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Rush Dominance in Wet Pastures: Spatial Analysis, Trajectories and Drivers

Faculty of Engineering and Applied Sciences
Advanced GIS and Remote Sensing

MSc
Academic Year: 2024 - 2025

Supervisor: Dr Daniel Simms
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This thesis is submitted in partial fulfilment of the requirements for
the degree of MSc Advanced GIS and Remote Sensing

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Abstract

Lowland wet pastures are biodiversity-rich ecosystems but are increasingly threatened by the expansion of rush (*Juncus* spp.), which can dominate and displace species of conservation value. This study quantified the spatial extent, temporal dynamics, and key drivers of rush distribution in Kingcombe Meadows Reserve, Dorset, using high-resolution aerial imagery (2005, 2020) and deep learning methods. A pretrained U-Net convolutional neural network (CNN) was trained on randomly selected annotated image samples to produce reserve-wide rush maps, achieving overall accuracies above 91%. Bias-corrected area estimations showed that rush cover increased substantially over the study period, rising from 7.6% in 2005 to 20% in 2020, indicating both localised spread and establishment in previously unoccupied areas. Topