude, frequency and timing indicators exhibited clear spatial distributions, which suggested large-scale climate and/or catchment characteristics. High concentration of SSC was identified at catchments in dry and mountainous regions, but SSC events of longer durations were found in the northern US. The coastal region in the west and Puerto Rico received consistent timings of high SSC in winter and autumn, respectively. The indicators are useful in further climate studies and better describing complex SS generation and transport dynamics (e.g., M95, M50, Cofe0.6, D0.6 and P.p.e0.6).

Secondly, associations were identified between the new MFT indicators and catchment characteristics at 120 sites in the US. The MFT indicators were applied annually and seasonally to create 23 models. The novel GWR models were generated from each OLS model, then GWR coefficients were analysed by ecoregion. The contribution of knowledge from the OLS models is that land covers, rainfall erosivity, BFI and soil types were found as the most common predictor variables. GWR coefficients showed significant changes across the continent. Agricultural lands were positively associated with SSC events of low frequency, while forest covers and urban areas predicted events of higher frequency, except the sites in the desert. PPT30 was generally a negative predictor variable for magnitude of SSC, except MWCF.

Finally, the impact of climate oscillations on the temporal dynamics of SSC were investigated at four sites in the US using cross-wavelet analysis. Average annual

time series of the novel SS dynamic indicators were used to implement wavelet coherence analyses for the seasons most impacted by the oscillation. The contribution of knowledge is that the research found that climatic oscillations affect on short term SS transport dynamics. It demonstrated that small seasonal shifts in temperature and precipitation impact several of the SS transport indicators, especially P.p.e. The results were strongest for the shorter period oscillations caused by ENSO, but significant results were also obtained for the multi-decal AMO. These findings deepen our understanding of the impact of climate on SSC transport which can support which is useful better prediction of future SS dynamics.

Overall, this study applied new methods to study SS transport dynamics in rivers using SSC, catchment and climate data across a continent to identify sources of climate vulnerability. By developing and testing new indicators, identifying spatial patterns in SS transport dynamics, investigating the influence of catchment factors, and determining the effects of climate oscillations on temporal variation, the research improves the scientific understanding of SS generation and transport to support future studies on the impacts of climate change. The research questions were addressed that clear MFT patterns by climate regions in different seasons and distinctive processes between ecoregions associated with climate and catchment controls were confirmed. Leading cases of MFT dynamics from climate oscillations also were identified as useful baselines for better understanding of SSC and implementing predictive models. Suspended sediment management is important to safeguard water resources, ecology, clean energy generation, etc.

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APPENDICES

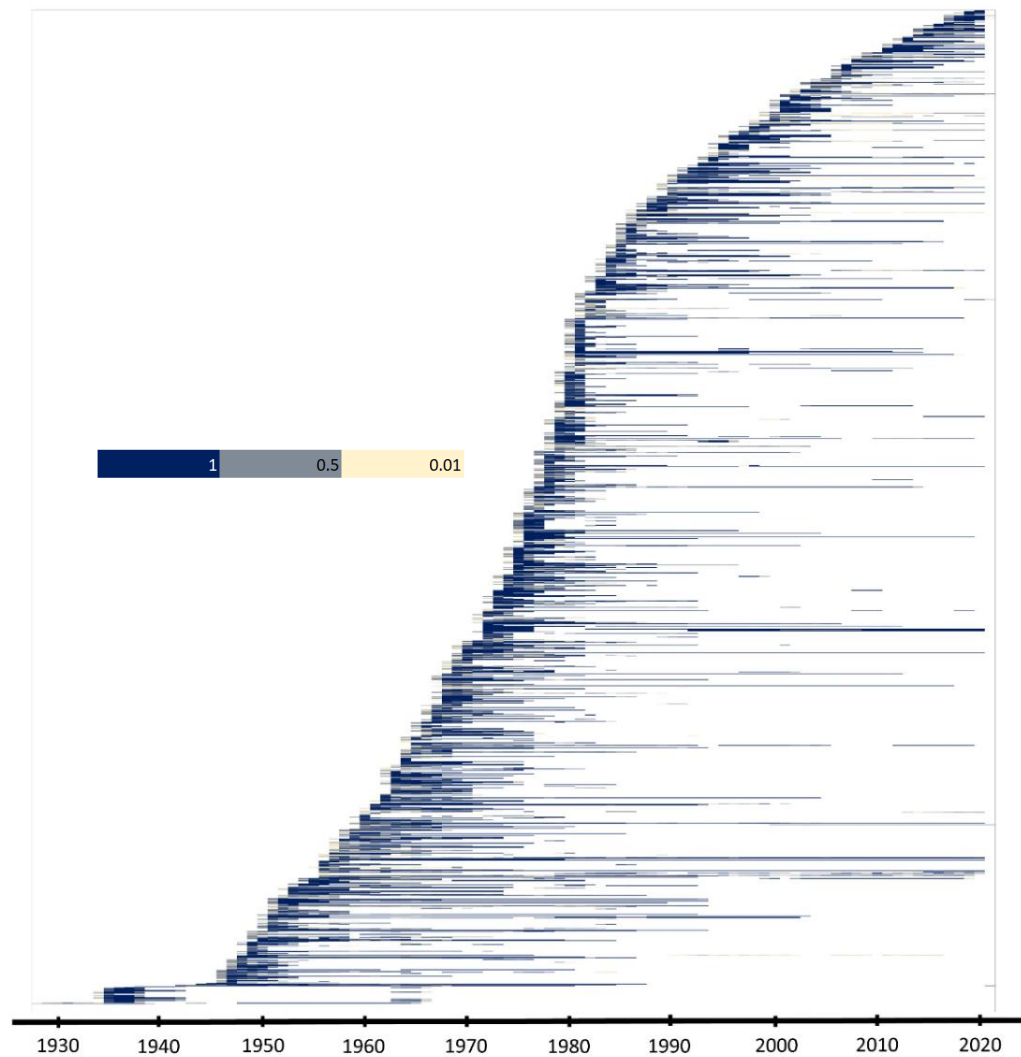
Table A1-1. Contribution of authors to chapters from 2 to 6: Chapter 2 & 3 have been published, and they required writing and editing by co-authors.

Author	Chapter 2	Chapter 3	Chapter 4	Chapters 5 & 6
Jae hun Shin	<ul style="list-style-type: none"> • Literature review • Data collection • Methodology development • Software • Visualization • Layout writing 	<ul style="list-style-type: none"> • Literature review • Data collection • Methodology development • Software • Visualization • Layout writing 	<ul style="list-style-type: none"> • Literature review • Data collection • Methodology development • Software • Visualization • Layout writing 	<ul style="list-style-type: none"> • Layout writing
Dr. Robert Grabowski	<ul style="list-style-type: none"> • Guidance on structure, advice, editing • Guidance on methodological approach • Writing – Review • Conceptual advice 	<ul style="list-style-type: none"> • Data collection • Guidance on structure, advice, editing • Guidance on methodological approach • Supervision on statistical approach • Writing – Review • Conceptual advice 	<ul style="list-style-type: none"> • Guidance on structure, advice, editing • Conceptual advice 	<ul style="list-style-type: none"> • Guidance on structure, advice, editing
Prof. Ian Holman	<ul style="list-style-type: none"> • Conceptualization • Guidance on methodological approach • Conceptual advice • Writing - Review 	<ul style="list-style-type: none"> • Conceptualization • Supervision on statistical approach • Conceptual advice • Writing - Review 	<ul style="list-style-type: none"> • Conceptualization • Guidance and supervision on methodological approach • Conceptual advice 	<ul style="list-style-type: none"> • Guidance on structure, advice, editing

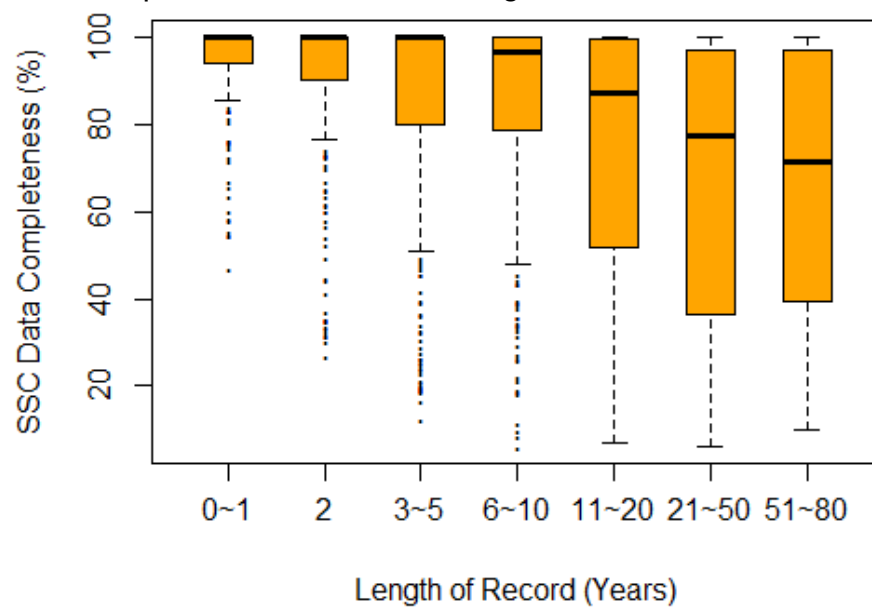
List of published/submitted works

- 1) Shin J, Grabowski RC & Holman IP (2023) 'Indicators of suspended sediment transport dynamics in rivers', Hydrology Research, Available online 21 July 2023. Dataset/s: 10.17862/cranfield.rd.22233829
- 2) Shin J, Grabowski RC & Holman IP (2023) 'Catchment and climatic influences on spatio-temporal variations in suspended sediment transport dynamics in rivers', Hydrology Research, Available online 04 August 2023. Dataset/s: 10.17862/cranfield.rd.22233721
- 3) Conferences
 - British Society of Geomorphology: Spatial Patterns in Indicators of Suspended Sediment Transport Dynamics at Continental Scale (<https://www.geomorphology.org.uk/annual-conferences/>)
 - British Hydrological Society: Climatic Influences on Spatio-Temporal Variation of Suspended Sediment Dynamics in Rivers (<https://www.lancaster.ac.uk/lec/graduate-school/professional-training/bhs2022/>)
 - Early Career People in Water Conference: Climate Change Impacts on Suspended Sediment Dynamics in Rivers (<https://www.cranfield.ac.uk/events/events-2022/early-career-people-in-water-conference>)
 - Peter Wolf Symposium 2024: Climate Oscillations Affect Suspended Sediment Dynamics in Rivers: Implications for Climate Change (https://www.hydrology.org.uk/meetings_events.php)

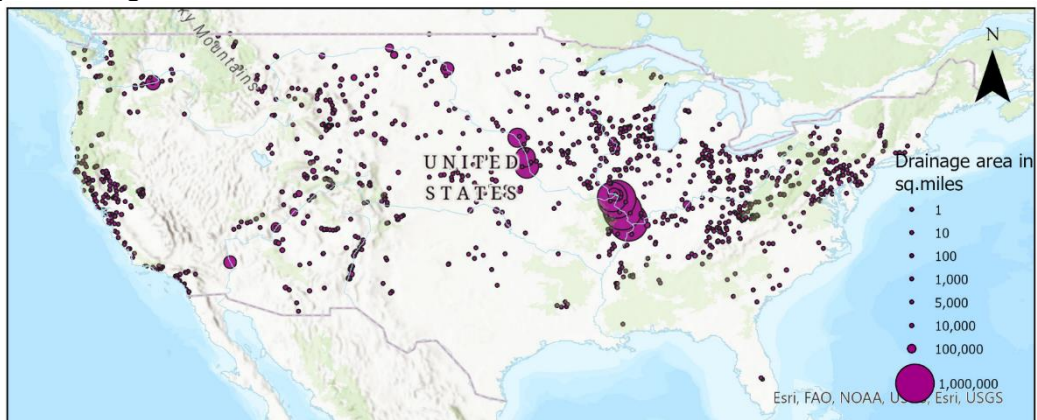
a) Data quality (Yearly data completeness (%)) listed per first year



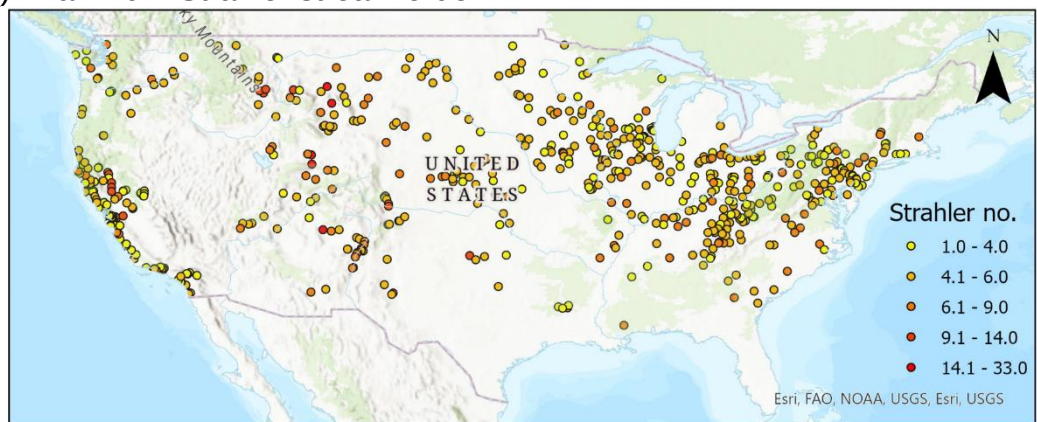
b) SSC data completeness for different lengths of record



c) Drainage areas



d) Maximum Strahler stream order



e) Avg number of samples per year

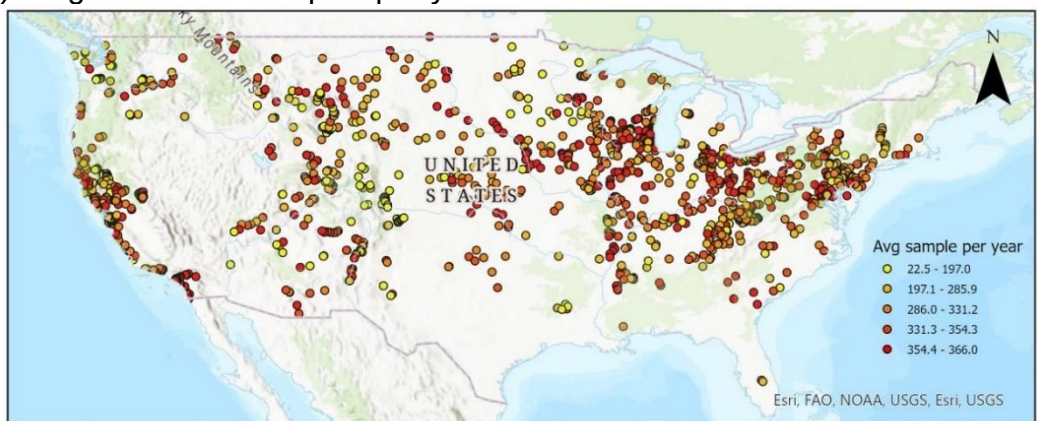
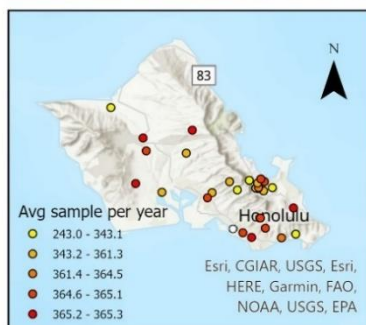
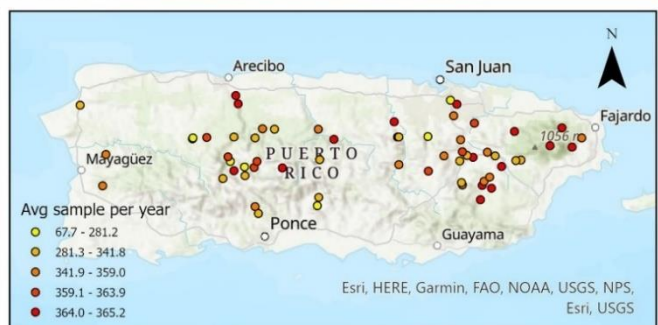
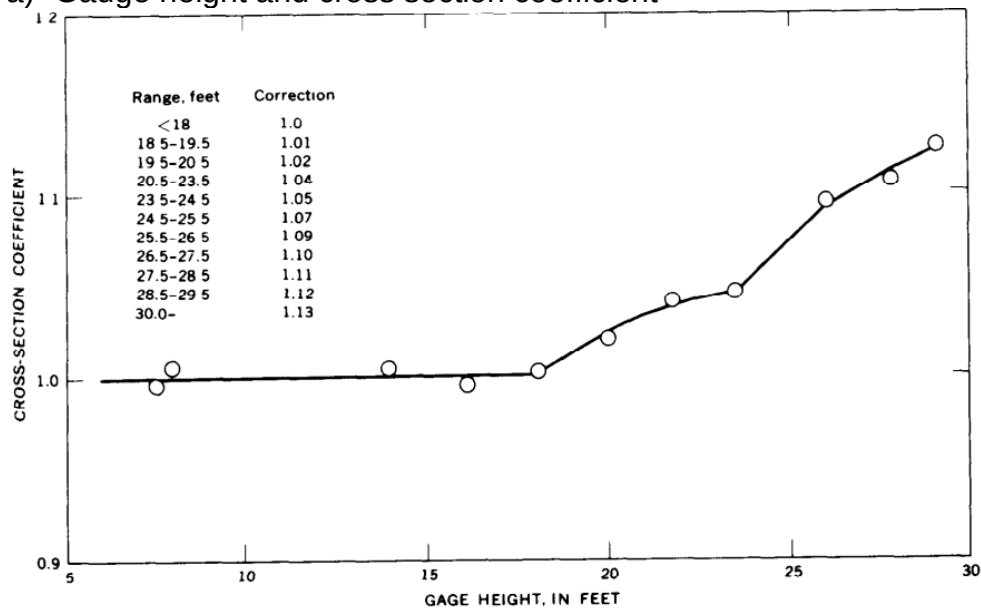


Figure A2-1. Plots of data quality and additional site attributes

a) Gauge height and cross section coefficient



b) Example of relationship between discrete sample, adjusted concentration and gauge height

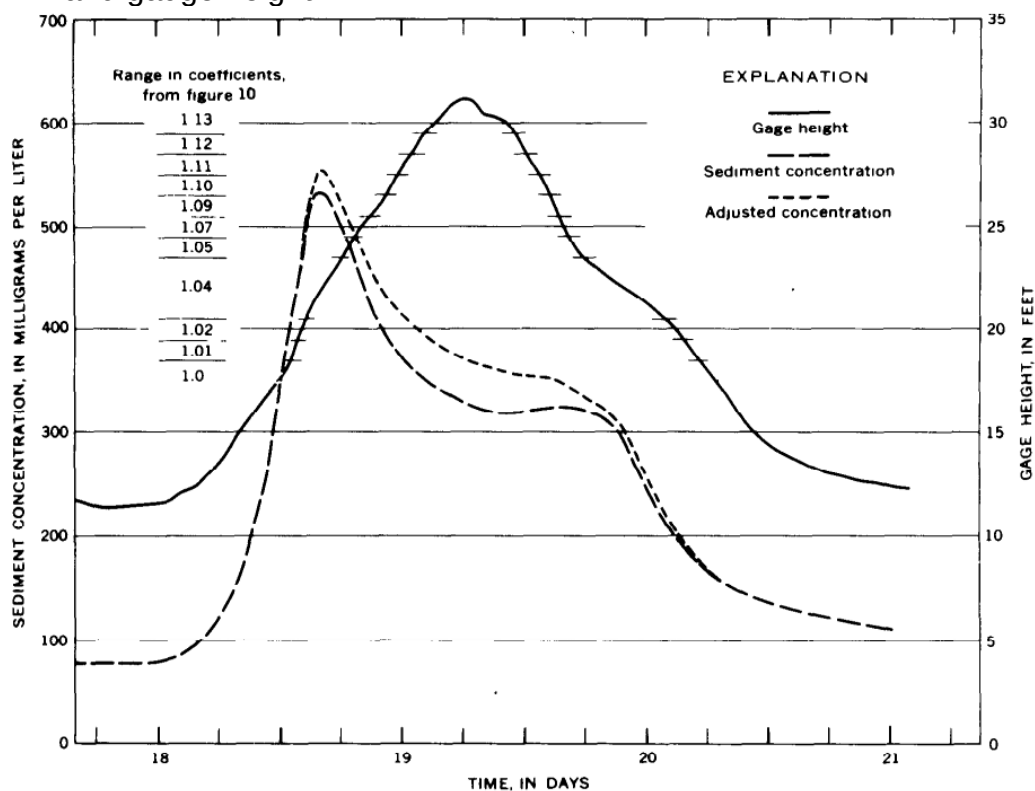


Figure A2-2. Relation between cross section coefficient and height of gauge (Porterfield, 1972): The correction coefficient is determined from the relationship between gauge height (a). An example of adjusted discrete samples is shown in (b) along with gauge height.

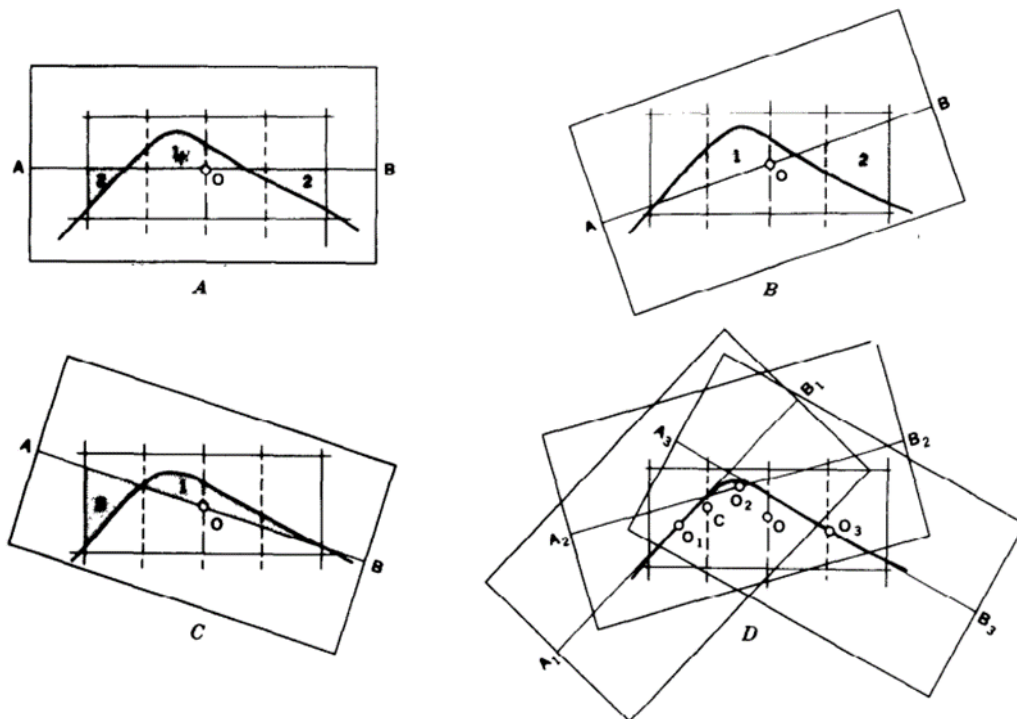
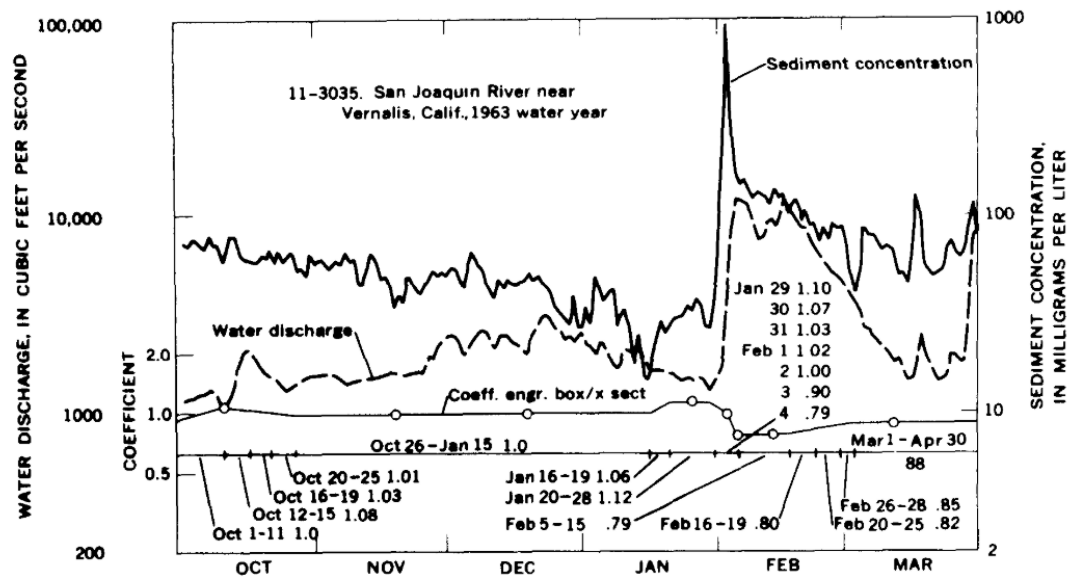


Figure A2-3. Graphical method used in USGS for determination of daily mean SSC (Porterfield, 1972): Clear plastics with a size of 6 inches long and 3 inches high (A~C) are placed over discrete value points to determine the daily mean (D).

a) Oct to Mar



b) Apr to Sep

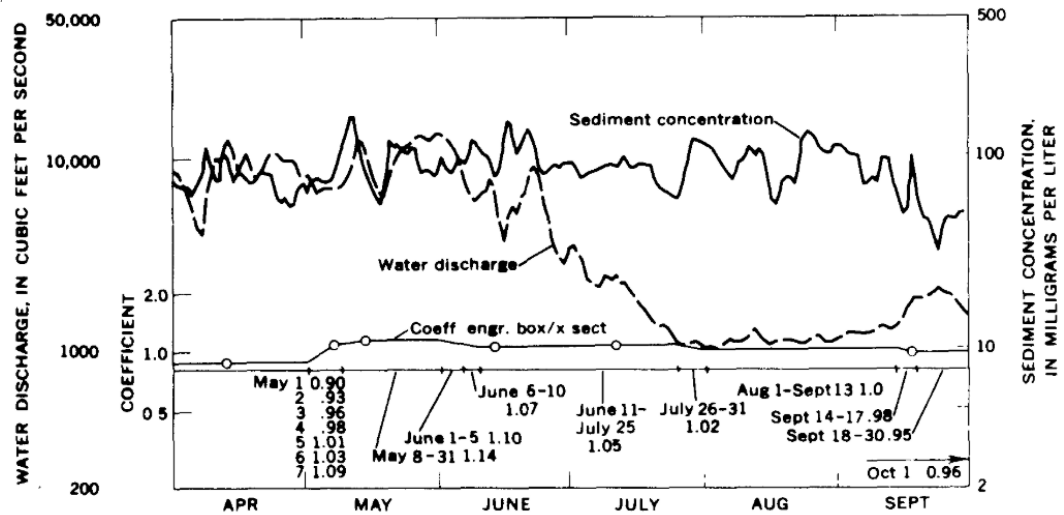
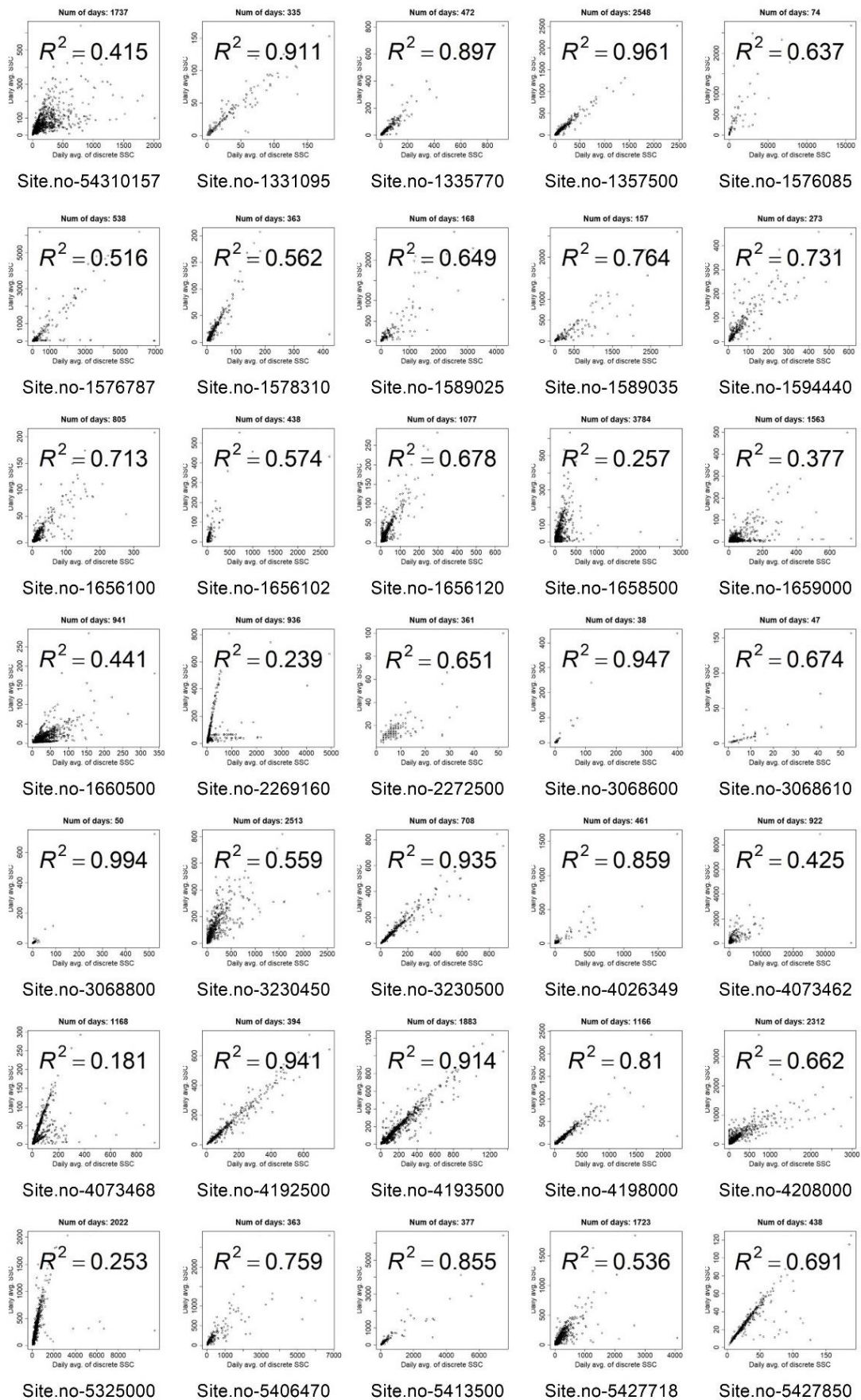
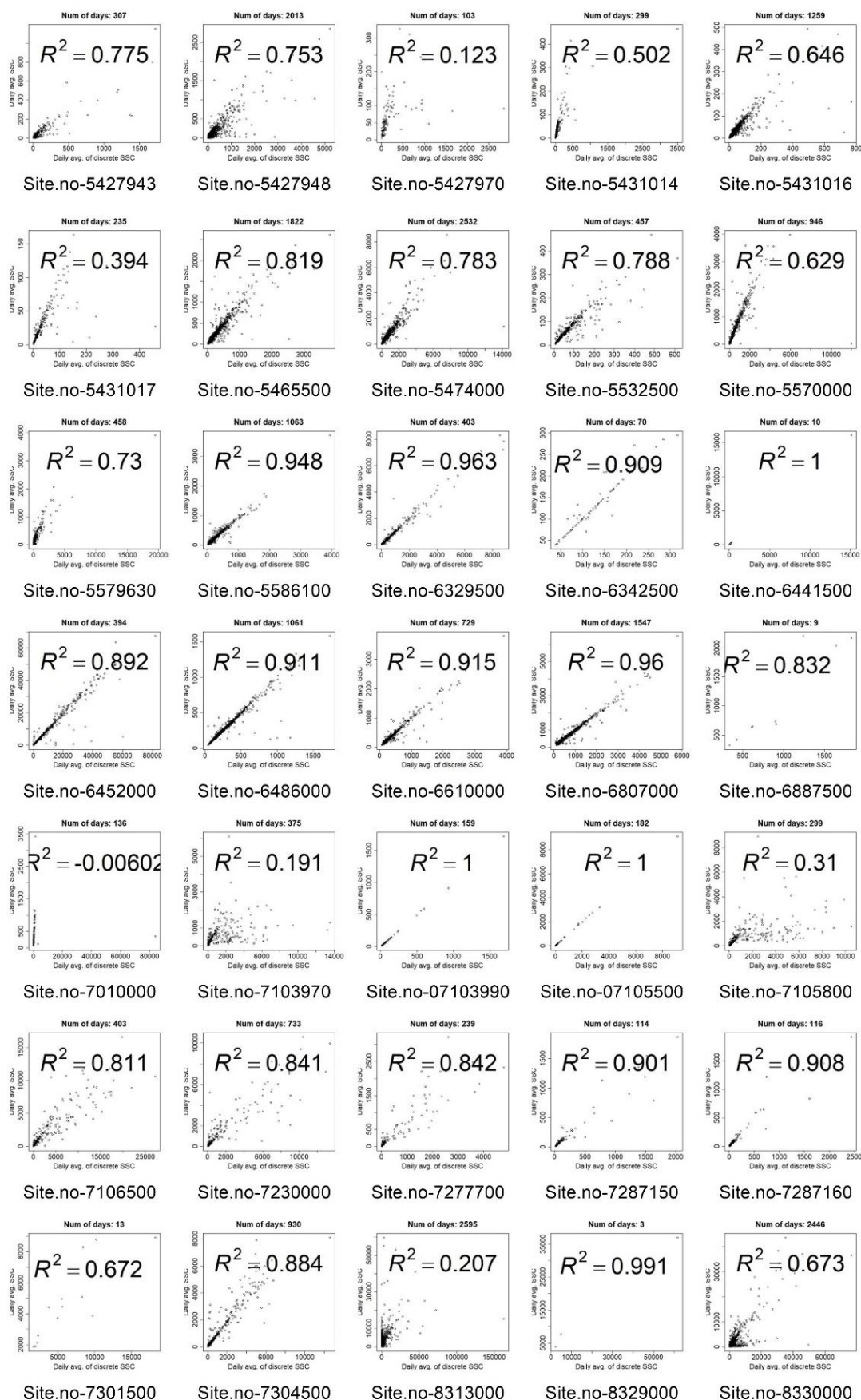


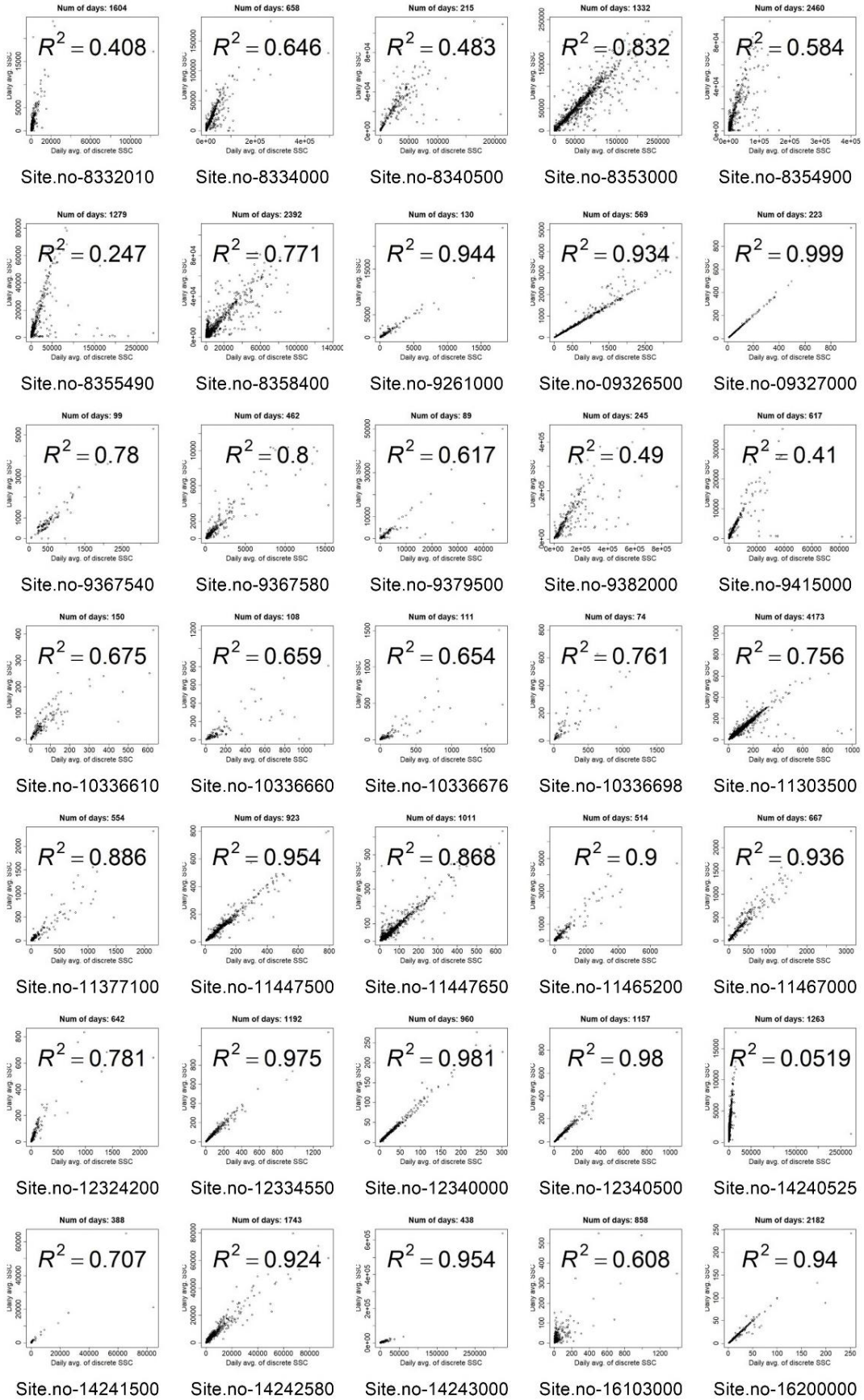
Figure A2-4. Examples of correction coefficients from water discharge and sediment concentration, applied to a cross section of a single vertical sample.

Table A2-1. Uncertainty from using daily SSC e.g., mean calculation using graphical method, unequal number of discrete samples from time averaging, application of unit conversion factor and uses of sediment rating curves

Parameters / Methods	Daily SSC	Discrete SSC	Reference
Parameter code	80154	80154	
Unit	mg/l	mg/l	
Cross sectionally averaging sampling	NA	Used during sampling	(Edwards and Glysson, 1999)
Graphical method	<u>Used for estimation of mean concentration</u>	NA	(Porterfield, 1972)
Correction (Cross section coefficient)	NA	Used when load is computed e.g., multiplied by 1.09, 1.03 etc.	(Porterfield, 1972)
Time weighting / Time averaging	To derive (integrate) mean of daily concentrations from discrete measurement	Used for time weighted cross section coefficient during depth width integrated samples	(Porterfield, 1972; Koltun et al., 1994; Holtschlag, 2001; David K. et al., 2005)
Discharge weighting	Computation of mean by dividing the daily load by daily mean discharge with <u>unit conversion factor of 0.0027</u>	Used during sampling e.g., discharge weighted mean concentration from depth integrated sampling	(Porterfield, 1972; Koltun et al., 1994)
Flow weighting (Term used in 2016 by Sommerfield for total load computation)	Total load divided by total stream flow for a cross section	NA	(David K. et al., 2005; Sommerfield, 2016)
Rating curve (Flow weighting) / Flow duration curve	Daily <u>sediment rating curves</u> (Flow weighting) were used to compute (integrate) average sediment discharge for long period	Flow duration curves were used to compute average sediment discharge for long period	(Porterfield, 1972; Holtschlag, 2001)
Flow weighting regression / Regression estimator	Possible with long term daily mean SSC and streamflow data	NA	(Holtschlag, 2001)
	Sediment rating curve approach is commonly used	NA	(Holtschlag, 2001)







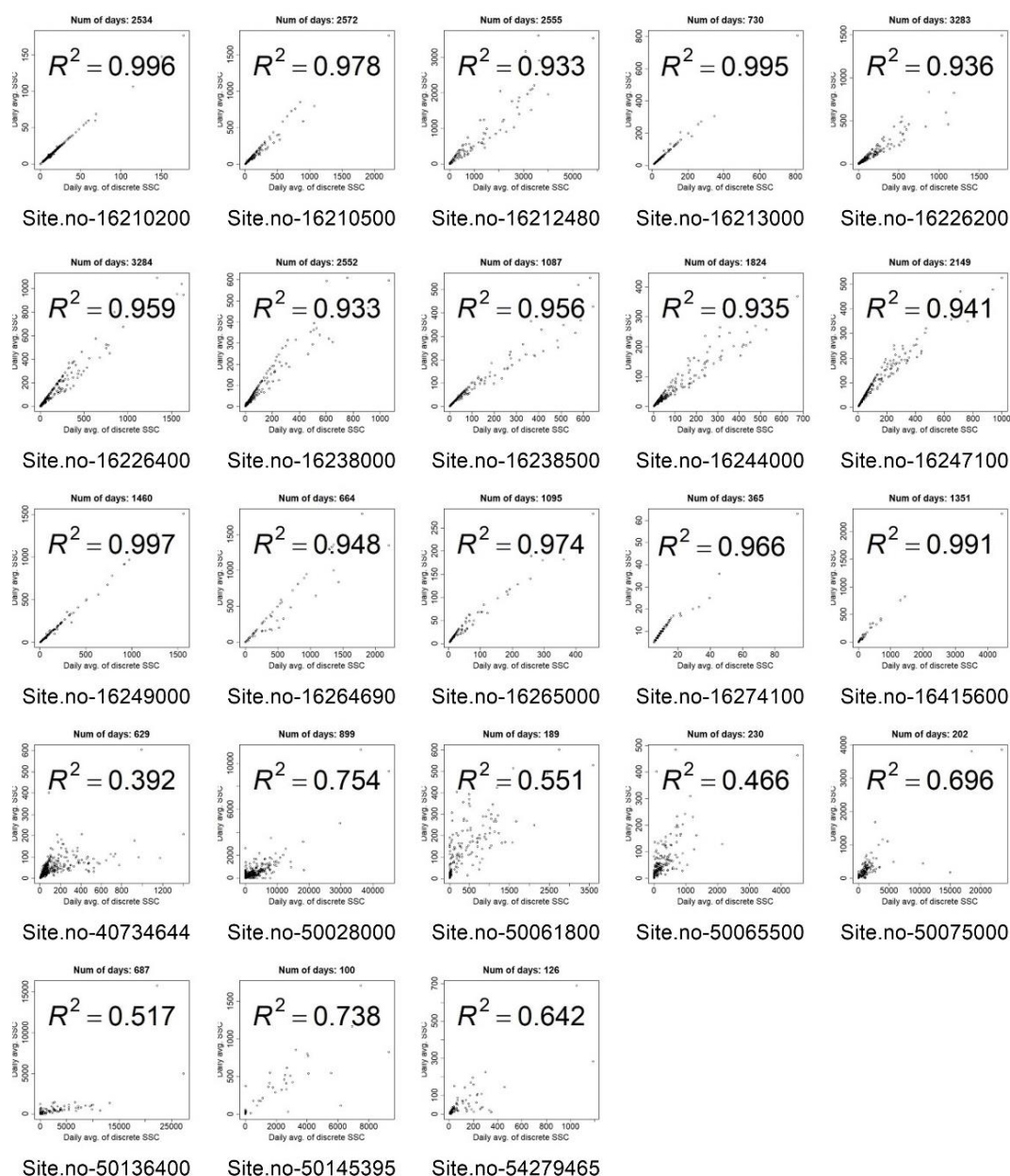


Figure A2-5. Comparison of daily average of available discrete SSC and daily mean SSC

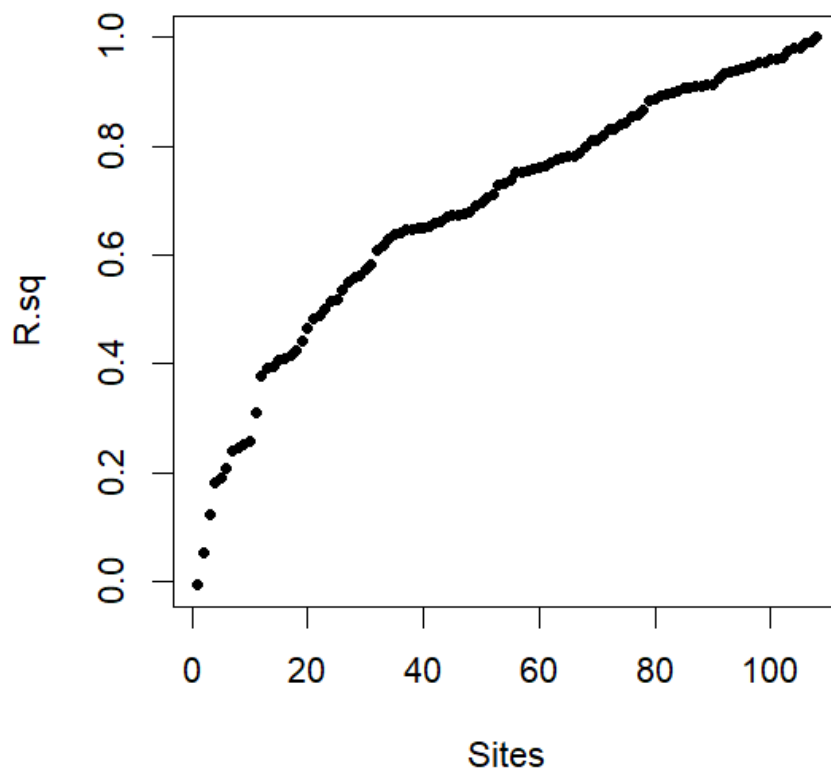


Figure A2-6. R^2 of sites having both discrete SSC and daily mean on the same days: R^2 of the sites used in Figure A2-5 for each sites is plotted (Min -0.006, median- 0.735, max- 1.0). The min R^2 of -0.006 occurred at site 7010000 due to an exponentially high value in the discrete data.

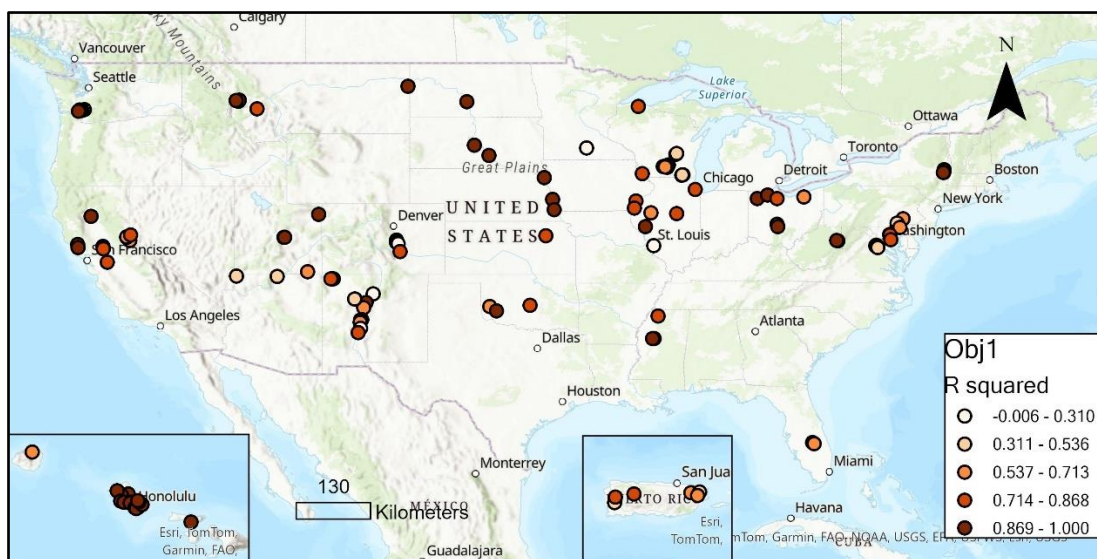


Figure A2-7. R^2 between daily average of discrete SSC and daily SSC for sites available in Obj1.



Figure A2-8. R^2 between daily average of discrete SSC and daily SSC for sites available in Obj2.



Figure A2-9. R^2 between daily average of discrete SSC and daily SSC for sites available in Obj3.

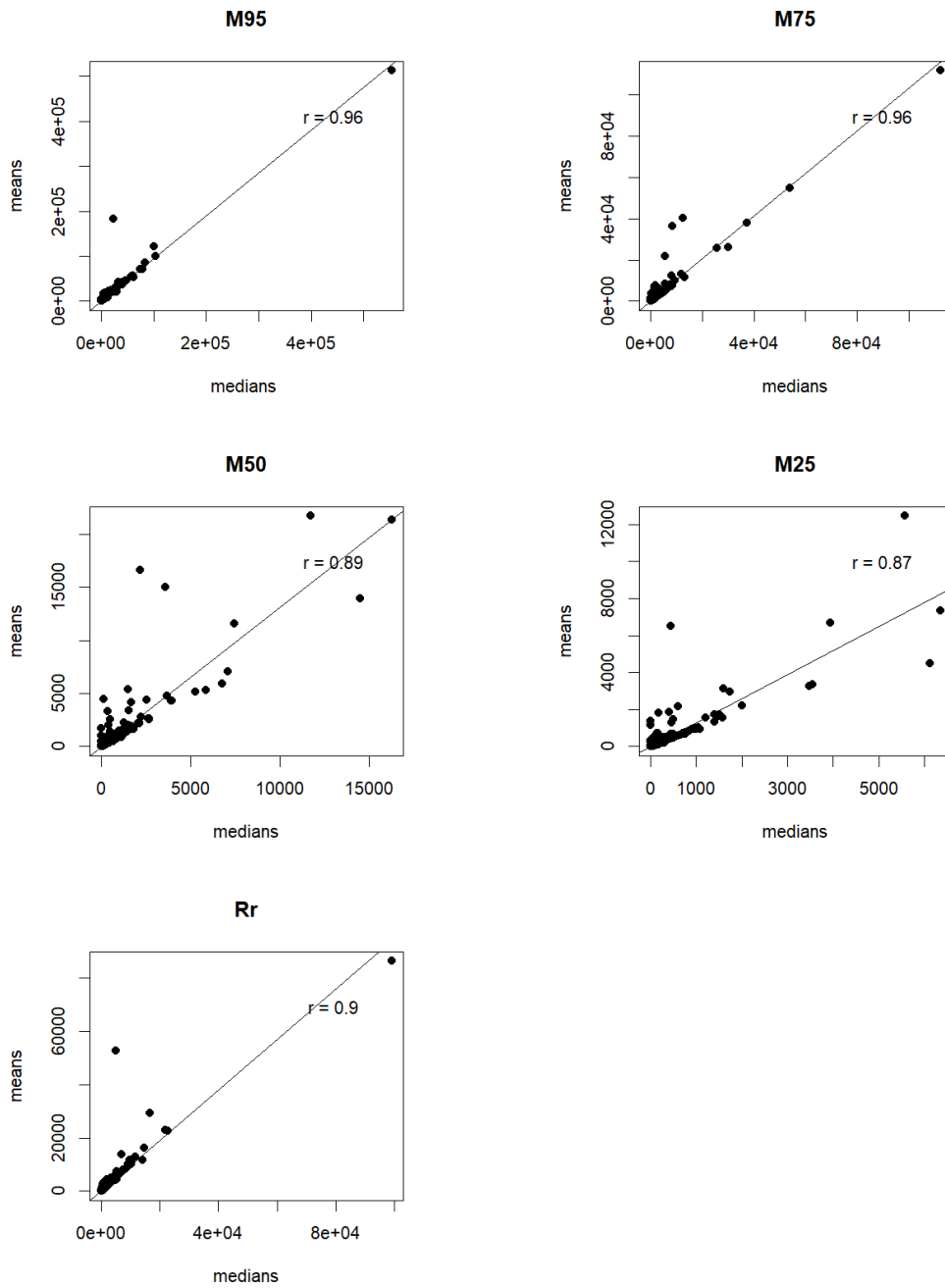


Figure A2-10. Scatter plots for means and medians from each annual time series of magnitude indicators (r =Pearson correlation coefficient)

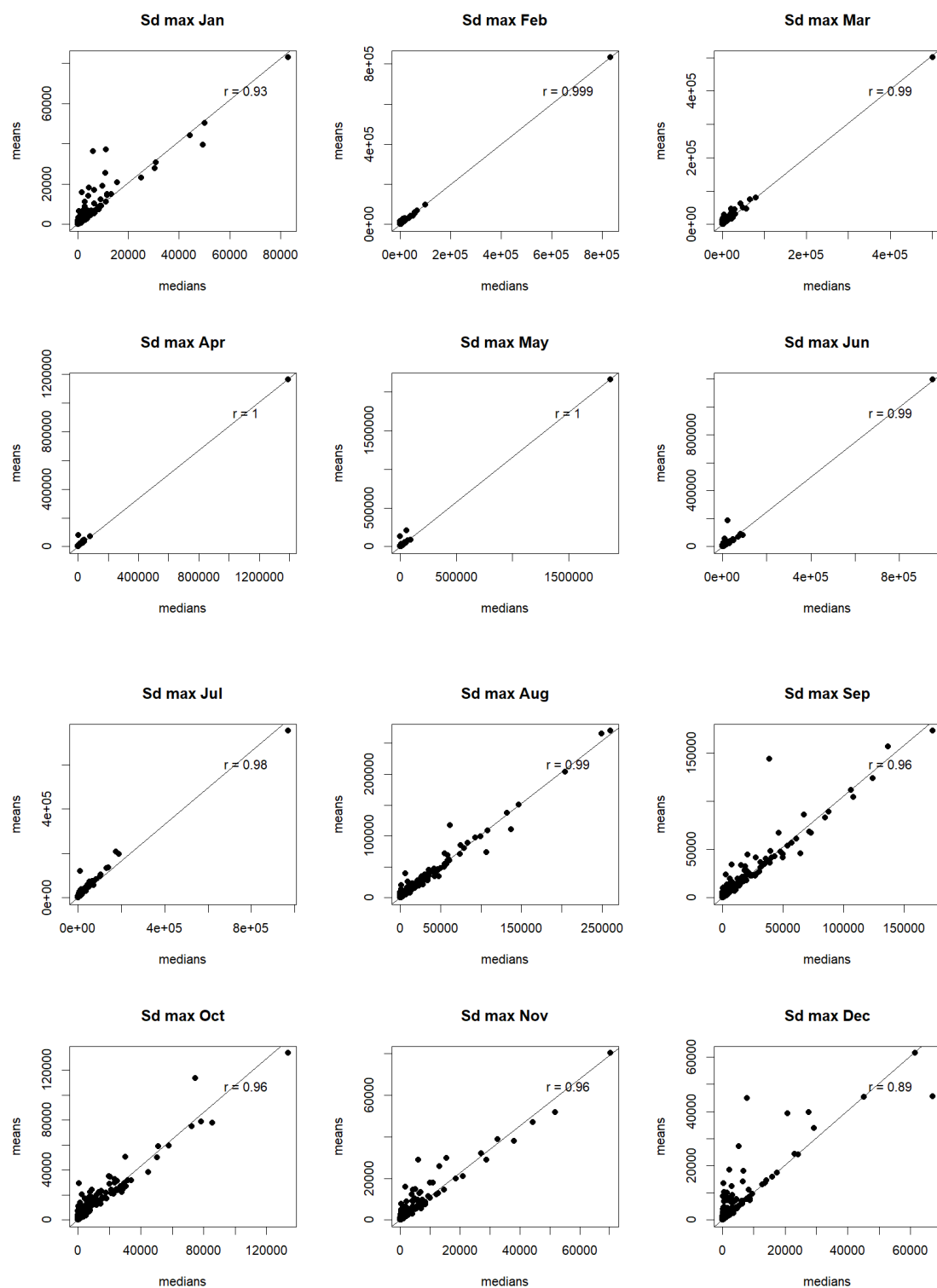


Figure A2-11. Scatter plots for means and medians from each annual time series of Std monthly max indicators (r=Pearson correlation coefficient)

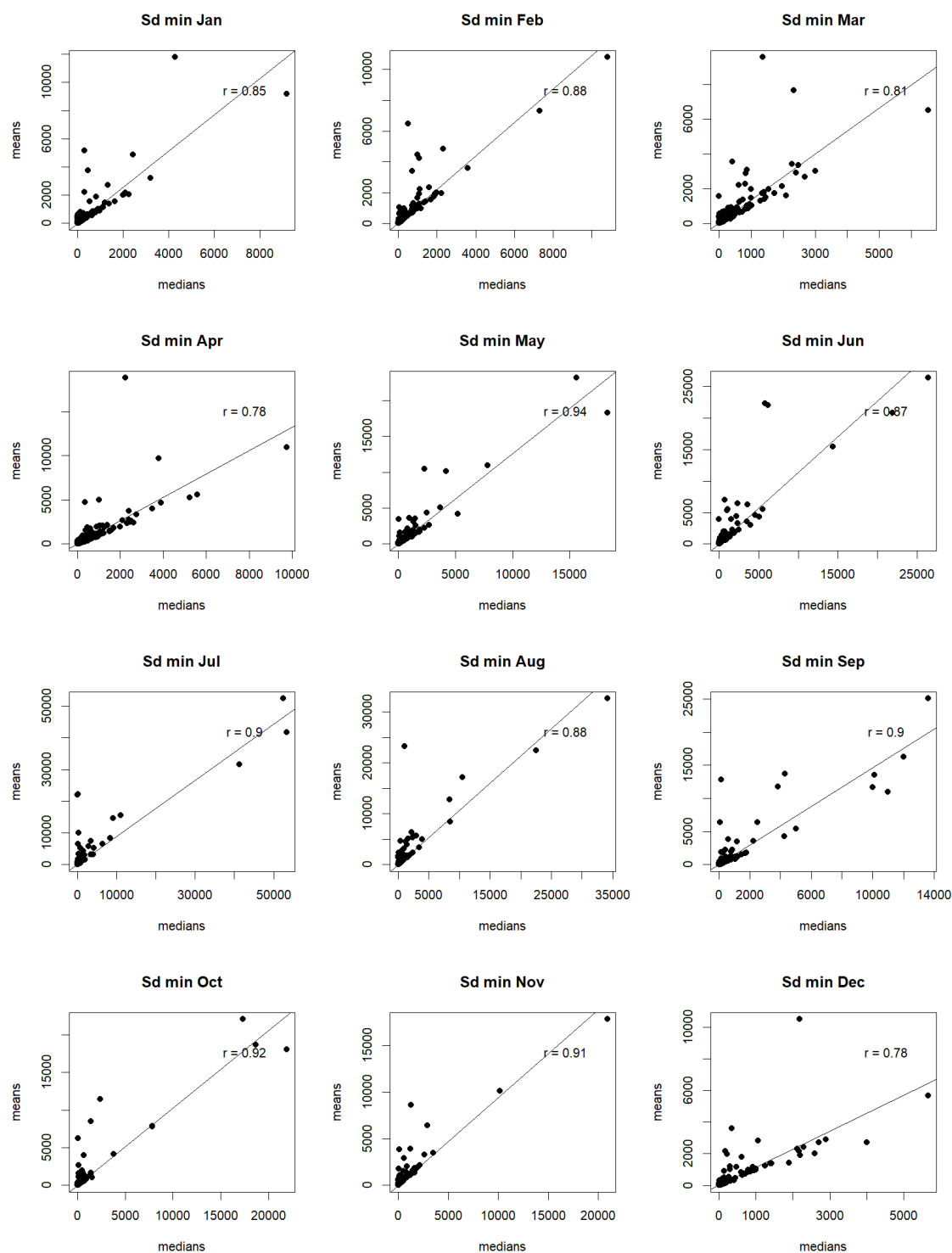


Figure A2-12. Scatter plots for means and medians from each annual time series of Std monthly min indicators (r=Pearson correlation coefficient)

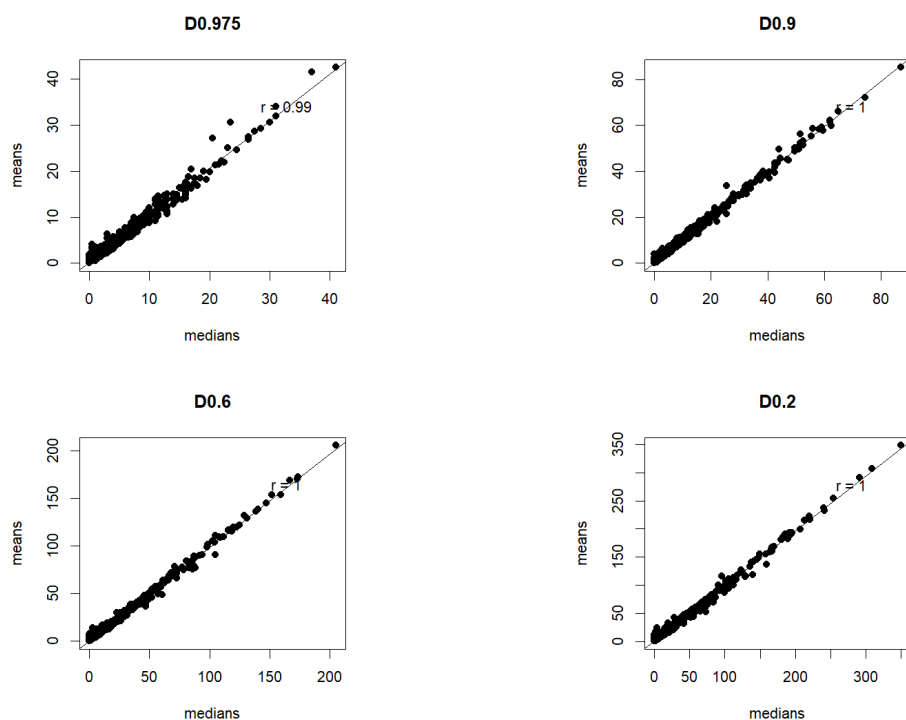


Figure A2-13. Scatter plots for means and medians from each annual time series of duration of event indicators (r =Pearson correlation coefficient)

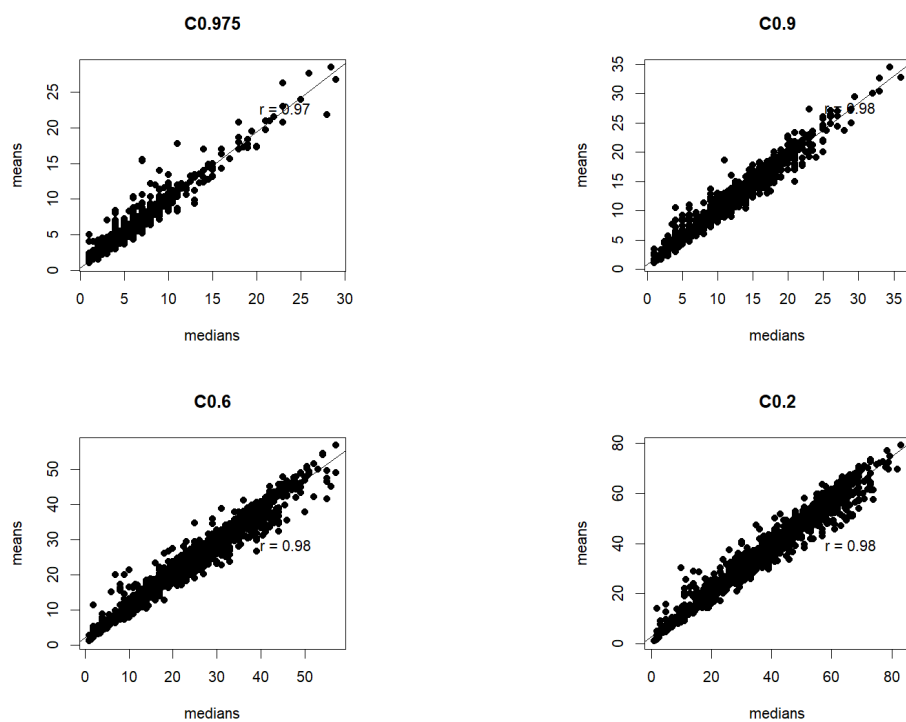


Figure A2-14. Scatter plots for means and medians from each annual time series of duration of event indicators (r =Pearson correlation coefficient)

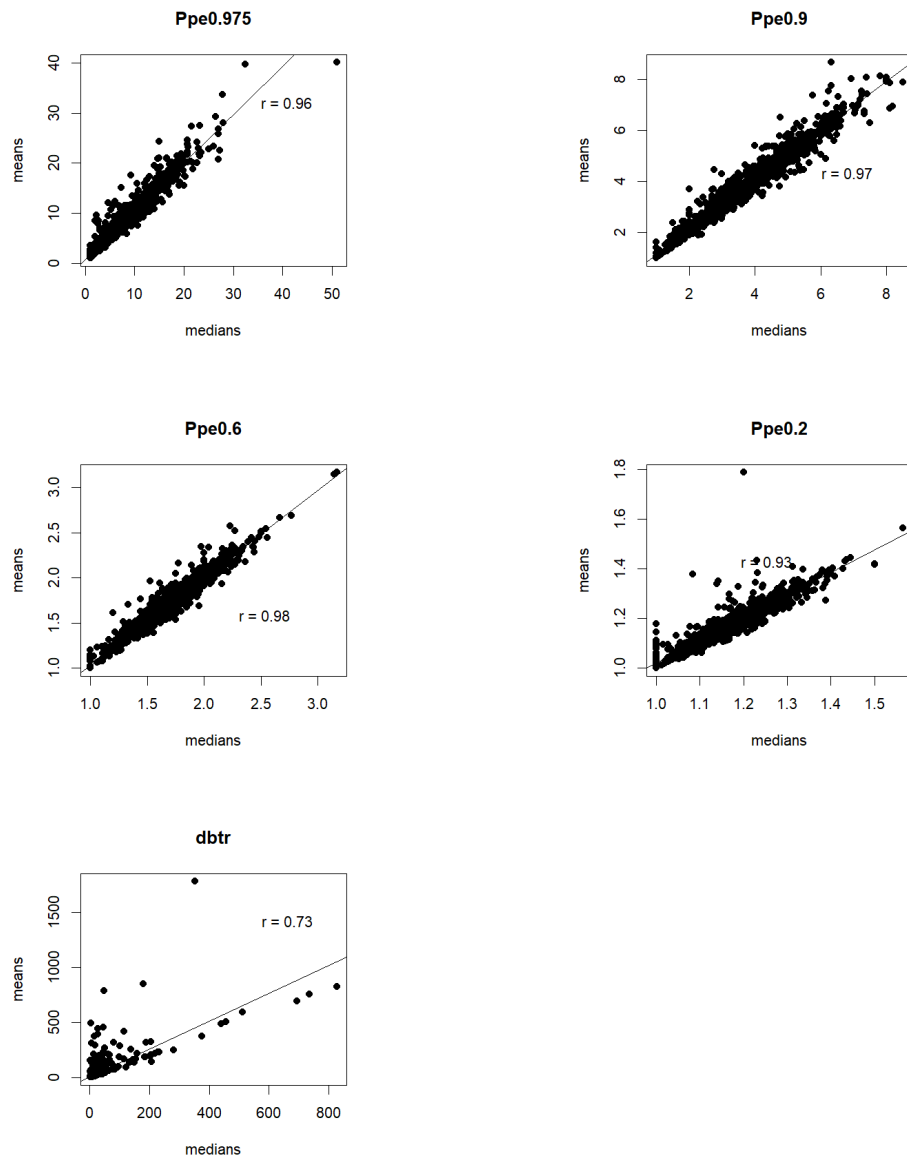
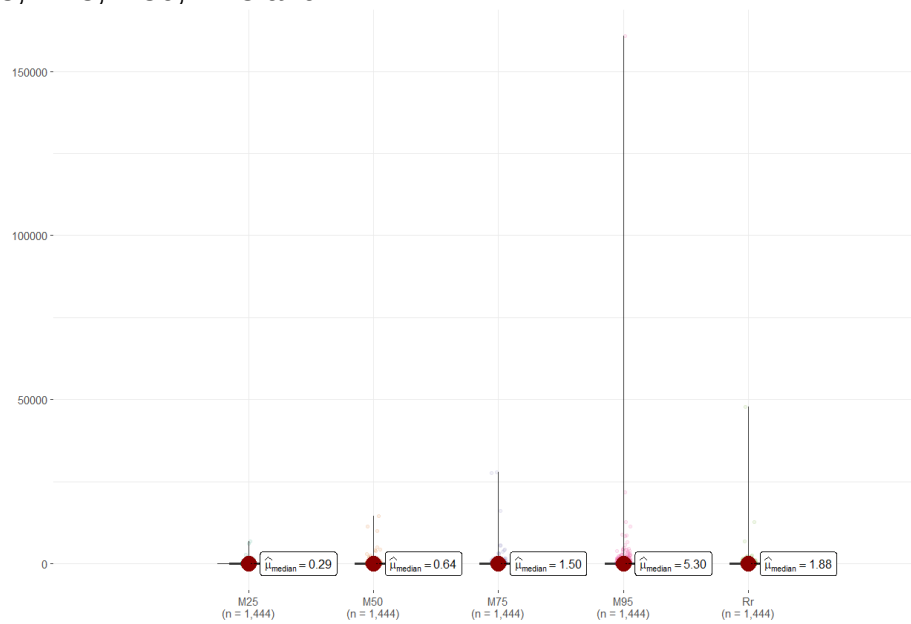
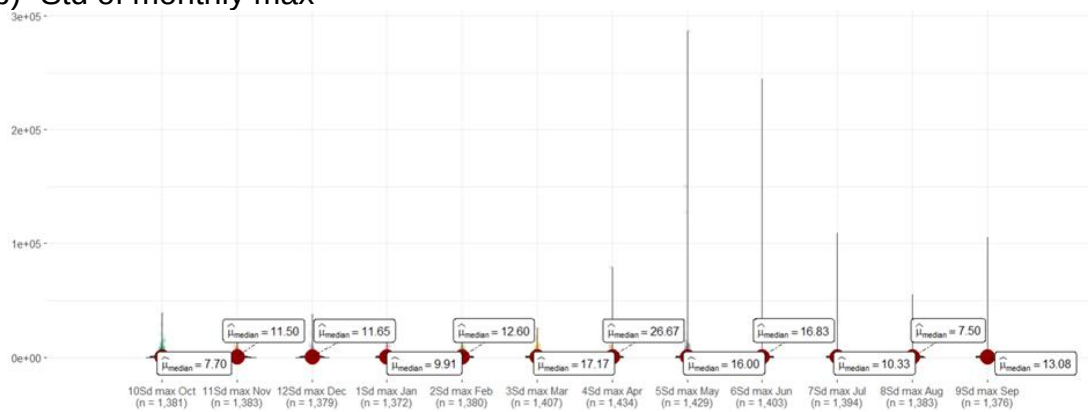


Figure A2-15. Scatter plots for means and medians from each annual time series of duration of event indicators (r =Pearson correlation coefficient)

a) M95, M75, M50, M25 and Rr



b) Std of monthly max



c) Std of monthly min

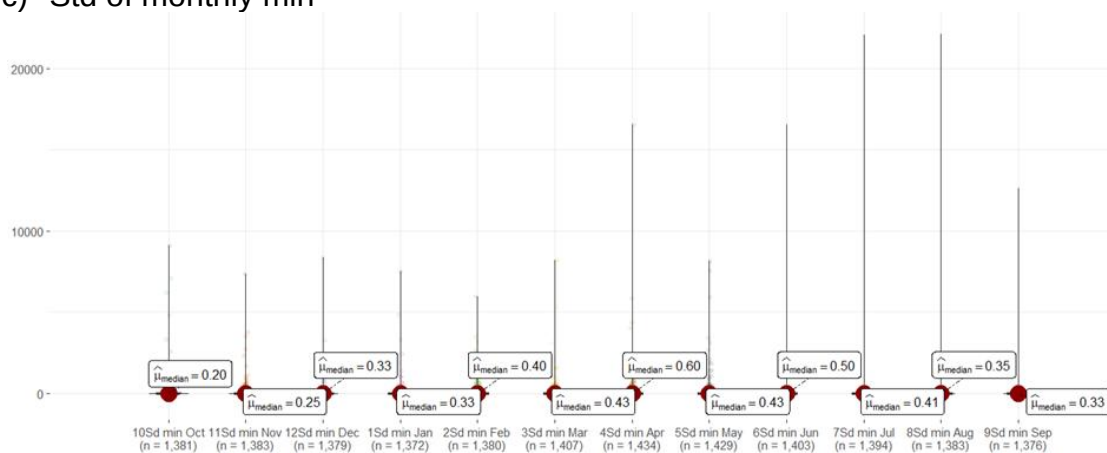
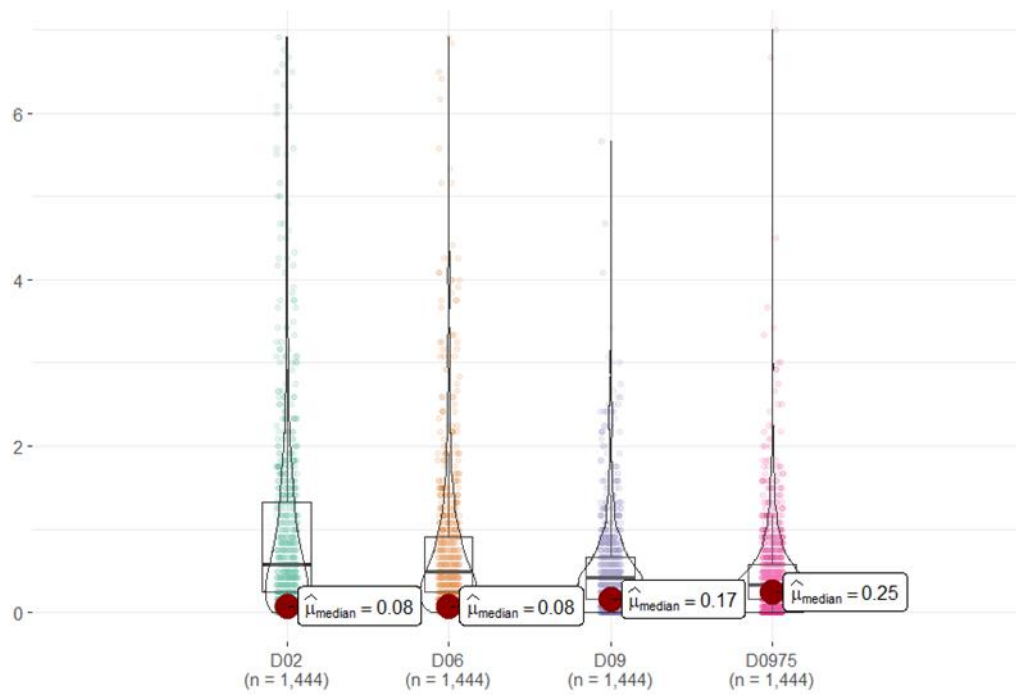
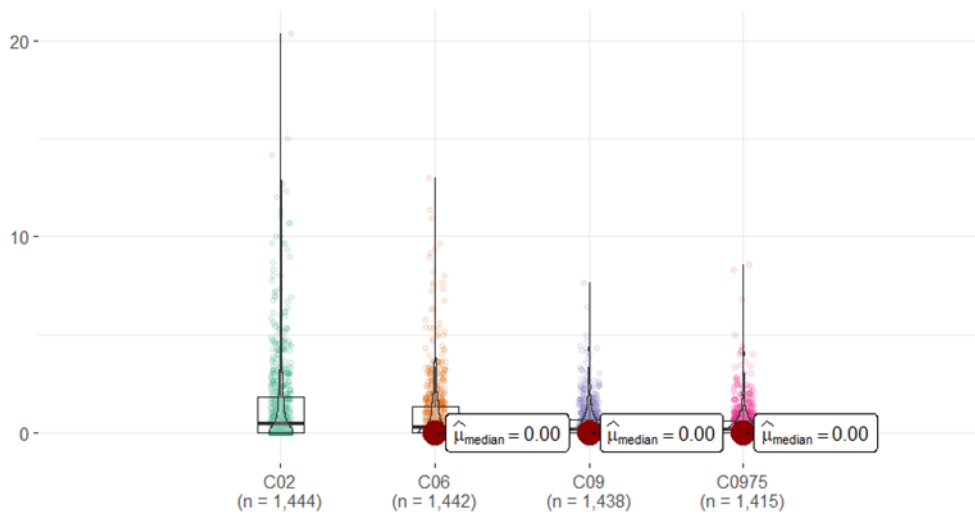


Figure A2-16. Boxplots for differences between means and medians from each annual time series of magnitude indicators

a) Duration of event



b) Count of event



c) Peaks per event

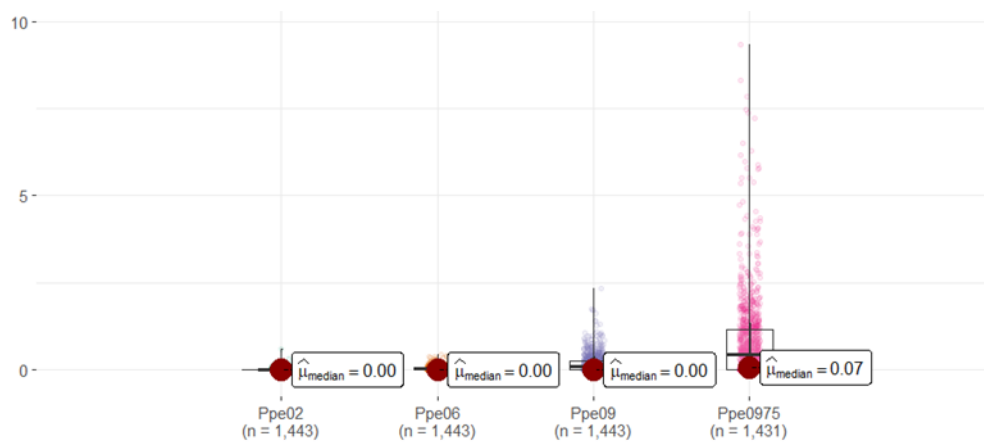
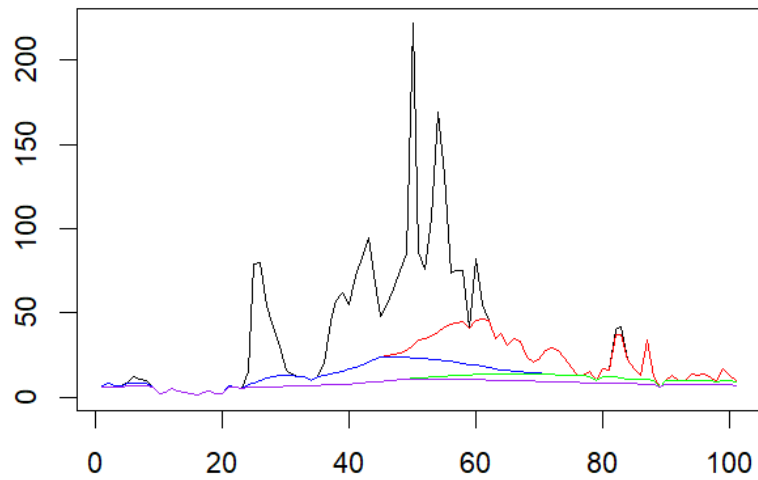


Figure A2-17. Boxplots for differences between means and medians from each annual time series of frequency indicators

Table A2-2. Rationale for choice of alpha values from differing durations of events at five different sites in different corners of the continent

Site	Observation on graphs per year from alpha value	Results from annual average calculation on duration of events
11447650 (CA)	<ul style="list-style-type: none"> • α 0.9 mostly captures month long events. • α 0.6 mostly captures week interval events. • α 0.15 mostly captures small peaks and peaks on the rising and falling limbs. 	<ul style="list-style-type: none"> • α 0.9 captures 30 day event. • α 0.5 captures 10 day event. • α 0.15 captures 7 day event.
06452000 (SD)	<ul style="list-style-type: none"> • α 0.9 captures month long events. • α 0.6 mostly captures around 10 day events. • α 0.2 captures small peaks on the rising and falling limbs. 	<ul style="list-style-type: none"> • α 0.85 captures 30 day event. • α 0.1 captures 10 day event.
08358400 (NM)	<ul style="list-style-type: none"> • α 0.9 mostly captures month long event. • α 0.6 mostly captures 7 day events. • α 0.2 captures small peaks on the rising and falling limbs. 	<ul style="list-style-type: none"> • α 0.9 captures 30 day event. • α 0.25 captures 7 day event.
01335770 (NY)	<ul style="list-style-type: none"> • α 0.9 mostly captures month interval events. • α 0.2 mostly captures small peaks on the rising and falling limbs. • α 0.6 mostly captures week interval event. 	<ul style="list-style-type: none"> • α 0.975 captures 30 day event. • α 0.55 captures 7 day event.
05544385 (WI)	<ul style="list-style-type: none"> • α 0.9 mostly captures month interval events. • α 0.6 mostly captures week interval events. • α 0.2 mostly captures small peaks on the rising and falling limbs. • But from 1997, α 0.9 mostly captures all events as the magnitude was significantly reduced. 	<ul style="list-style-type: none"> • α 0.7 captures 30 day event. • α 0.05 captures 18 day event.
Choice of three alpha values from judgement	<ul style="list-style-type: none"> • α 0.9 (For monthly duration) • α 0.6 (For weekly duration) • α 0.2 (for small peaks) 	

a) $\alpha=0.975$



b) $\alpha=0.2$

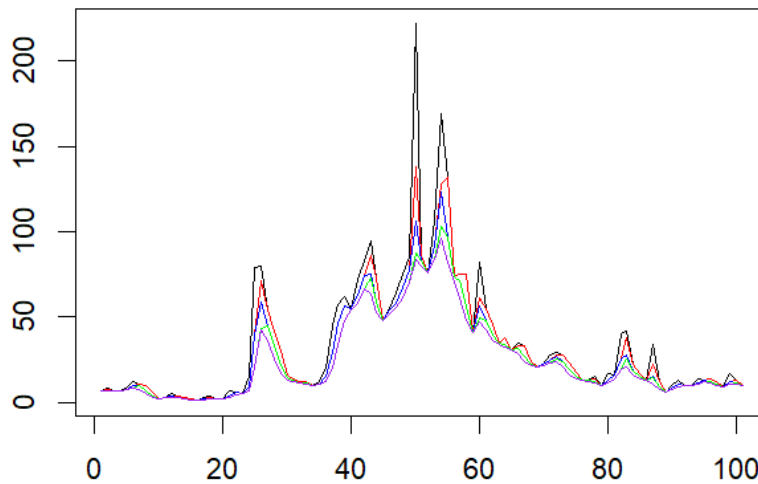


Figure A2-18. Examples of Lyne and Hollick filtering iterations (α of 0.975 and 0,2) over a SSC time series: Red is the first forward filtering. Blue is the first backward filtering. Green is the second forward filtering. Purple is the second backward filtering. Different baseflow recession was identified between alpha values that higher alpha values created up and downward sloping curves in lower gradient. However, lower alpha values created higher gradient curves. Thus, the difference between forward and backward filtering was decreased. The choice of alpha values significantly affected contact points, identifying variety of SS transport durations.

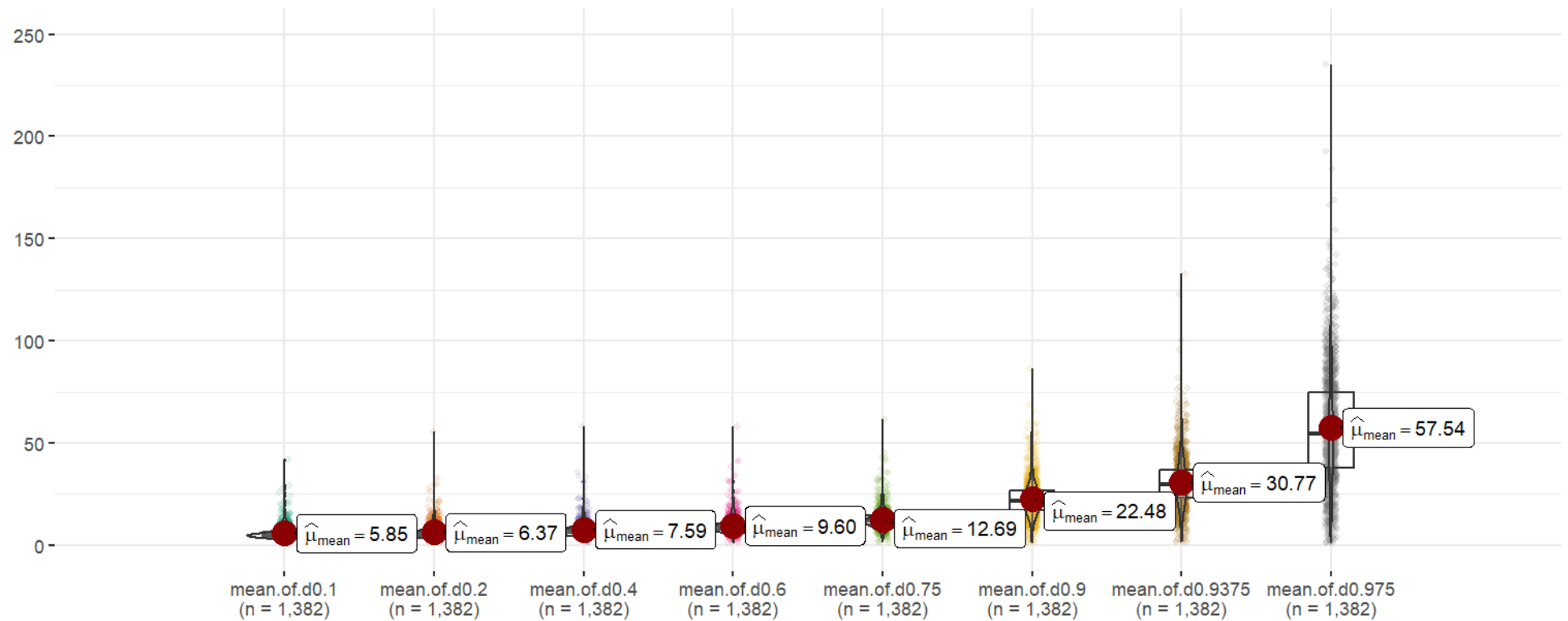


Figure A2-19. Average annual values of duration of events for all sites from alpha values of 0.975, 0.9375, 0.9, 0.75, 0.6, 0.4, 0.2 and 0.1

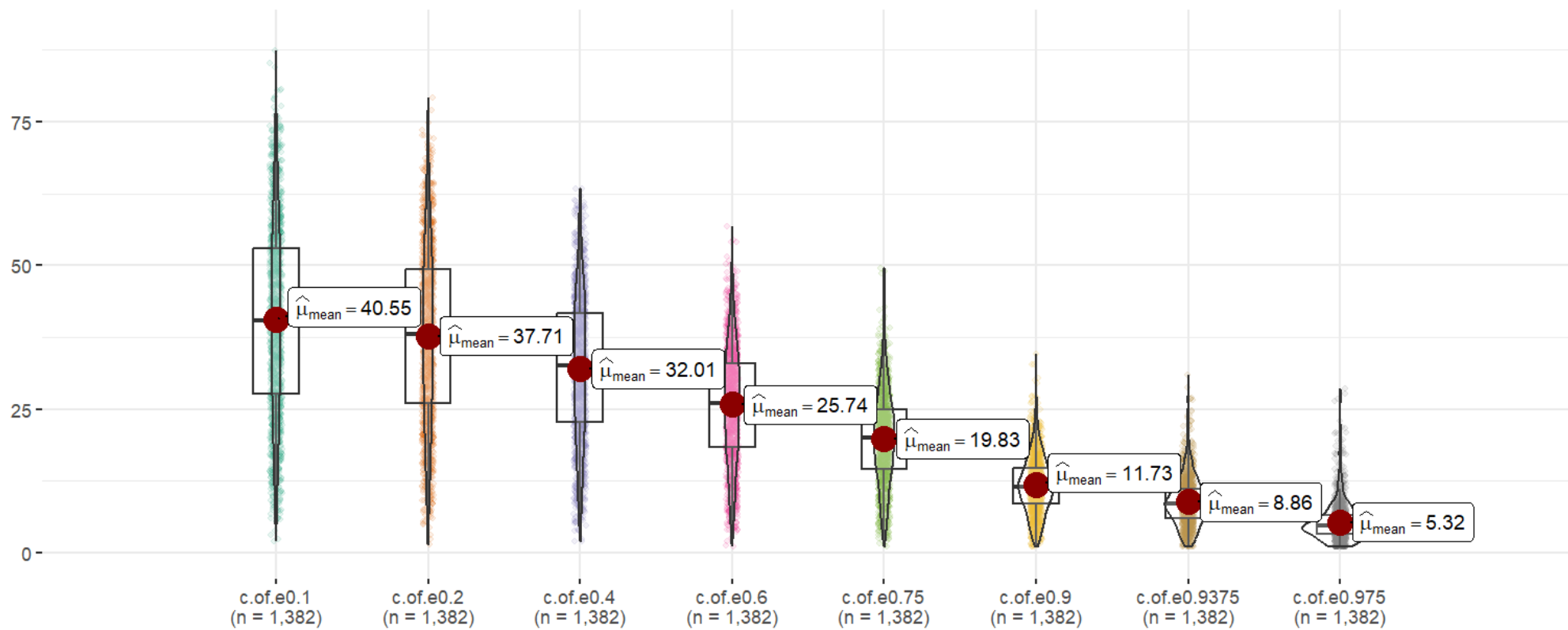


Figure A2-20. Average annual values of count of events for all sites from alpha values of 0.975, 0.9375, 0.9, 0.75, 0.6, 0.4, 0.2 and 0.1

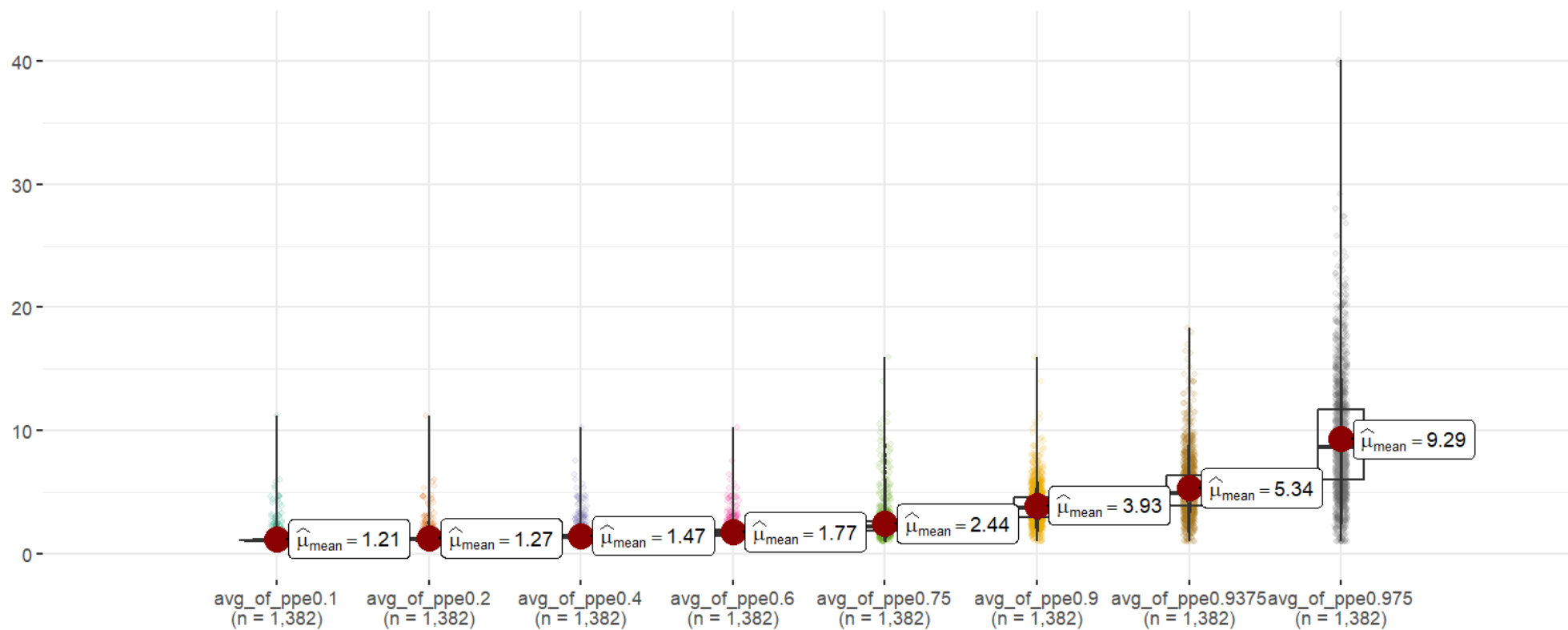


Figure A2-21. Average annual values of number of Peaks per event for all sites from alpha values of 0.975, 0.9375, 0.9, 0.75, 0.6, 0.4, 0.2 and 0.1

Incorporation of Field significance in trend analyses

Use of FDR (False discovery rate) allows incorporation of condition that multiple tests are implemented at the same time in each different site (Cammalleri *et al.*, 2016). FDR was applied to trend analysis to account for field significance (Gudmundsson and Seneviratne, 2015). Walker's p is applied as following (Wilks, 2006).

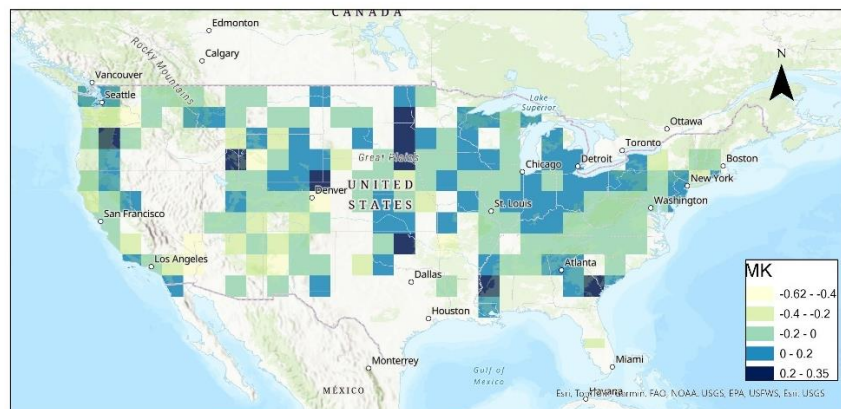
$$\text{Walker's } p = 1 - (1 - \alpha_{\text{global}})^{\frac{1}{K}}$$

Where, α_{global} was inserted as 0.05

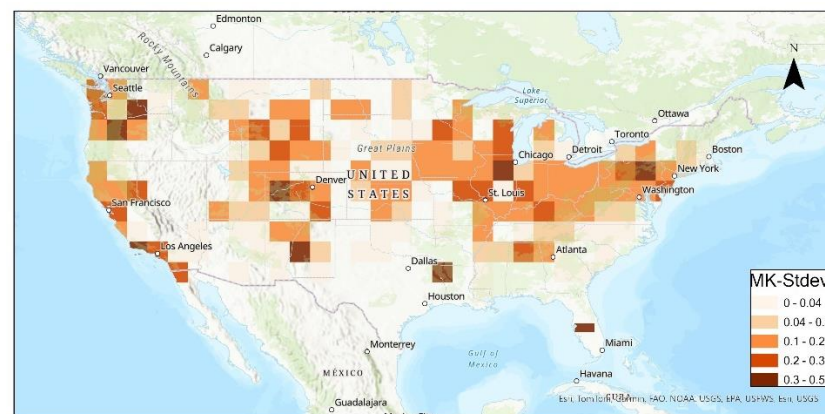
K was inserted as 1,329 (sites in the continent, excluding Islands due to the distances and varying precipitation patterns)

Field significance (p value of 3.859466×10^{-5}) associated with FDR is applied to MK trend analyses, which identified different number of sites with trends. More obvious decreasing trends of SSC after performing block statistics was identified from daily time series than without the field significance case (Figure A2-22, a). Stdev of the difference in the block statistics showed smaller spatial patterns due to the less number of sites identified after applying the new p value (3.859466×10^{-5}) in Figure A2-22, b. Substantially reduced number of sites after applying the field significance were identified from MK trends of average annual time series of the indicators selected. The reduced numbers of the sites are 351 from all time series, 151 from M95, 89 from D0.9, 114 from D0.6 and 74 from Ppe0.6. M95 with much less sites identified than the case without considering the field significance shows mostly decreasing trend except a site in New Mexico (Figure A2-22, c). Increasing D0.9 was only visible in New Mexico (Figure A2-22, d). The increasing D0.6 sites were reduced to New Mexico, South Dakota, Minnesota, Wisconsin and Washington (Figure A2-22, e). The number of sites greatly reduced from Ppe0.6 that only a site with increasing trend is visible in Minnesota (Figure A2-22, f).

a) MK – All time series



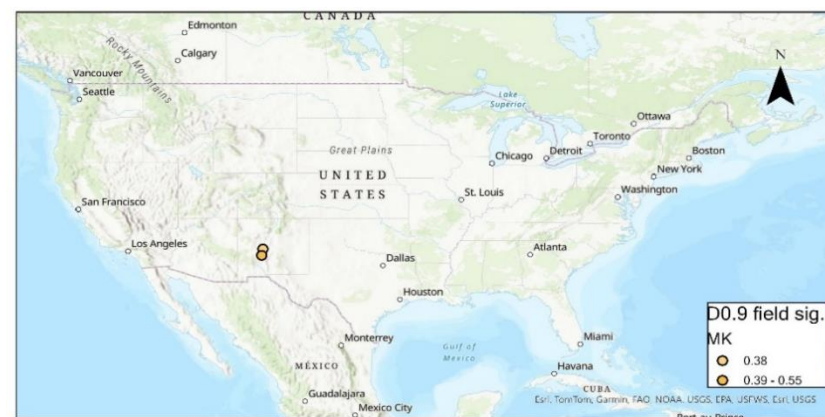
b) MK – Stdev



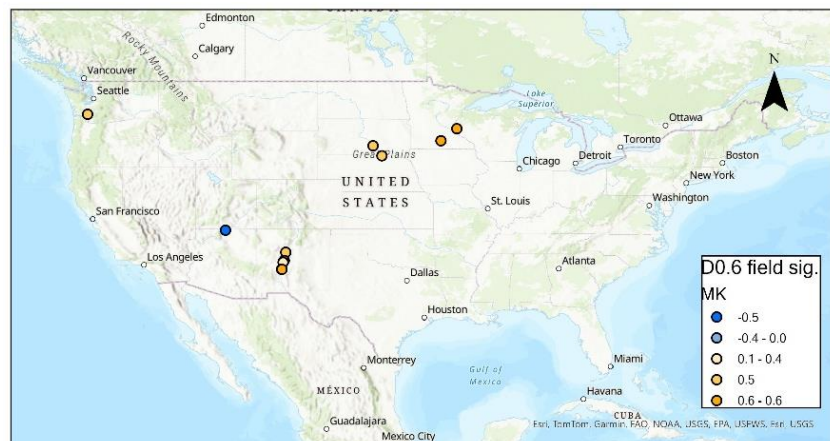
c) MK-95



d) MK-D0.9



e) MK-D0.6



f) MK-P.p.e0.6

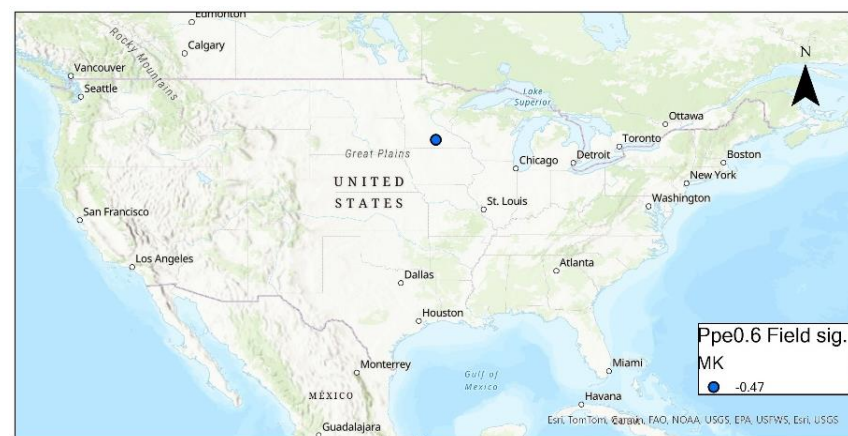
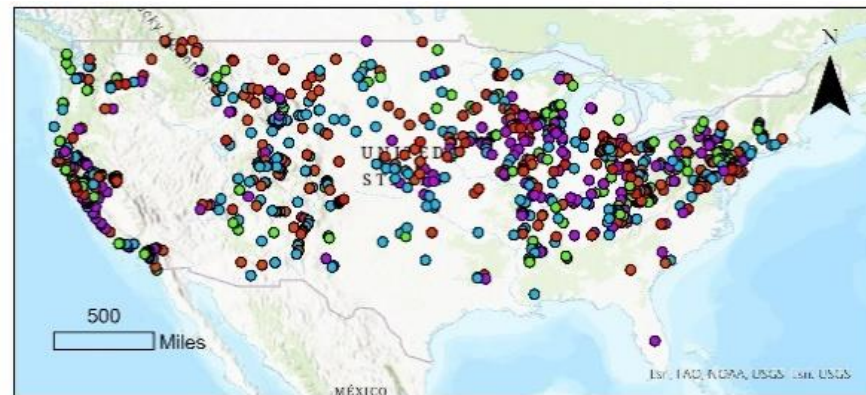
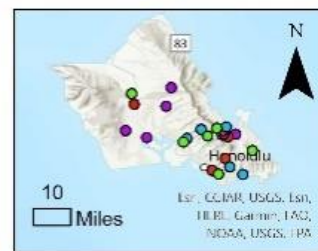


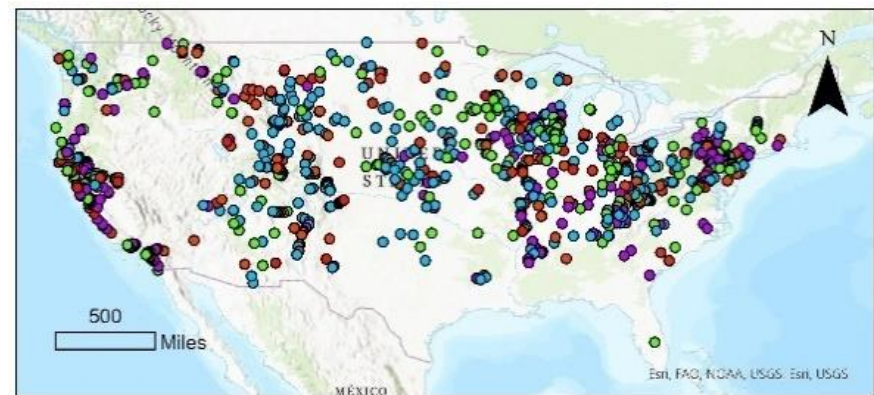
Figure A2-22. MK trend analyses with field significance ($p < 3.859466 \times 10^{-5}$)

a) $\alpha=0.975$



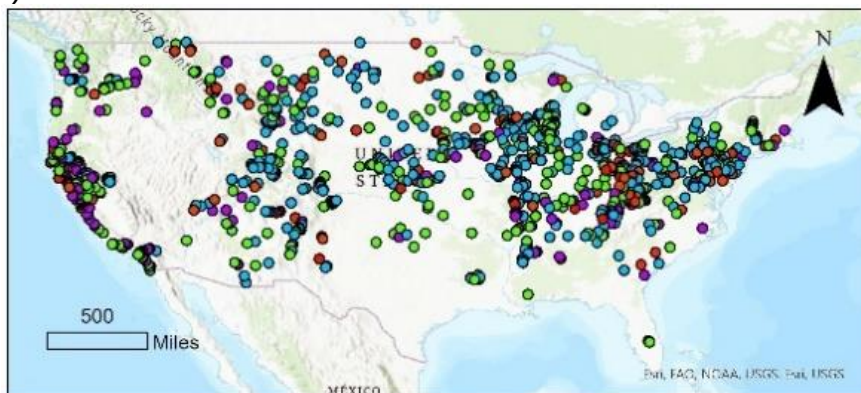
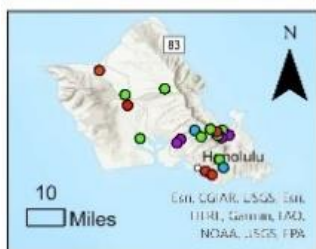
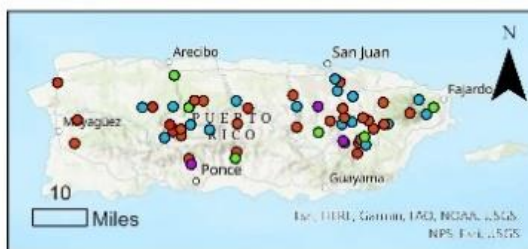
- Number of NAS=432

b) $\alpha=0.9$



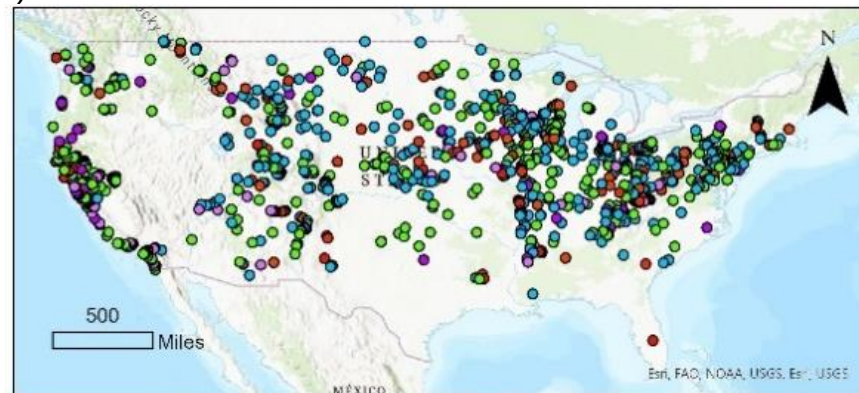
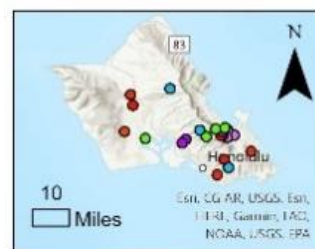
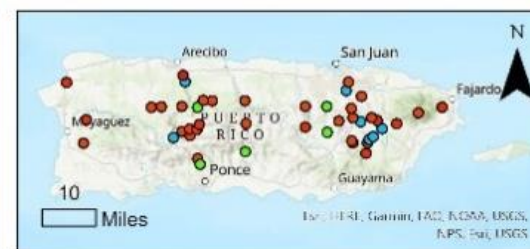
- Number of NAS=354

c) $\alpha=0.6$



- Number of NAs=229

d) $\alpha=0.2$



- Number of NAs=195

Figure A2-23. Spatial distribution of timing indicator (max months of number of inflection points): Seasons represented as colours (Purple: DJF, Green: MAM, Blue: JJA, Red: SON).

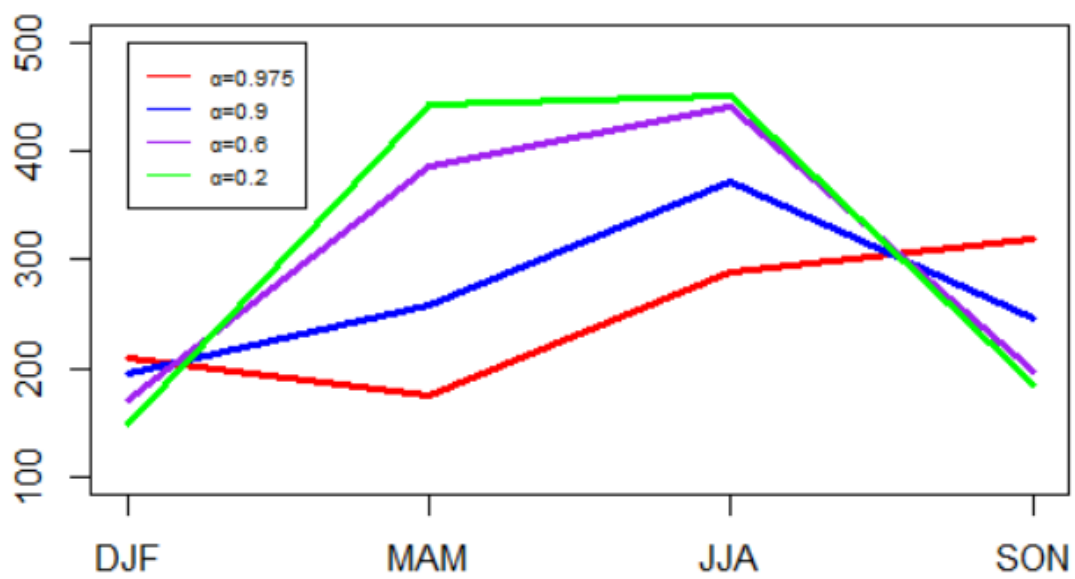
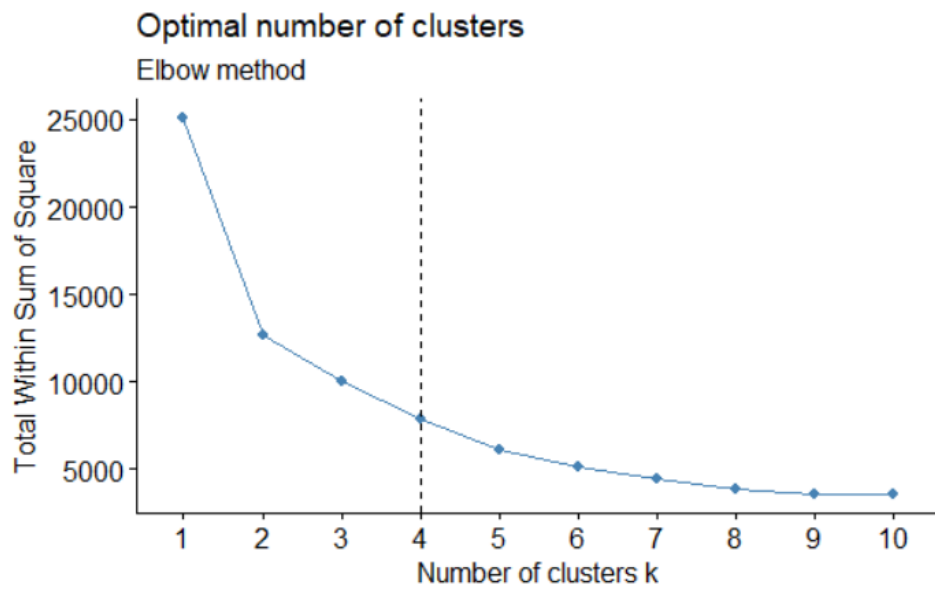


Figure A2-24. Number of sites per α values from Max months of number of inflection points: Number of sites vary depending on alpha values as excessive gaps yielded no result.

a) Elbow method



b) Silhouette method

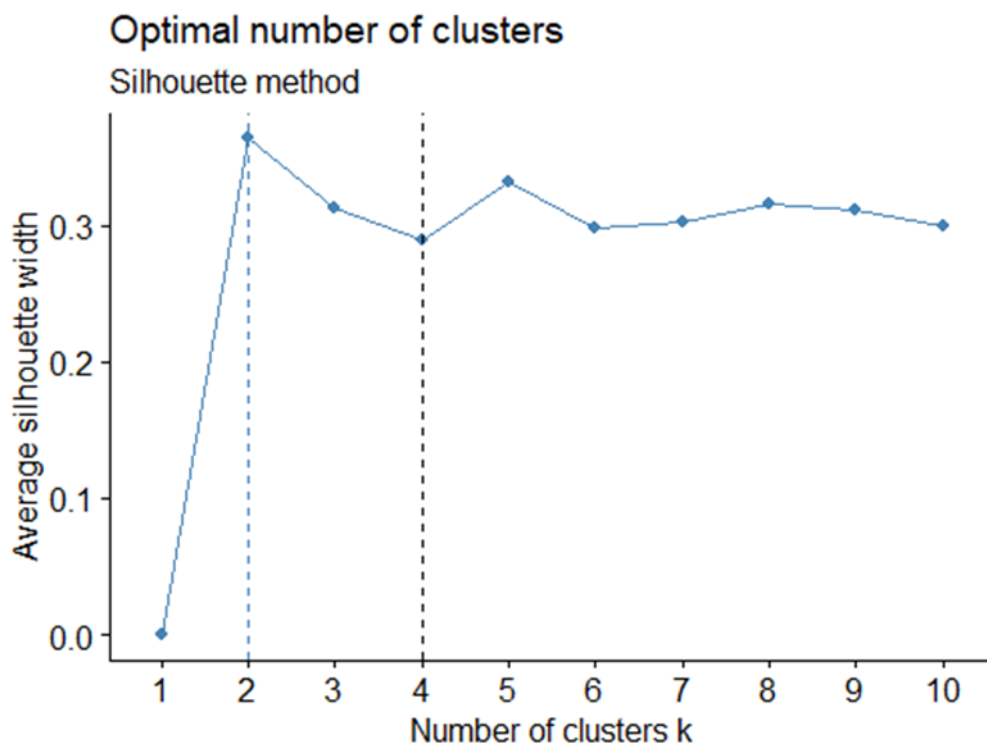


Figure A2-25. Result of (a) Elbow and (b) Silhouette methods for clustering analysis and decision on the number of clusters (Black dashed line). Cluster number two (Blue dashed line) is shown as the preferable clustering number but the chosen number of four does not show drastic changes in the evaluation scores.

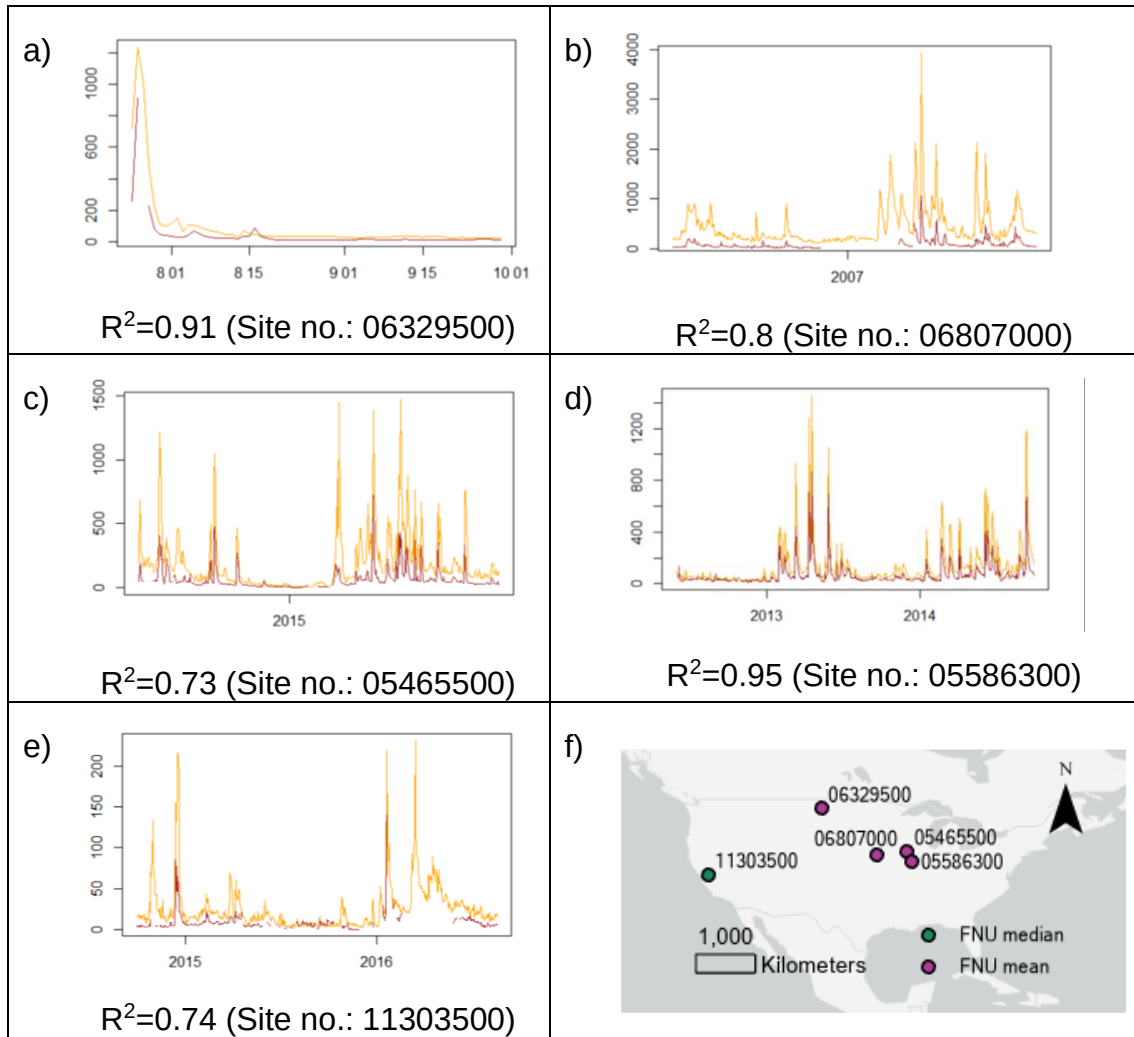


Figure A3-1. a-e) Daily turbidity (FNU, brown colour) and suspended sediment concentration (SSC in mg/l, orange colour) time series for the five sites in the dataset with concurrent daily data records at pre-processed sites. f) Map of data location

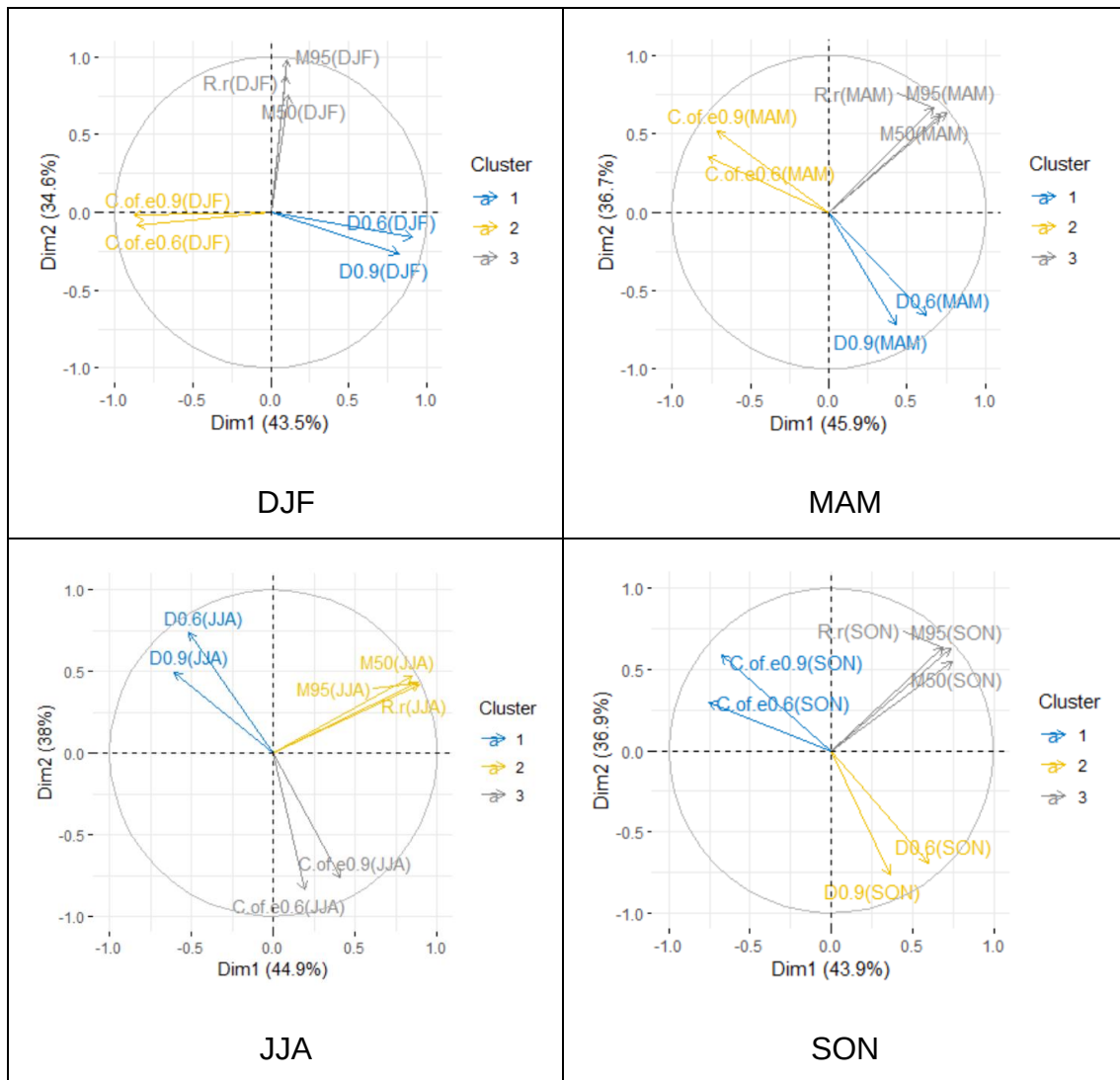
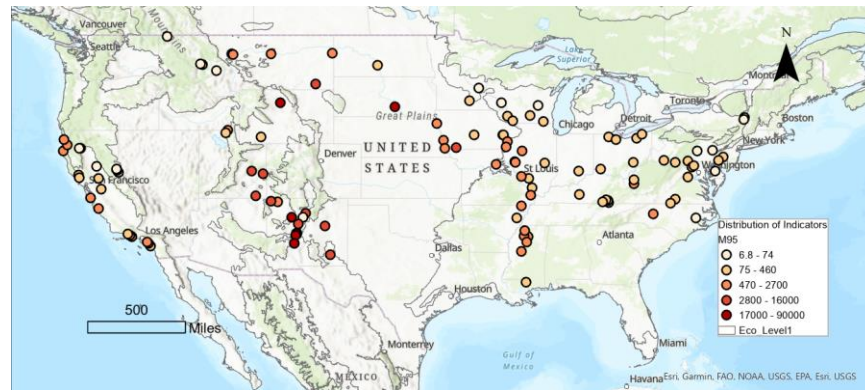
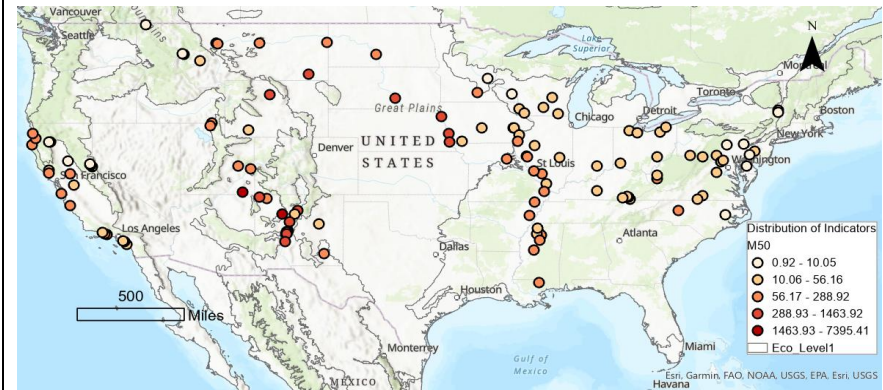


Figure A3-2. PCA results of seasonally subset indicators using 3 centred K-means

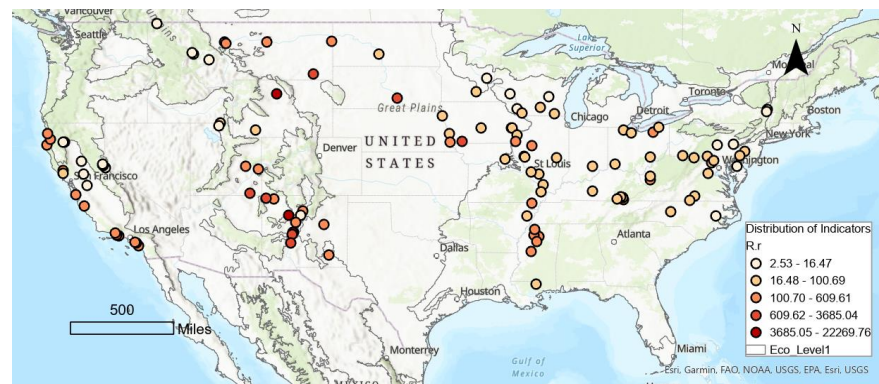
Description of Indicators



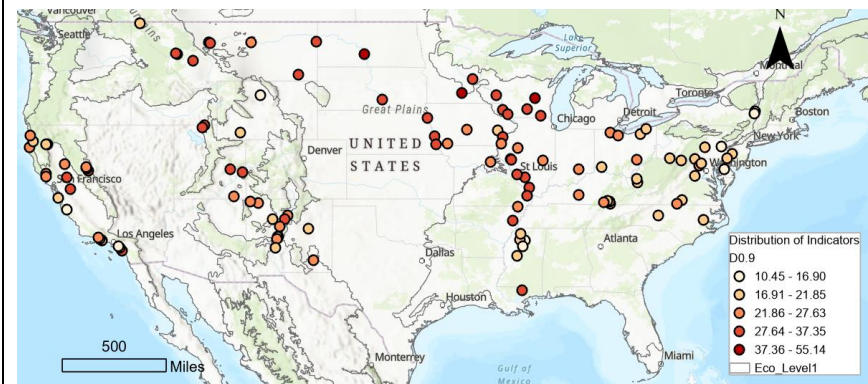
<M95>



<M50>



<R.r>



<D0.9>

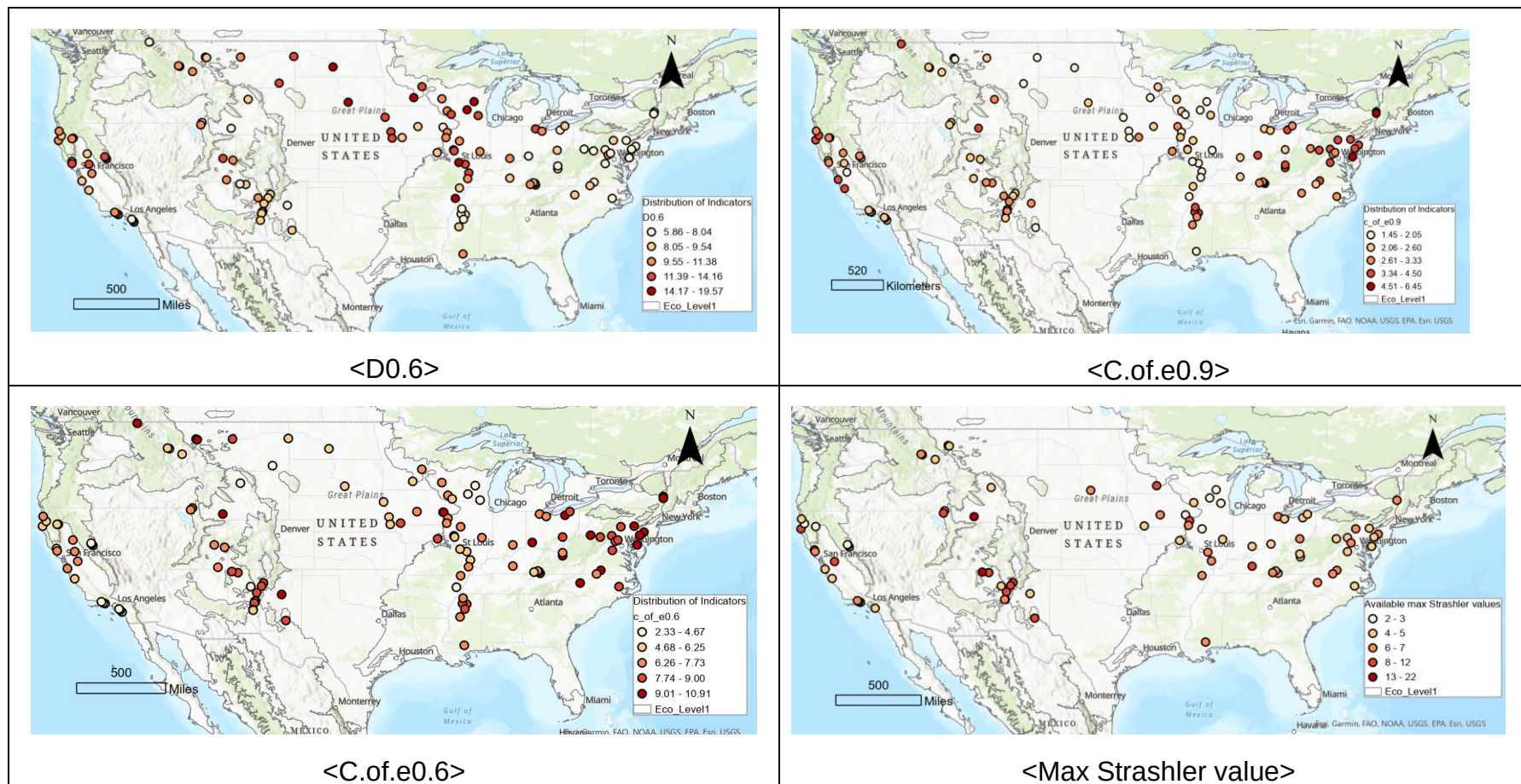
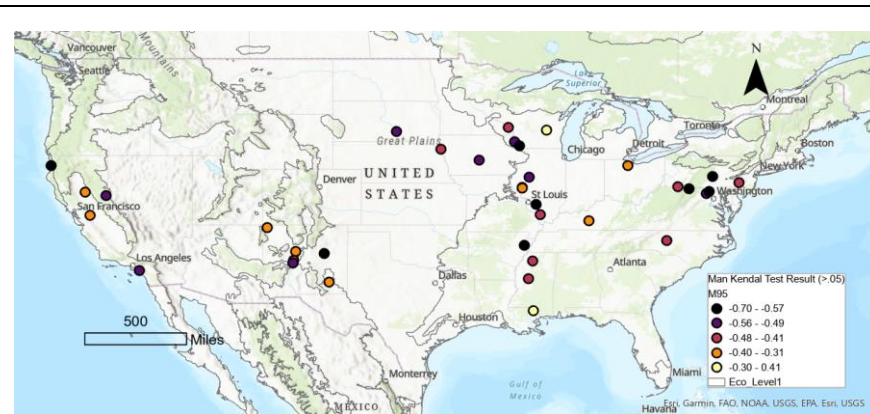
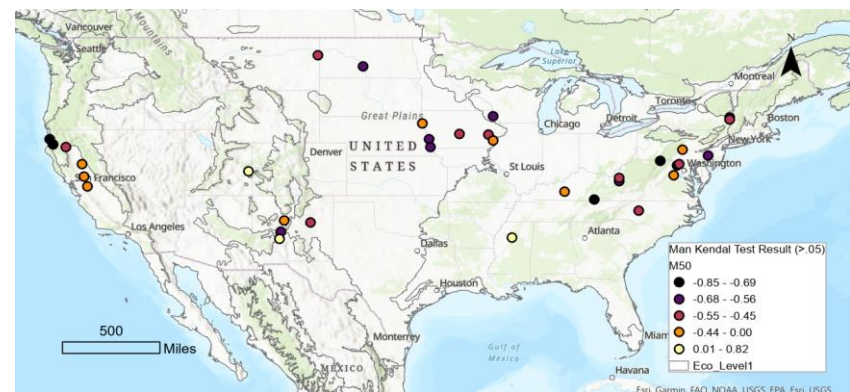


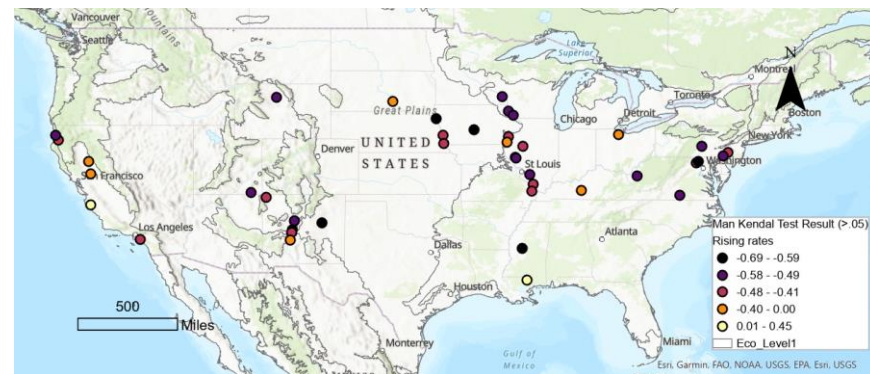
Figure A3-3. Spatial distribution of SS dynamics indicators (Annual)



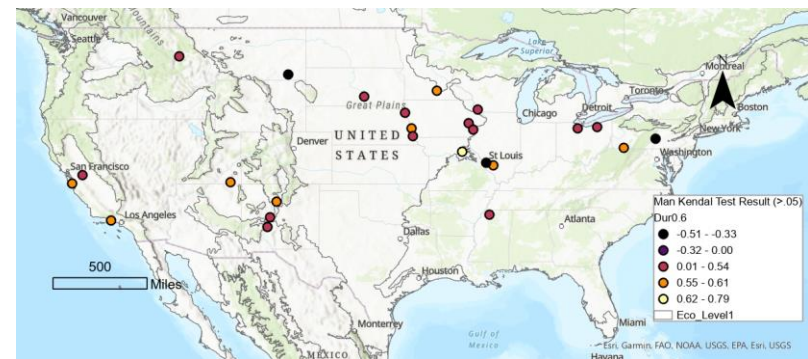
<M95>



<M50>



<R.r>



<D0.6>

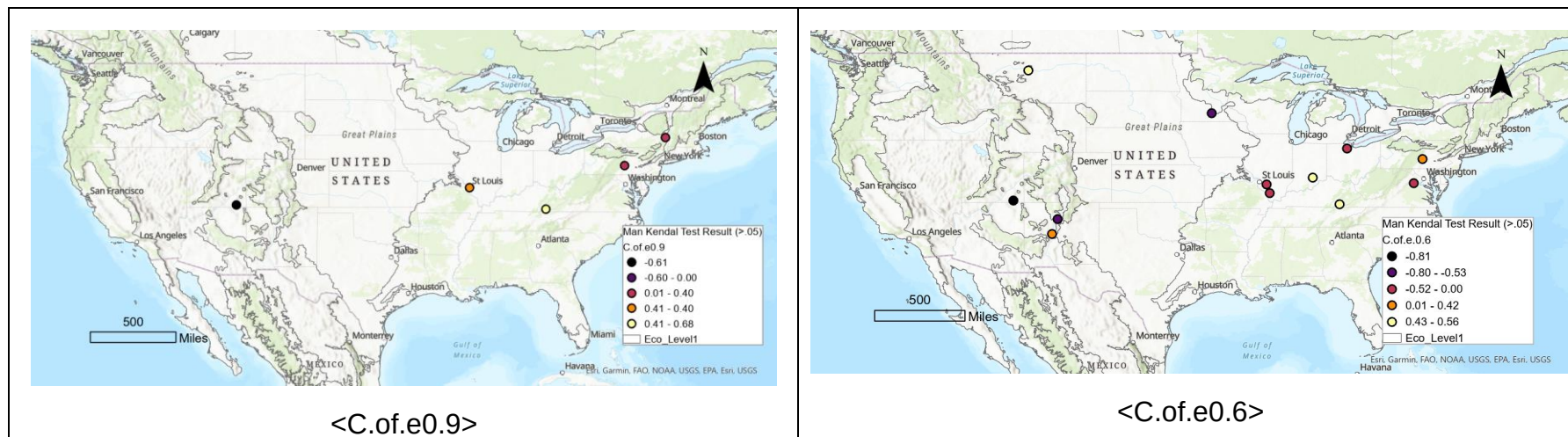


Figure A3-4. Man Kendall test results ($p < 0.05$)

Correlation plot

Correlation plot showed that magnitude, frequency and site attributes correlate each other (Figure A3-5~9). Significant correlation between magnitude indicators were identified. Magnitude and frequency indicators had different correlation with site attributes. The correlation plot indicates that PPT30 correlates with Cofe 0.9 and 0.6. Rfact and PPT30 correlate each other. BFI is negatively correlated with Rfact but positively correlated with PERM. Kfact is negatively correlated with BFI and PERM. Forest perc has good correlation with PPT30 and Cofe0.9 but negatively correlated with D0.9. Agperc has good correlation with Kfact, and negatively correlated with PERM. Major_dams is correlated with Catch.A. R.stroage correlates with Major_dams and Catch.A. Clay correlates with Agperc and Kfact but negatively correlates with BFI and PERM. Sand is negatively correlated with Clay, Silt, Agperc, BFI and PERM but positively correlated with Kfact. More silt means more Clay, Rfact, Agperc and Kfact but less BFI and PERM. Flow 50th & 95th percentiles had very strong correlation with Major_dams, R.storage and Catch.A.

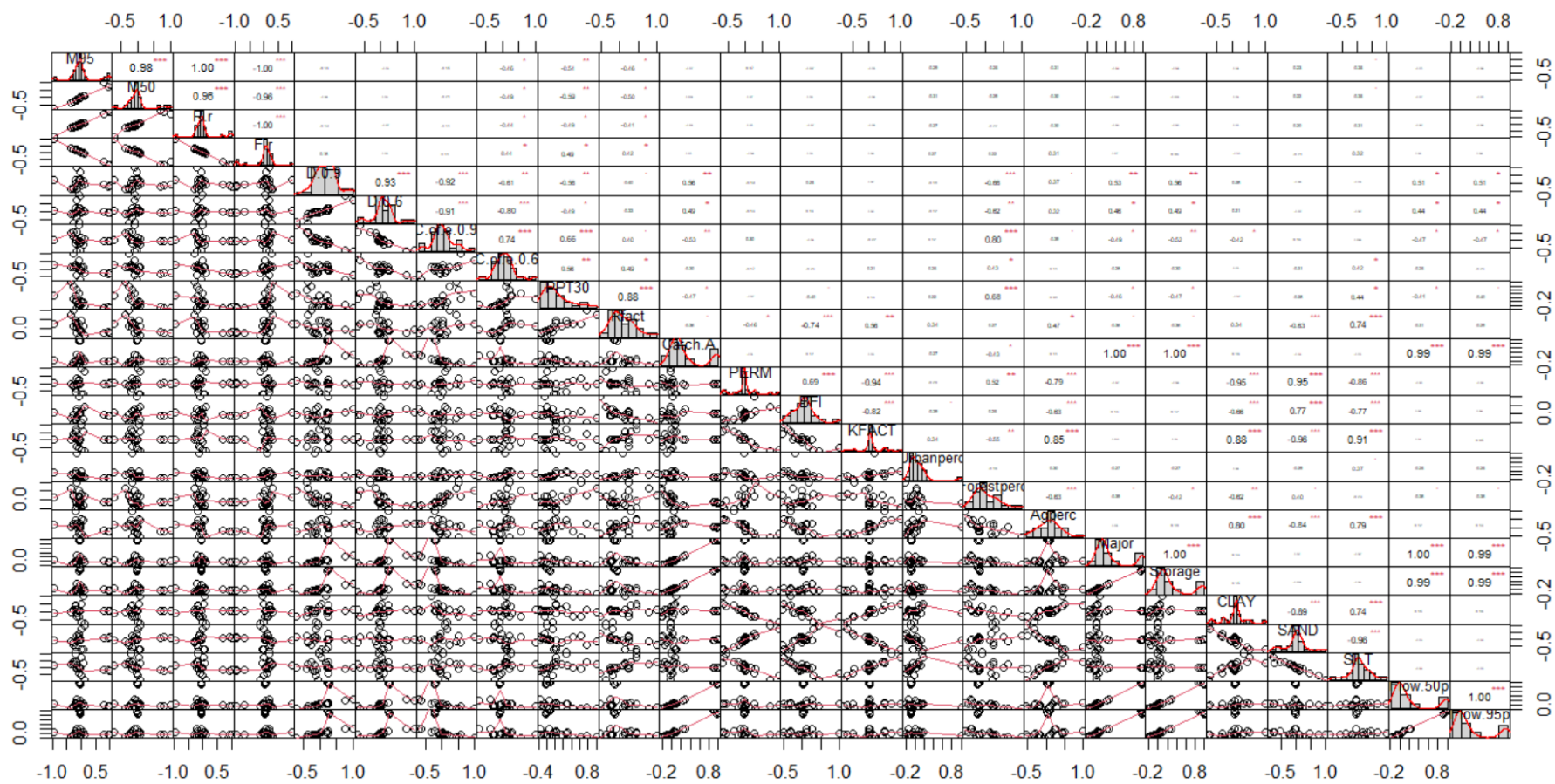


Figure A3-5. Correlation matrix for indicators and site attributes: From top left to bottom right, M95, M50, R.r, F.r, D0.9, D0.6, C.of.e0.9, C.of.e0.6, PPT30, Rfact, Catch.A, PERM, BFI, KFACT, Urbanperc, Forestperc, Agperc, Major Dams, R.Storage, CLAY, SAND, SILT, Flow.50p, Flow.95p (Table 3-2).

Figure.A3-6~9 shows the correlation matrix in different seasons i.e., DJF, MAM, JJA, SON.

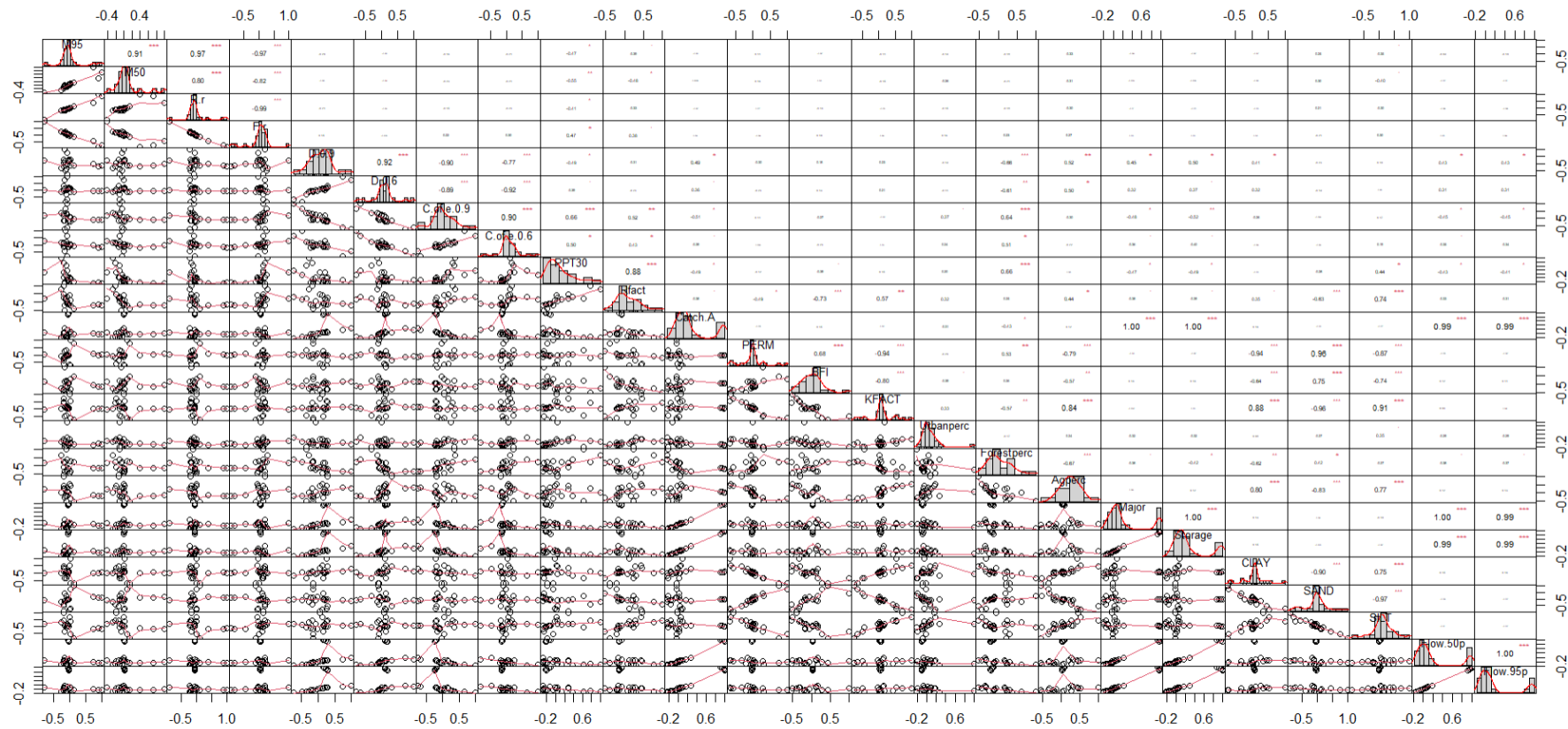


Figure A3-6. Correlation chart for fixed indicators (DJF)

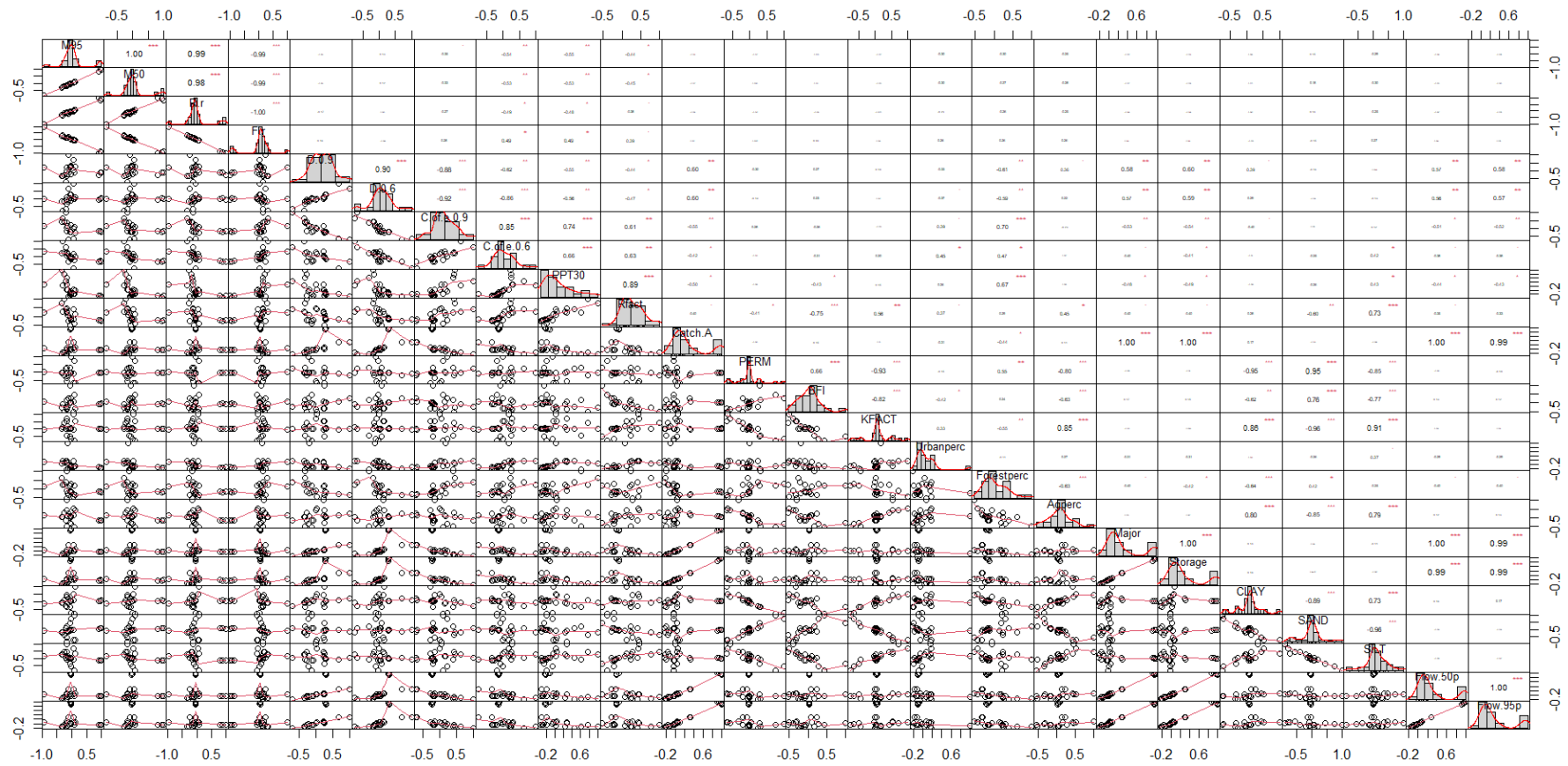


Figure A3-7. Correlation chart for fixed indicators (MAM)

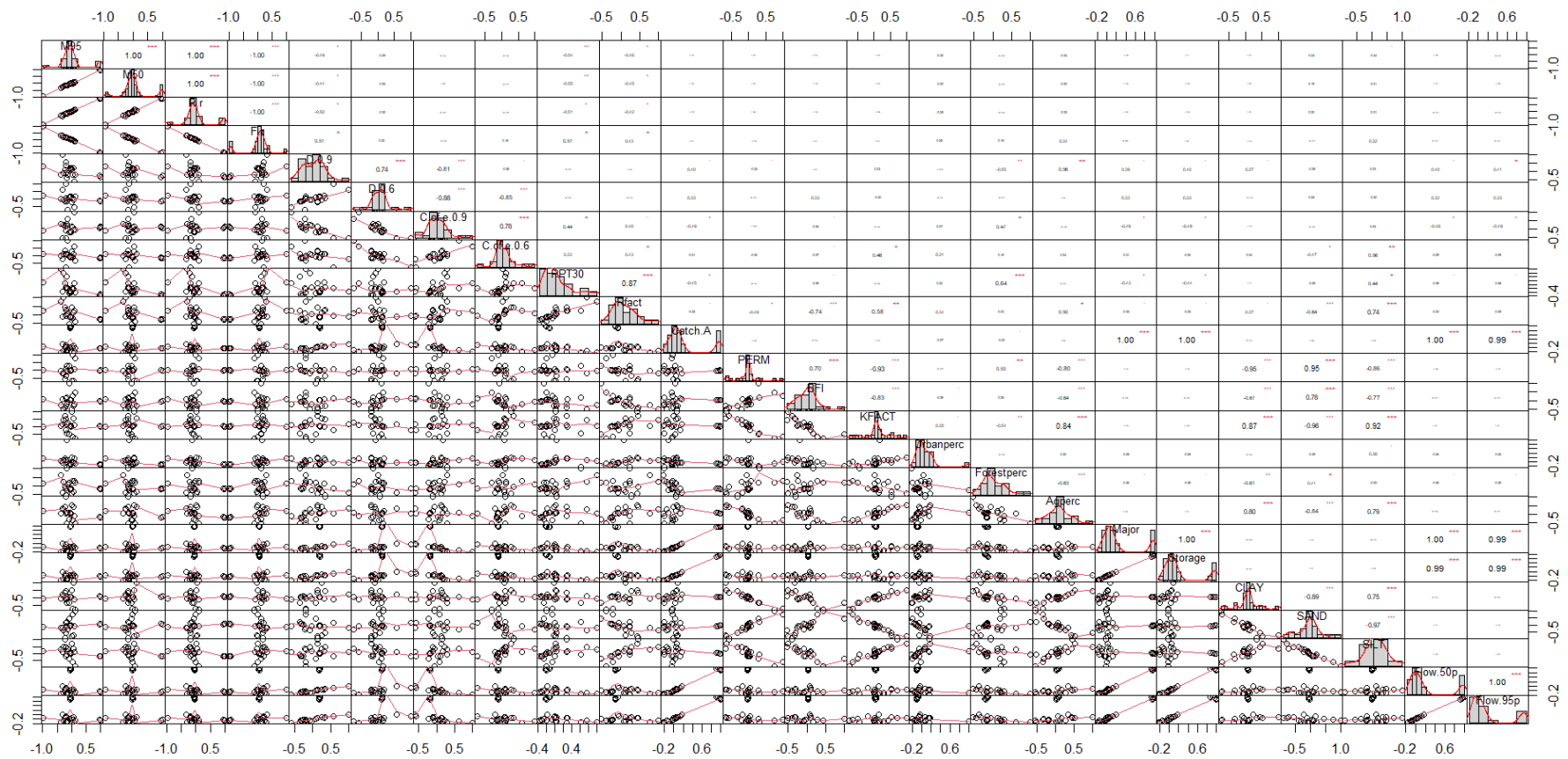


Figure A3-8. Correlation chart for fixed indicators (JJA)

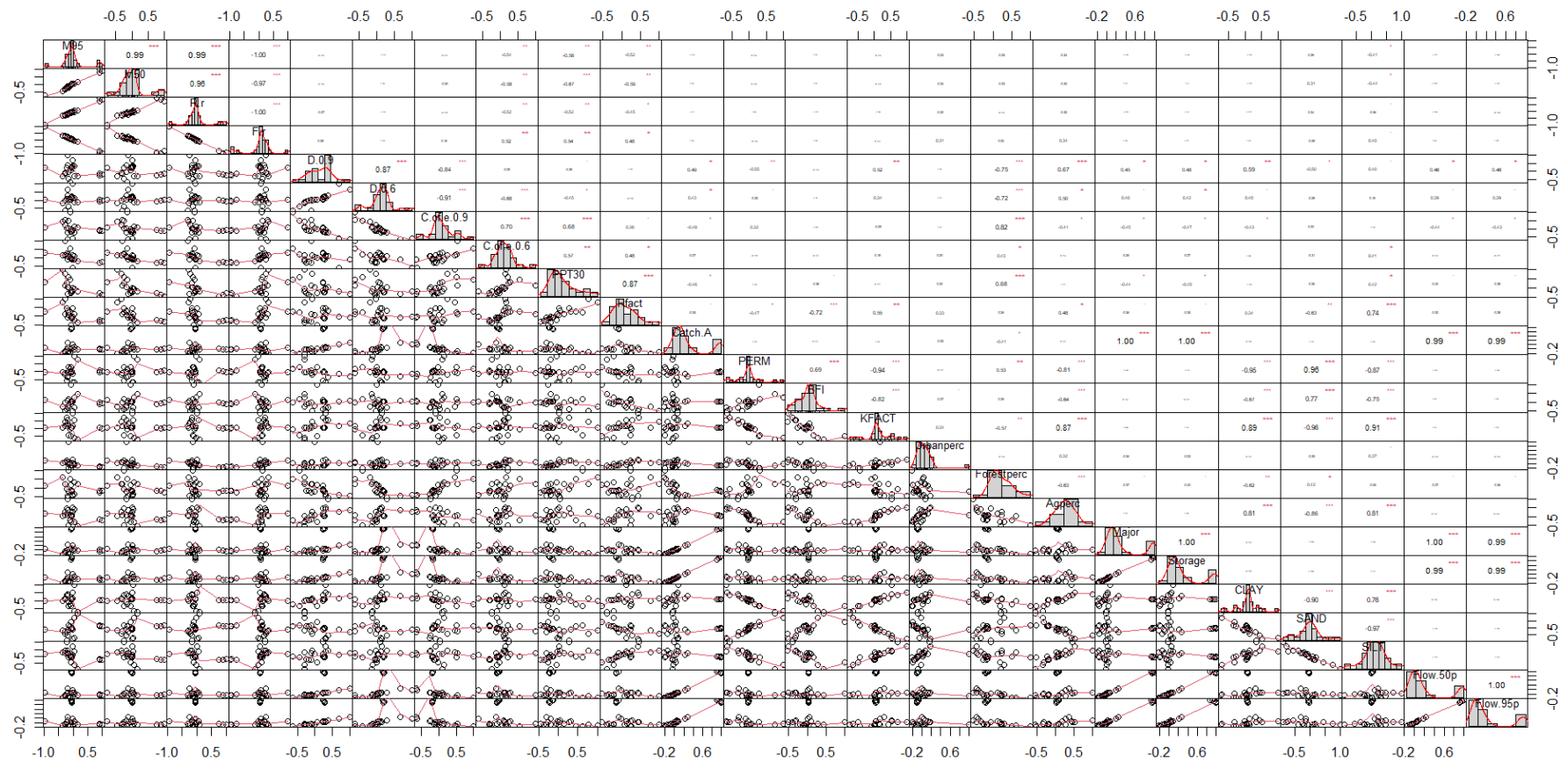


Figure A3-9. Correlation chart for fixed indicators (SON)

Table A3-1. Comparison of modeling performance between OLS regression and GWR models: The p-value of Moran's I larger than 0.05 are in bold.

Response variable		OLS						GWR (Fixed bandwidths)				
		Model	Intercept	Observed Moran's I	Moran's I p-value (KNN=4)	R ²	AIC	Observed Moran's I (Bandwidths)	Moran's I p-value	R ²	AIC	Bandwidths (Coordinate)
M95	Annual	-0.0099(PPT30)-0.0598(BFI)-0.0106 (Urbanperc)-0.0101(Agperc)-0.0418 (Clay)+0.0018(BFI*Clay)	5.797	0.199	1.40E-05	0.626	175.602	-0.072	0.639	0.826	100.069	4.63
	DJF	-0.0051(PPT30)-0.0631(BFI)-0.0118(Agperc)-0.043(Clay)+0.0017(BFI*Clay)	5.437	0.230	1.51E-06	0.593	157.030	-0.029	0.629	0.676	129.138	9.87
	MAM	-0.0099(PPT30)-0.0169(BFI)-0.0085(Urbanperc)-0.0084(Agperc)+0.04 (Clay)	3.734	0.176	9.15E-05	0.551	170.675	-0.074	0.256	0.818	85.809	3.68
	JJA	-0.0275(PPT30)+0.0106 (Rfact)+0.0095(Forestperc)+0.0758(Clay)-0.0002(Rfact*Clay)	2.292	0.399	9.80E-15	0.588	236.600	-0.055	0.295	0.838	136.398	4.93
	SON	-0.0109(PPT30)-0.022(BFI)-0.012 (Urbanperc)-0.0105(Agperc)+0.0459(Clay)	3.706	0.309	4.44E-10	0.512	226.849	-0.057	0.051	0.870	91.200	3.69
M50	Annual	-0.0158(PPT30)+0.0028(Rfact)+0.0156(Agperc)+0.0683(Clay)-0.0008 (Agperc*Clay)	1.396	0.199	1.4E-05	0.642	158.222	-0.029	0.030	0.812	88.252	5.91
	DJF	-0.008(PPT30)-0.0488(BFI)-0.0105(Urbanperc)-0.0442 (Clay)+0.0015(BFI*Clay)	4.252	0.230	1.51E-06	0.514	171.375	-0.046	0.111	0.759	100.765	4.71
	MAM	-0.0126(PPT30)-0.0134(BFI)-0.0119(Urbanperc)-0.0062(Agperc)+0.0384(Clay)	3.060	0.291	2.95E-09	0.627	165.549	-0.038	0.093	0.792	105.346	5.51
	JJA	-1.852e-02(PPT30)+7.990e-03(Rfact)-8.372e-03(Urbanperc)+7.273e-02(Clay)-2.213e-04(Rfact*Clay)	1.539	0.399	9.80E-15	0.68	174.096	-0.008	0.003	0.687	164.387	40.73
	SON	-0.0179(PPT30)+0.0032(Rfact)-0.0088 (Urbanperc)+0.0211 (Agperc)+0.0689(Clay)-0.001(Agperc*Clay)	1.442	0.342	3.21e-12	0.663	173.796	-0.003	0.000	0.702	152.779	21.69
R.I	Annual	-0.0085(PPT30)-0.0234(BFI)-0.0126(Agperc)+0.0351(Clay)	3.252	0.199	1.40E-05	0.459	214.289	-0.066	0.304	0.766	128.796	4.31
	DJF	-0.0563(BFI)-0.0065(Forestperc)-0.0161 (Agperc)-0.042(Clay)+0.0013(BFI*Clay)	4.600	0.230	1.51E-06	0.539	175.055	-0.013	0.282	0.592	156.775	14.57

Response variable	OLS						GWR (Fixed bandwidths)					
	Model	Intercept	Observed Moran's I	Moran's I p-value (KNN=4)	R ²	AIC	Observed Moran's I (Bandwidths)	Moran's I p-value	R ²	AIC	Bandwidths (Coordinate)	
	MAM	-0.0079(PPT30)-0.0208(BFI)-0.0101 (Agperc)+0.0386(Clay)	2.995	0.155	4.92E-04	0.458	197.275	-0.068	0.251	0.747	123.483	4.04
	JJA	-0.021(PPT30)+0.005(Rfact)-0.007 (Agperc)+0.04(Clay)	2.334	0.399	9.80E-15	0.44	271.229	-0.021	0.002	0.748	182.886	5.59
	SON	-0.0074(PPT30)-0.0613(BFI)-0.0122(Agperc)-0.0457(Clay)+0.0017(BFI*Clay)	4.958	0.432	3.21E-12	0.520	201.791	-0.061	0.215	0.781	124.433	4.29
D0.9	Annual	2.822e-03(BFI)-1.226e-03 (Forestperc)+9.309e-04(Agperc)+8.981e-10(R.storage)	1.266	0.199	1.4E-05	0.303	-210.032	-0.004	0.001	0.489	-246.467	8.35
	DJF	2.4e-03(BFI)-1.073e-03(Forestperc) 8.657e-10(R.storage)+5.536e-03 (Clay)	1.118	0.230	1.51E-06	0.274	-202.467	-0.079	0.377	0.691	-283.864	3.60
	MAM	-3.947e-06(Catch.A)+2.07e-03 (BFI)+1.371e-03(Agperc)+9.514e-08 (Catch.A*BFI)	1.215	0.155	4.92E-04	0.270	-214.197	-0.031	0.494	0.423	-243.284	8.82
	JJA	0.0018(BFI)+0.0018(Agperc)	1.202	0.399	9.80E-15	0.162	-181.073	-0.033	0.520	0.271	-197.219	8.48
	SON	0.0027(BFI)-0.0018(Forestperc)-0.0039 (Sand)	1.362	0.342	3.21E-12	0.269	-164.828	-0.052	0.819	0.505	-206.835	6.61
D0.6	Annual	5.895e-04(PPT30)+1.875e-07 (Catch.A)+1.605e-03(BFI)-1.851e-03 (Forestperc)	0.919	0.381	2.06E-13	0.196	-228.436	-0.052	0.002	0.722	-333.093	3.25
	DJF	1.962e-03(BFI)+2.076e-03(Agperc)+5.692e-09(R.storage)-1.362e-10(Agperc*R.storage)	0.841	0.230	1.51E-06	0.213	-143.218	-0.006	0.000	0.538	-204.719	6.95
	MAM	1.884e-07(Catch.A)-1.395e-03(Urbanperc)-1.006e-03(Forestperc)	1.029	0.155	4.92E-04	0.177	-248.748	-0.032	0.029	0.569	-317.007	4.57
	JJA	0.0011(PPT30)-0.8088(KFACT)-0.0028(Forestperc)	1.201	0.399	9.80E-15	0.195	-195.455	-0.062	0.545	0.583	-264.497	4.90
	SON	-0.0015(Forestperc)	1.014	0.342	3.21E-12	0.139	-215.166	-0.158	0.105	0.698	-308.074	1.66
C.of.e0.9	Annual	4.584e-01(KFACT)+2.826e-03(Forestperc)-7.427e-10(R.storage)-3.589e-03(Clay)	0.281	0.273	6.89E-08	0.379	-198.661	-0.078	0.748	0.712	-276.760	4.47
	DJF	-0.0019(BFI)+0.0034(Urbanperc)+0.0028 (Forestperc)	0.389	0.230	1.51E-06	0.268	-138.098	-0.008	0.037	0.273	-144.485	53.60
	MAM	-0.0021(BFI)+0.6881 (KFACT)+0.0024(Urbanperc)+0.0028(Forestperc)+0.0037(Sand)	0.096	0.155	4.92E-04	0.338	-201.663	-0.068	0.996	0.560	-238.288	6.68
	JJA	0.6145(KFACT)+0.0024 (Urbanperc)+0.0023 (Forestperc)	0.135	0.399	9.80E-15	0.206	-161.254	-0.042	0.275	0.481	-205.046	5.72
	SON	0.0016(PPT30)	0.271	0.342	3.21E-12	0.224	-166.267	-0.053	0.021	0.614	-239.327	3.32

Response variable		OLS						GWR (Fixed bandwidths)				
		Model	Intercept	Observed Moran's I	Moran's I p-value (KNN=4)	R ²	AIC	Observed Moran's I (Bandwidths)	Moran's I p-value	R ²	AIC	Bandwidths (Coordinate)
C.d.f.e0.6	Annual	-0.0021(PPT30)+1.3523(KFACT)+0.0082(Forestperc)+0.0039(Agperc)	1.354	0.273	6.89E-08	0.186	45.128	-0.027	0.108	0.454	0.930	7.29
	DJF	0.0017(Forestperc)	0.759	0.230	1.51E-06	0.059	-71.415	-0.069	0.440	0.429	-123.801	4.22
	MAM	-0.0013(PPT30)+0.0004(Rfact)+0.0024(Urbanperc)+0.003(Forestperc)+0.0014(Agperc)	0.771	0.155	4.92E-04	0.21	-206.858	-0.010	0.048	0.362	-236.506	14.97
	JJA	-0.0015(PPT30)+1.757(KFACT)+0.004(Forestperc)+0.011(Agperc)-0.0325(KFACT*Agperc)	0.334	0.399	9.80E-15	0.353	-172.859	-0.014	0.002	0.593	-223.397	6.98
	SON	0.0015(Forestperc)-0.003(Sand)	0.884	0.342	3.21E-12	0.149	-140.949	-0.073	0.720	0.483	-191.371	4.67

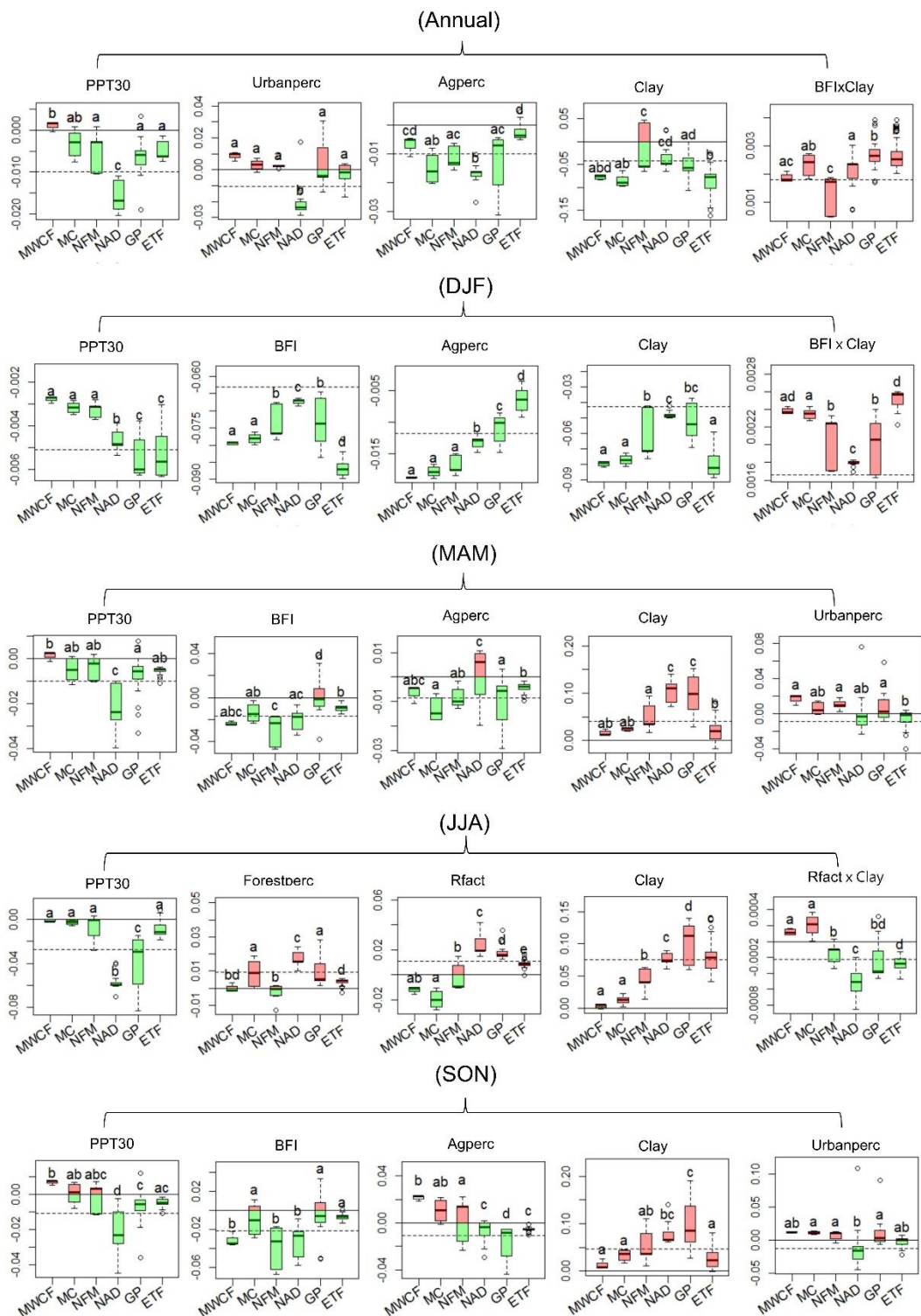


Figure A3-10. GWR coefficients for all variables associated with M95 (Log10 transformed)

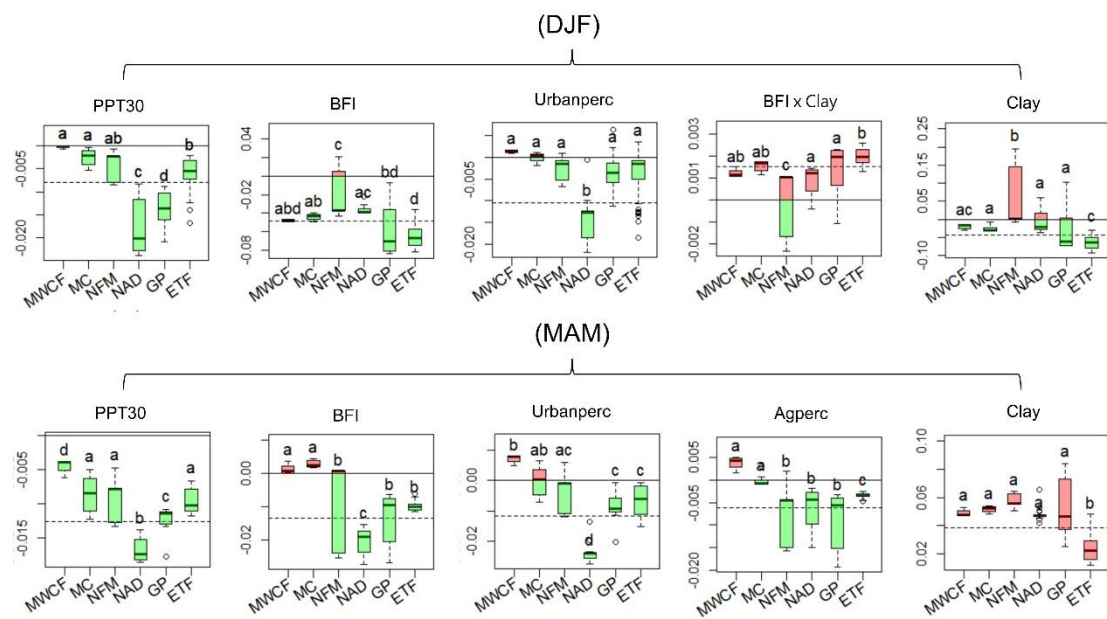


Figure A3-11. GWR coefficients for all variables associated with M50 (Log10 transformed)

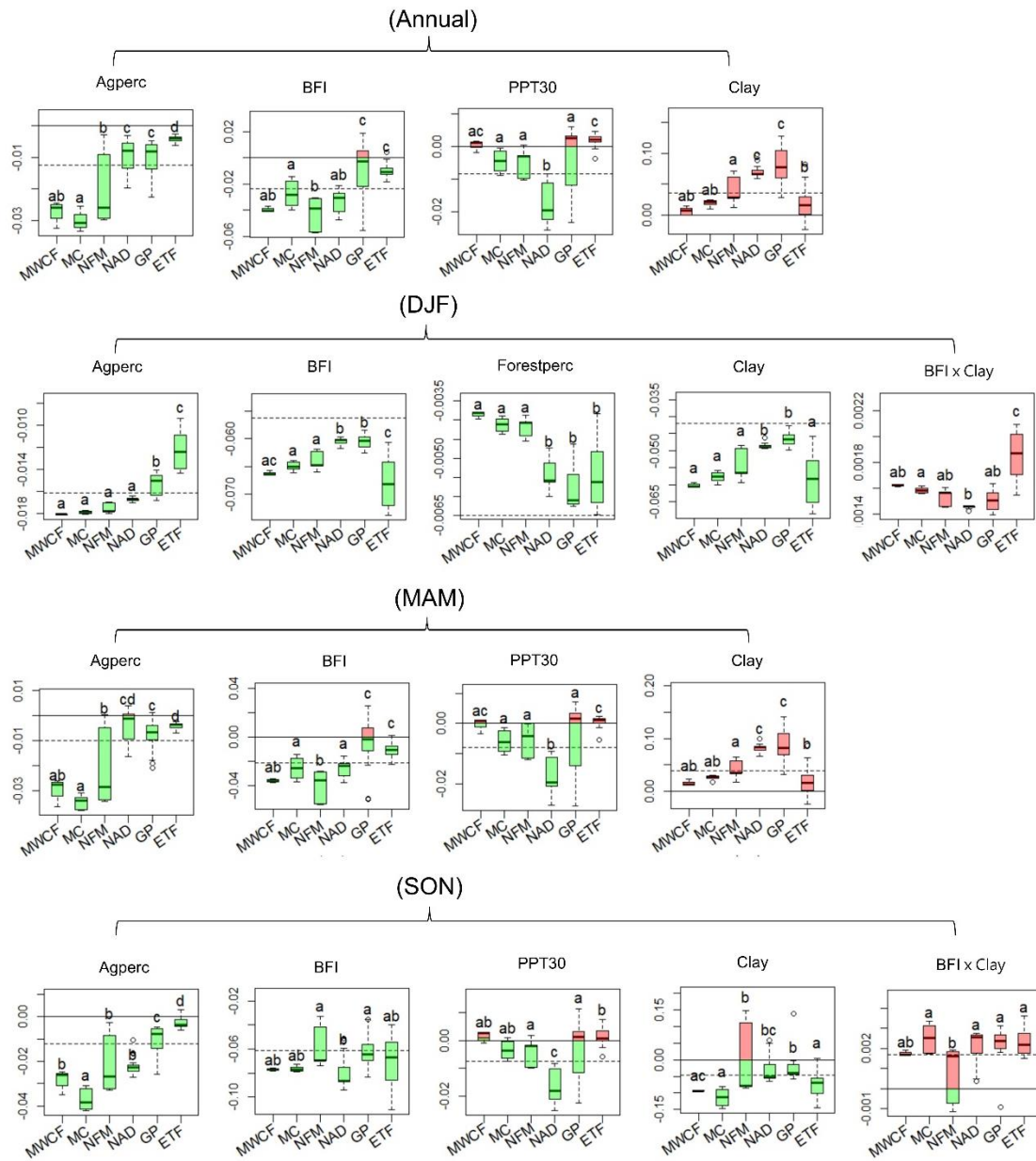


Figure A3-12. GWR coefficients for all variables associated with Rising rate (Log10 transformed)

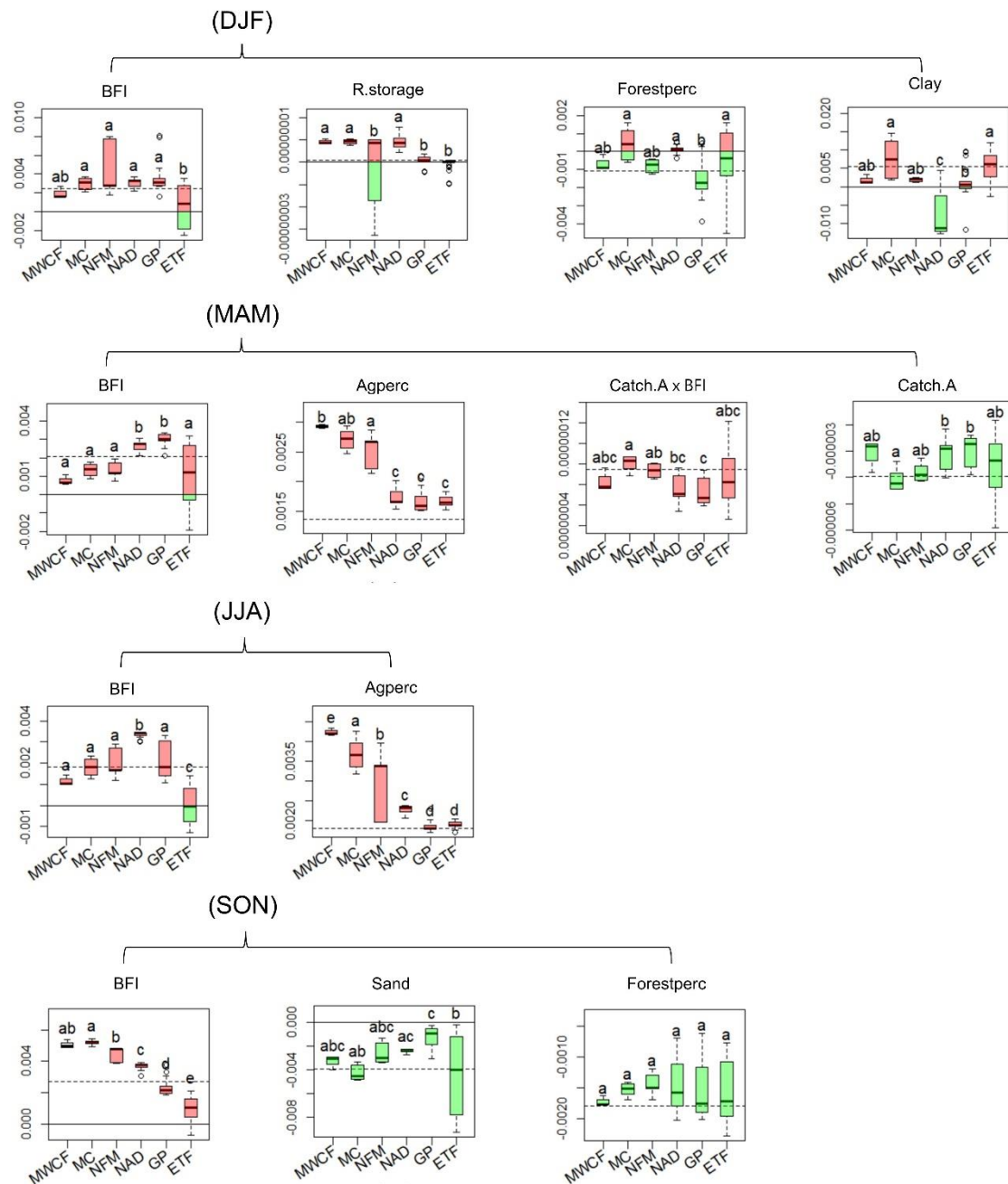


Figure A3-13. GWR coefficients for all variables associated with Duration of events ($\alpha = 0.9$, Log10 transformed)

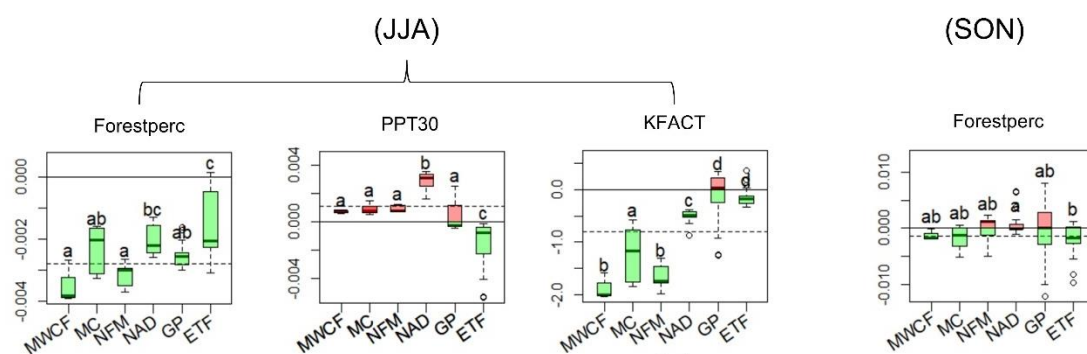


Figure A3-14. GWR coefficients for all variables associated with Duration of events ($\alpha = 0.6$, Log10 transformed)

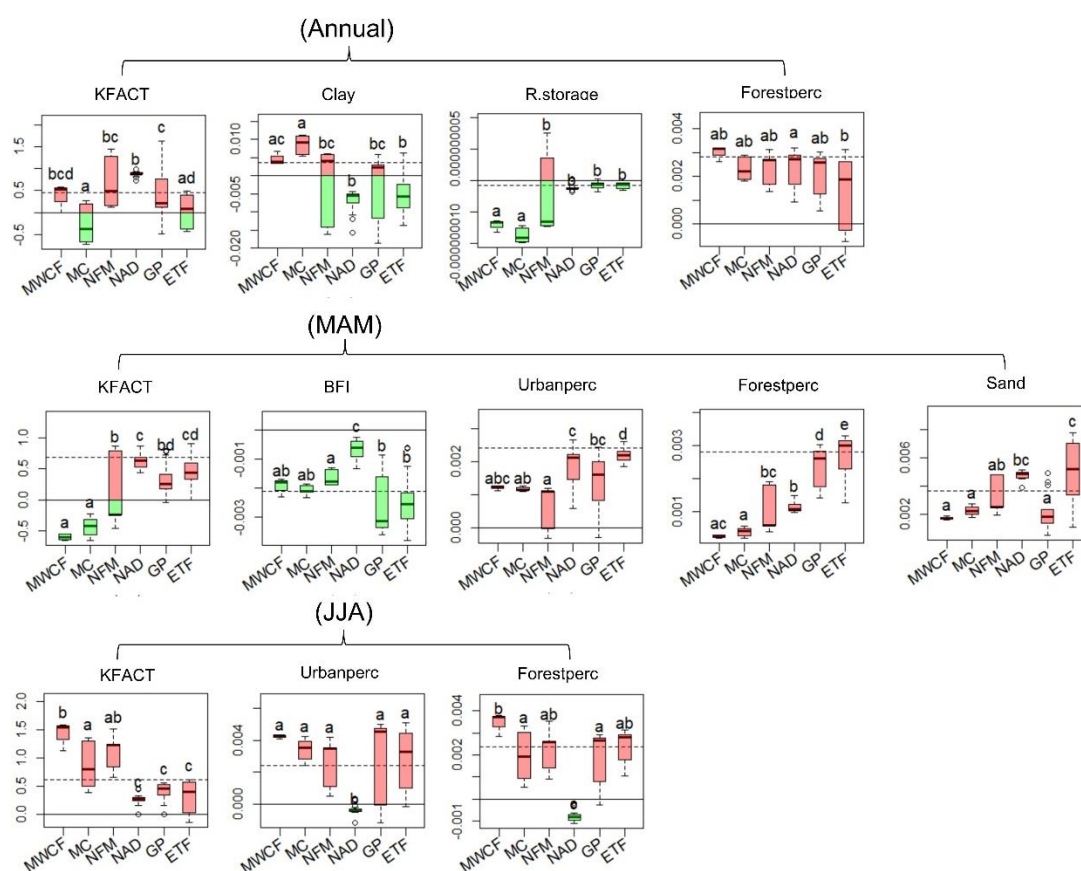


Figure A3-15. GWR coefficients for all variables associated with Count of events ($\alpha = 0.9$, Log10 transformed)

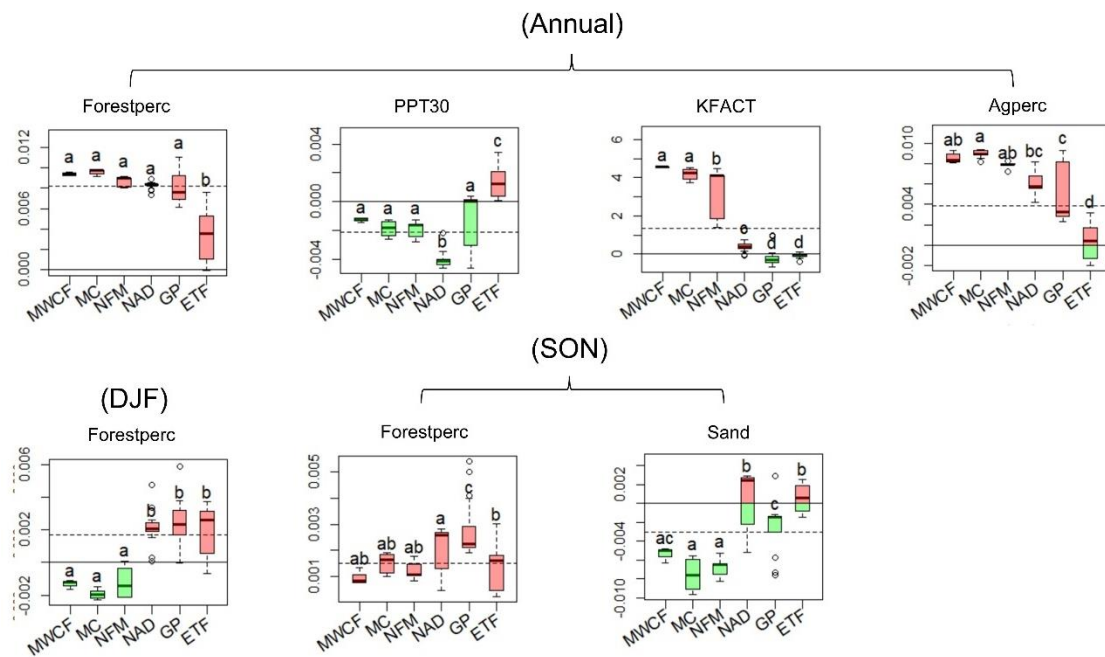


Figure A3-16. GWR coefficients for all variables associated with Count of events ($\alpha = 0.6$, Log10 transformed)

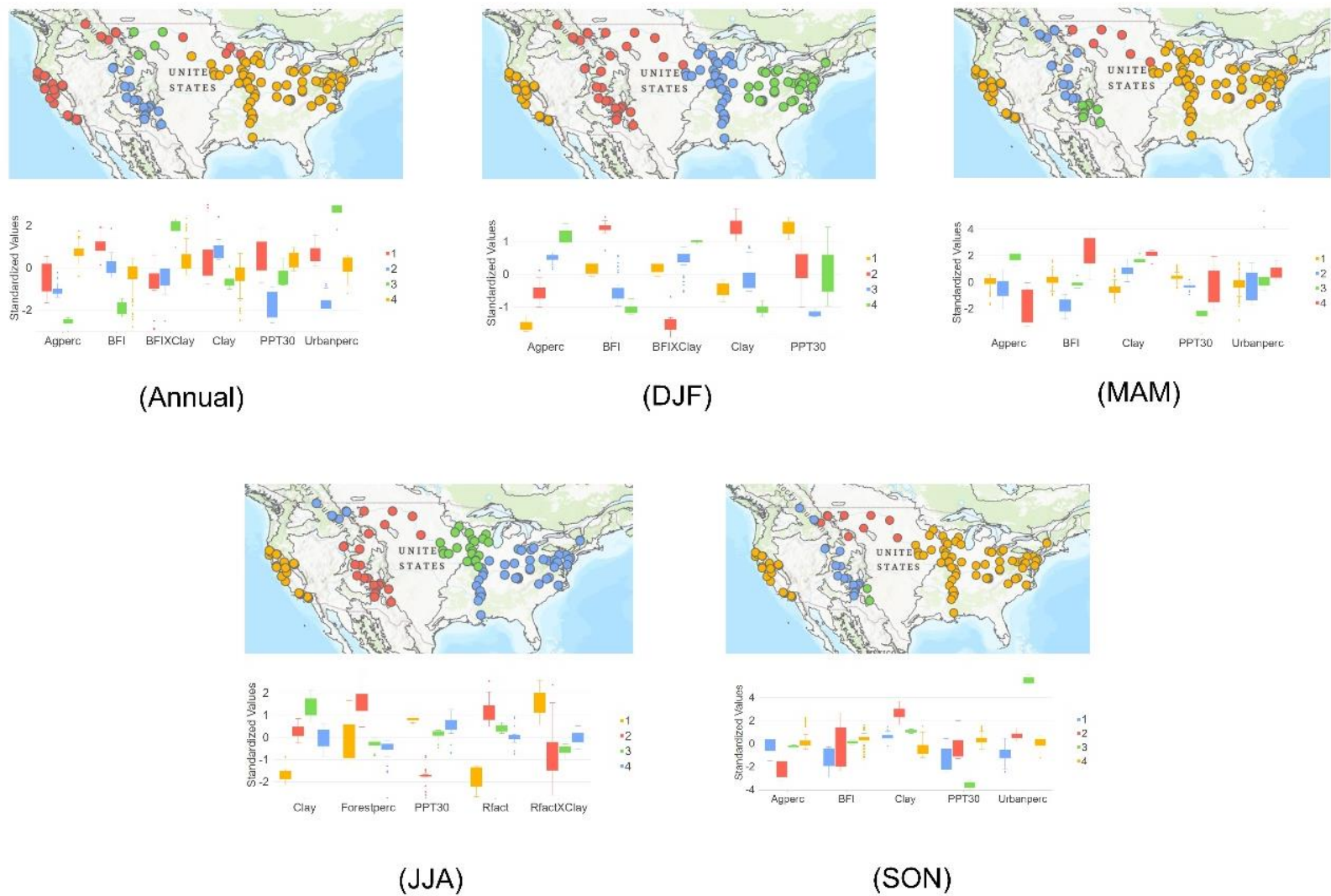


Figure A3-17. K-means clustering results (M95) on GWR coefficients

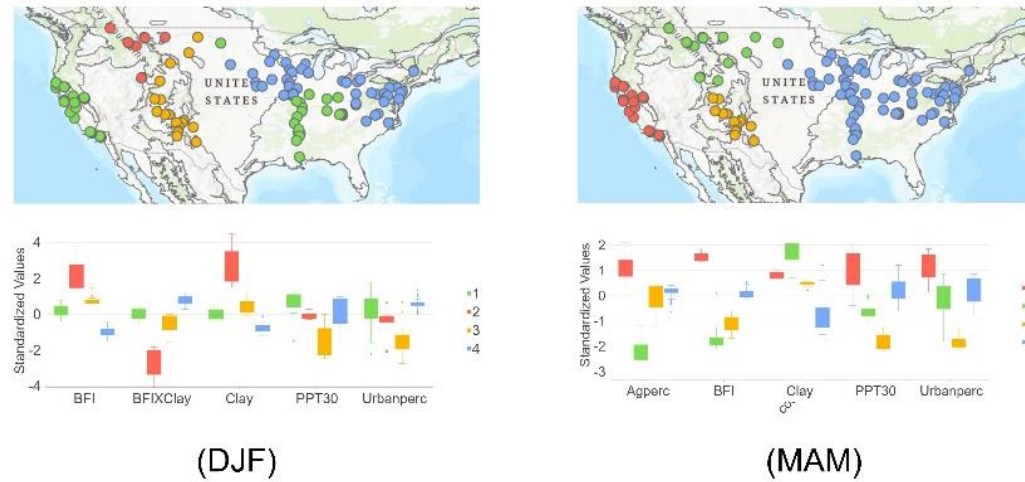
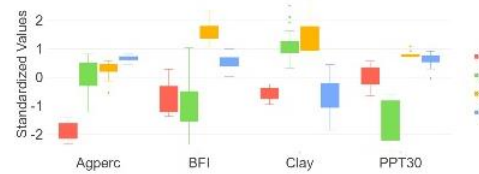
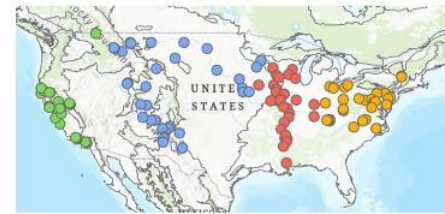


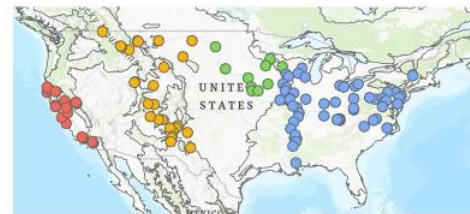
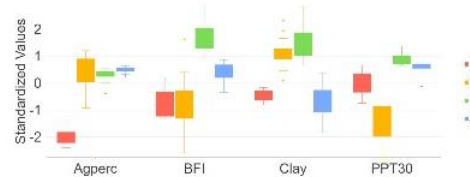
Figure A3-18. K-means clustering results (M50) on GWR coefficients



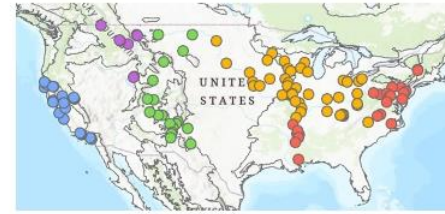
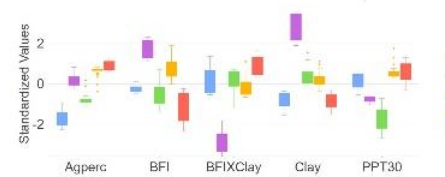
(Annual)



(DJF)



(MAM)



(SON)

Figure A3-19. K-means clustering results (Rising rate) on GWR coefficients

(a) D0.9

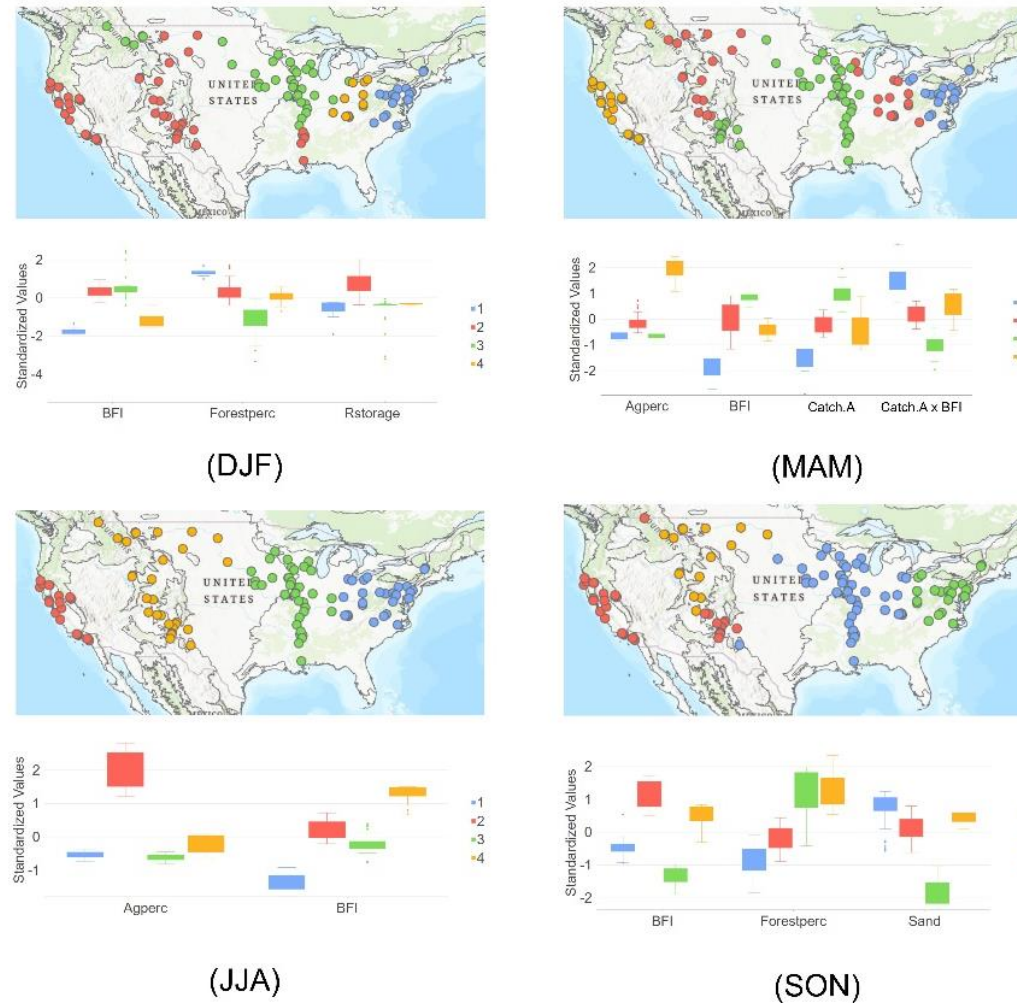
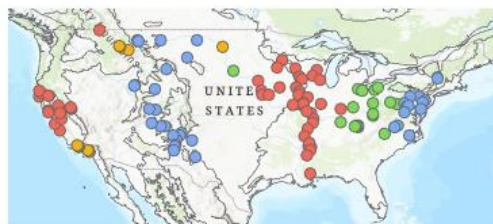
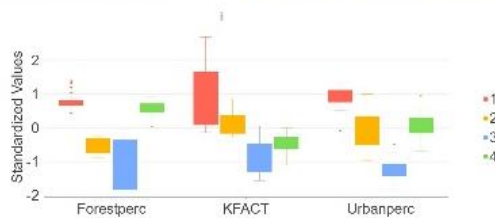


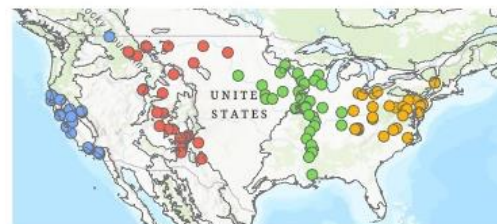
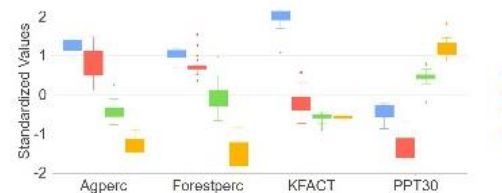
Figure A3-20. K-means clustering results (D0.9) on GWR coefficients

(a) C.of.e0.9



(JJA)

(b) C.of.e0.6



(Annual)

Figure A3-21. K-means clustering results (Count of events) on GWR coefficients

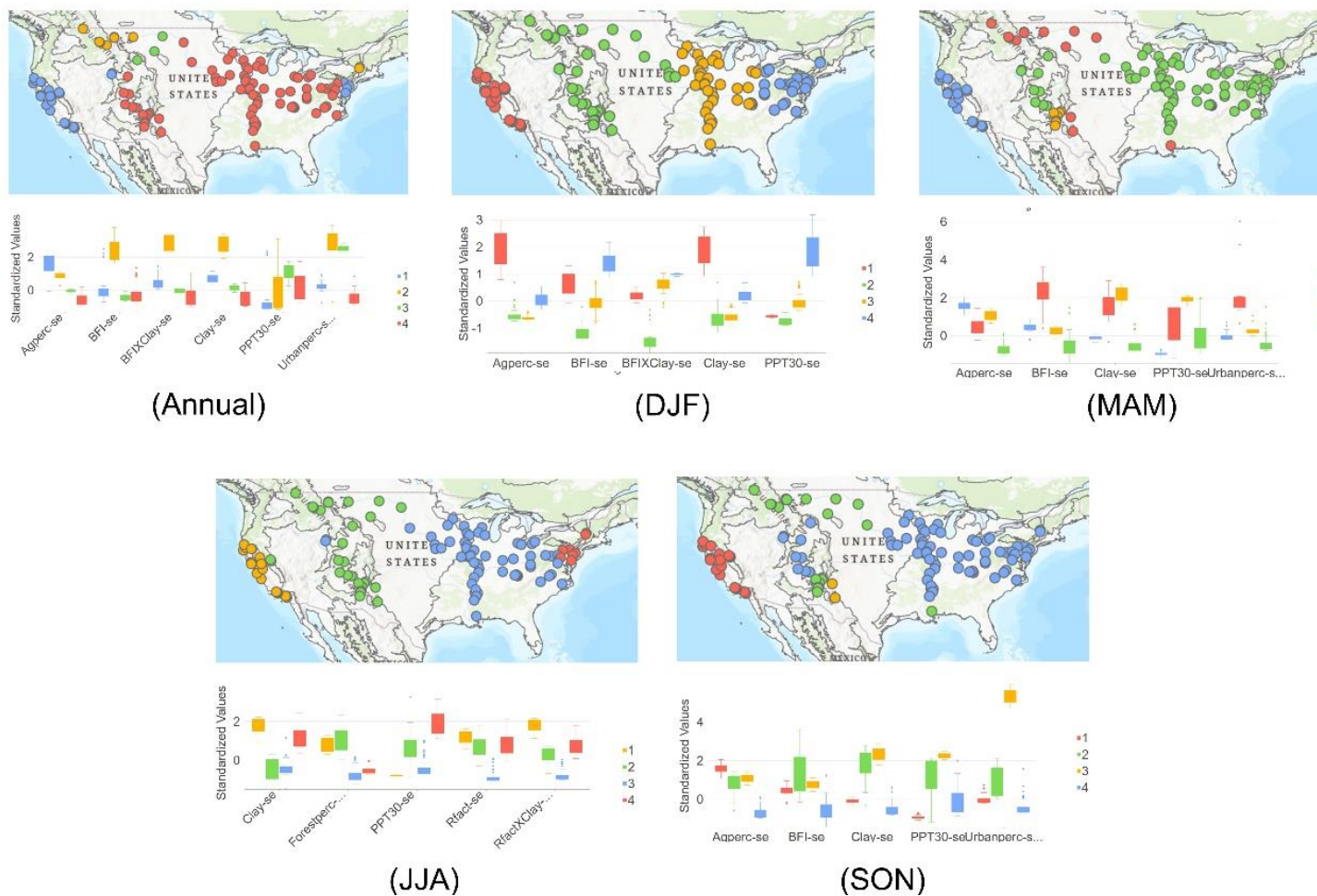


Figure A3-22. K-means clustering (M95) on s.e. of GWR coefficients: The clustering of s.e. followed the clustering of the coefficients but higher s.e. were identified in each GWR model, providing evidence of intermittent changes of LULC e.g., West coast and precipitation events e.g., East coast.

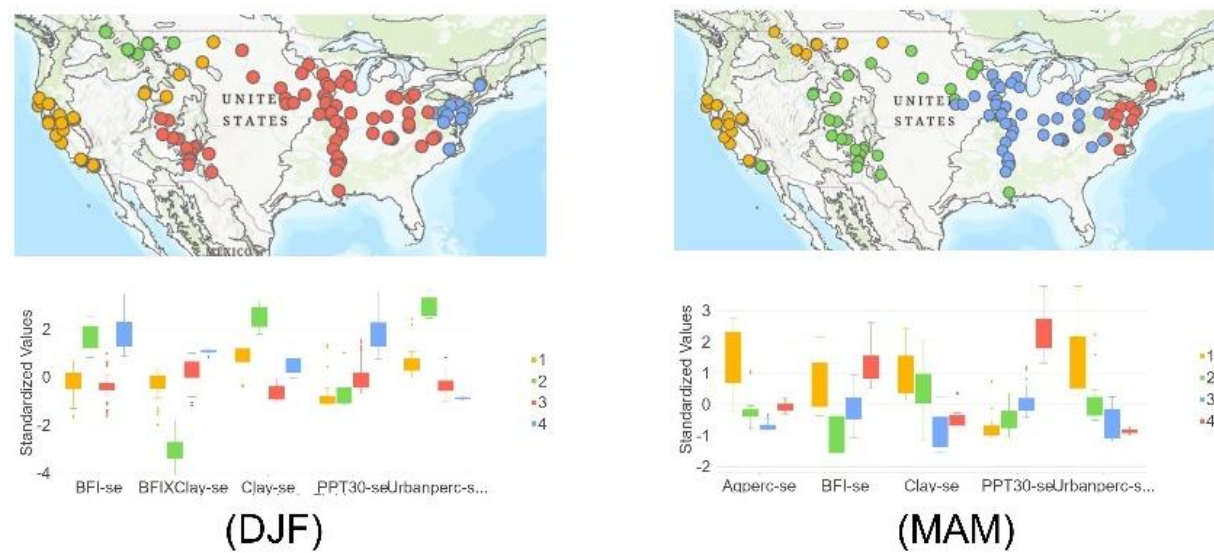
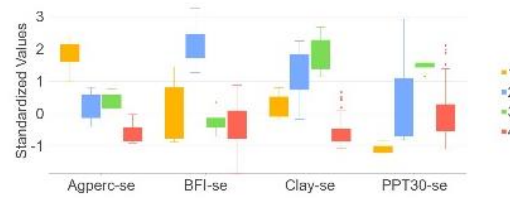
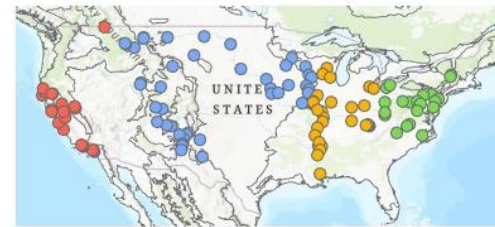


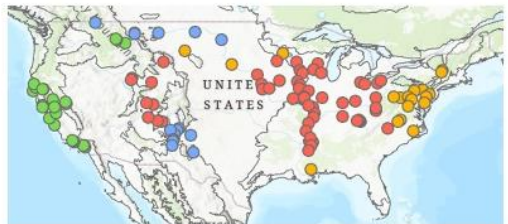
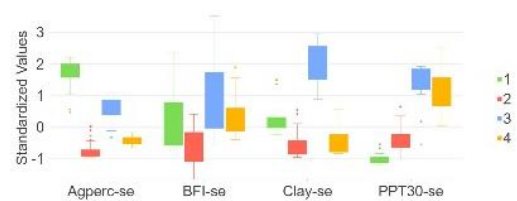
Figure A3-23. K-means clustering (M50) on s.e. of GWR coefficients



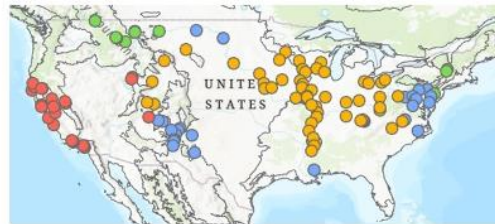
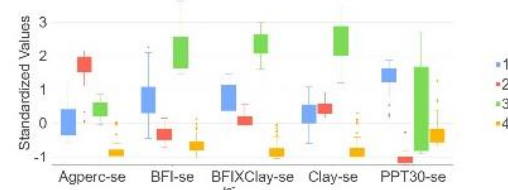
(Annual)



(DJF)



(MAM)



(SON)

Figure A3-24. K-means clustering (Rising rate) on s.e. of GWR coefficients (Rising rate)

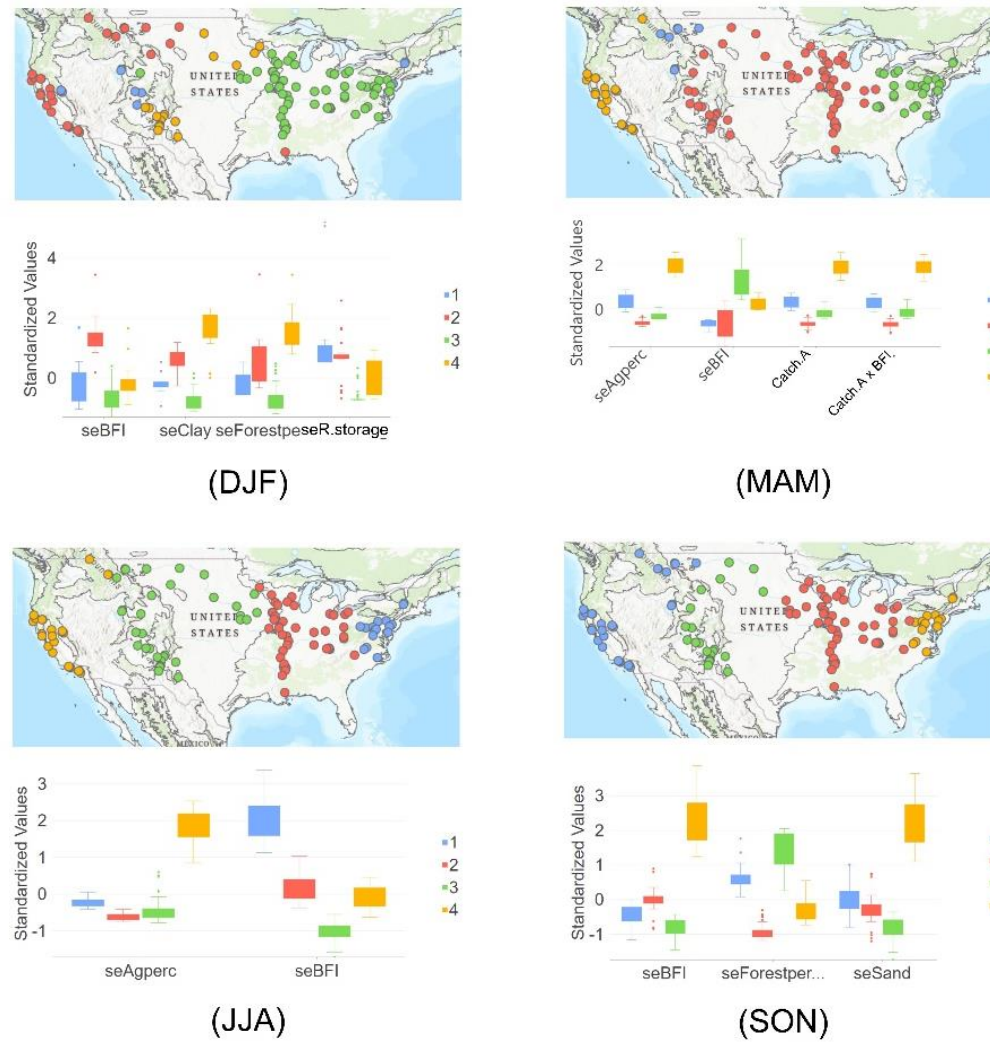
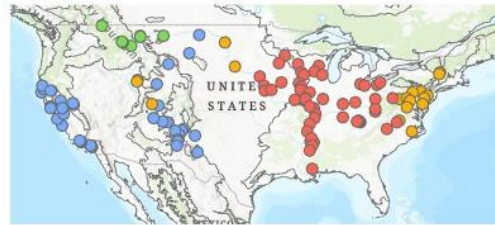
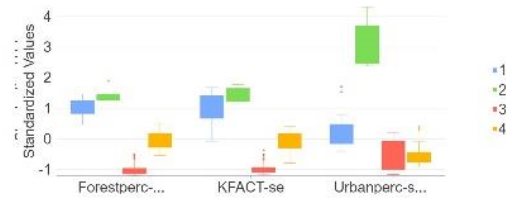


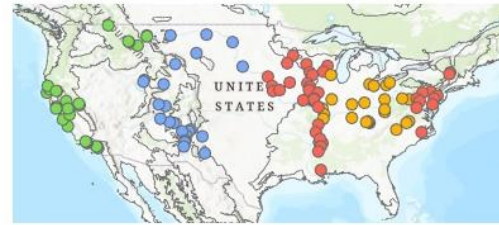
Figure A3-25. K-means clustering (D0.9) on s.e. of GWR coefficients

(a) C.of.e0.9 (s.e.)



(JJA)

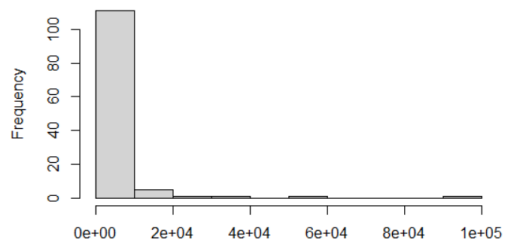
(b) C.of.e0.6 (s.e.)



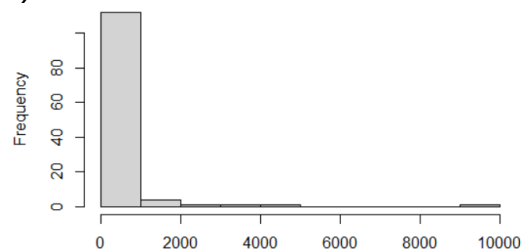
(Annual)

Figure A3-26. K-means clustering (Count of events) on s.e. of GWR coefficients

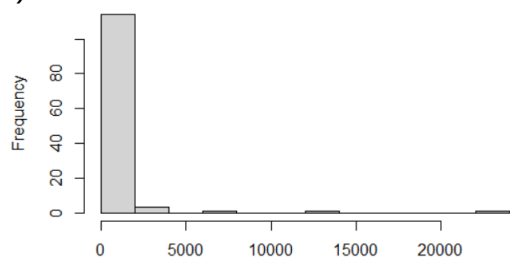
a) M95



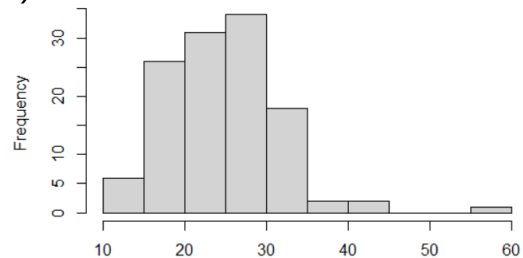
b) M50



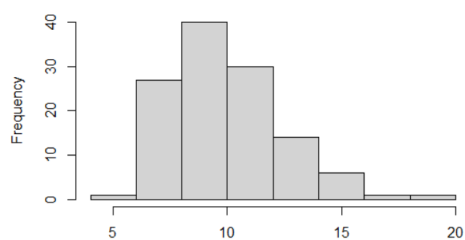
c) R.r



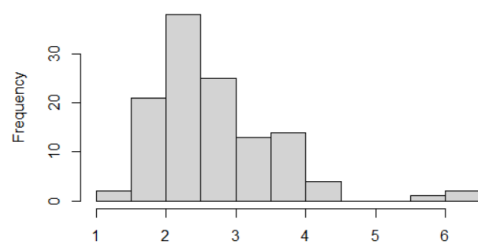
d) D0.9



e) D0.6



f) Cofe0.9



g) Cofe0.6

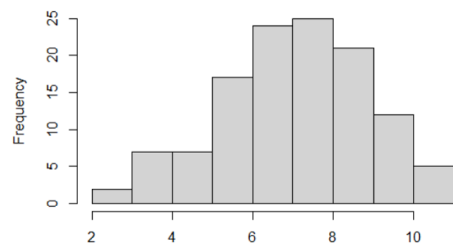
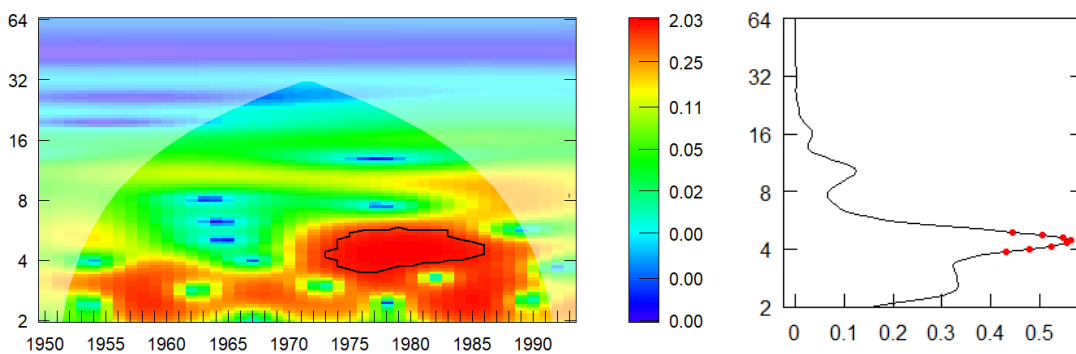


Figure A3-27. Histogram of SSC indicators for 120 sites prior to transformation

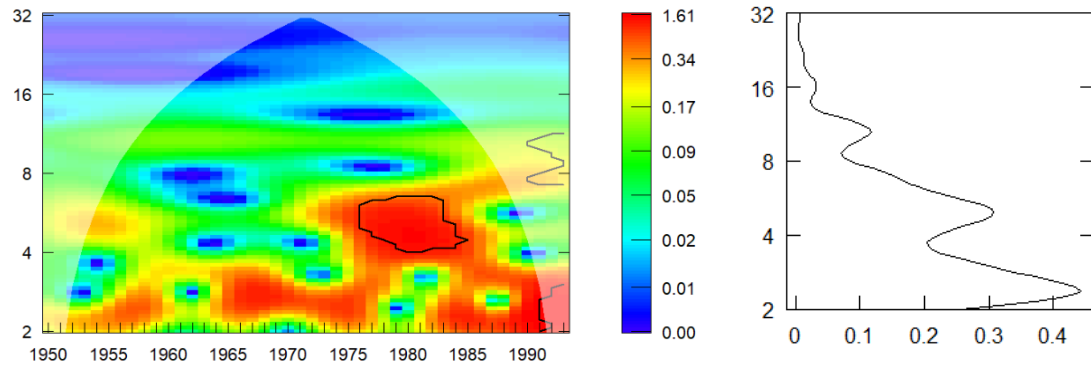
Mechanism of SS transport between SS drivers from continuous wavelet analysis

Site A was chosen to check how periodicities change between drivers of SS transport e.g., precipitation or streamflow (DJFM, Figure A4-1). Variation of CWT analysis results between SS drivers and hydrological environment (e.g., Seasonally subset precipitation, streamflow and SS indicators) show causal connection with the SS transport mechanism. Precipitation yielded 5 to 6 year periodicity in 70s to 80s (Figure A4-1, a). Then, streamflow received no statistically significant periodicity, but the significance level identified in the CWT analysis result shows similar 5 to 6 year periodicity, which shares similar pattern identified from precipitation. Meanwhile, SSC (Avg) received 16 year periodicity with less wavelet power (≈ 0.2 , Figure A4-1,c). A similar periodicity with precipitation was identified in early 70s. However, D0.2 had 8 year periodicity, which resembles the periodicity identified in precipitation without statistical significance (Figure A4-1, d). Cofe0.2 had clear 4 year periodicity in 50s and 60s (Figure A4-1, e). It did not follow the periodicity identified from precipitation. However, Ppe0.6 had significant 5 to 6 year periodicity over 70s and 80s, and Ppe0.2 had statistically significant 9 to 14 year periodicity from 60s to 80s (Figure A4-1, g). Another 4 year periodicity was identified in late 70s and early 80s without statistical significance, which shares the same periodicity from precipitation. It implies that over this catchment, Ppe0.6 and 0.2 had closer connection to the periodicities identified from precipitation. The CWT results show that the various periodicities of over 4 years from SSC dynamics were caused by a combination of precipitation and LULC e.g., SSC(Avg) D0.2 and Cofe0.2.

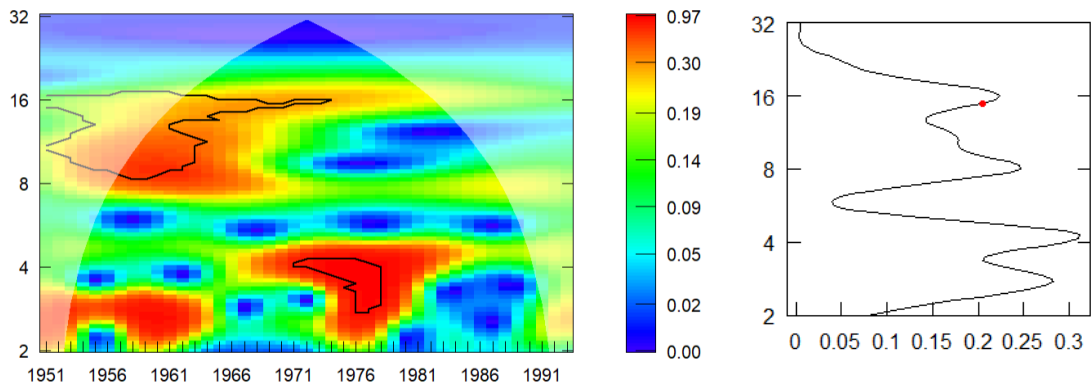
a) Precipitation (Avg)



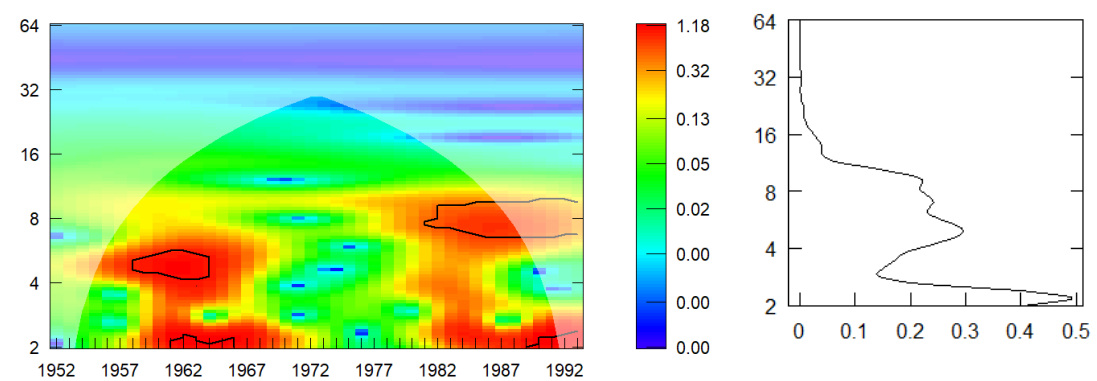
b) Streamflow (Avg)



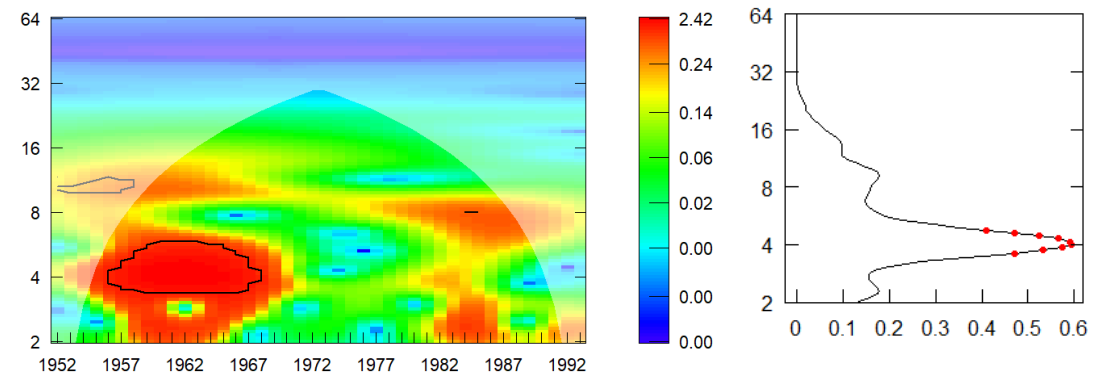
c) SSC (Avg)



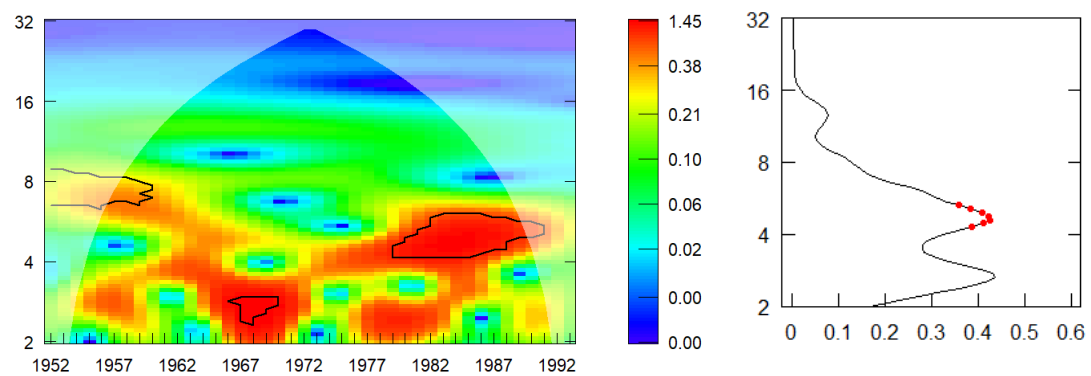
d) D0.2



e) Cofe0.2



f) Ppe0.6



g) Ppe0.2

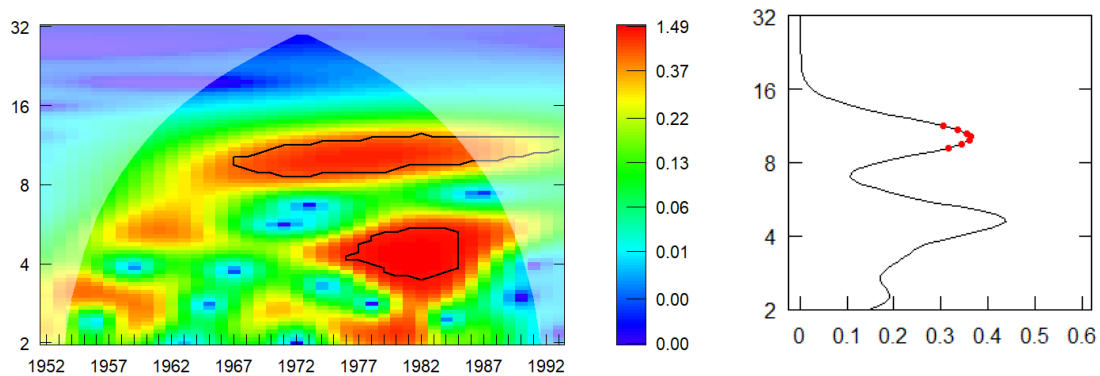


Figure A4-1. Continuous wavelet analyses on indicators SS dynamics and hydrological environment (DJFM) – Site A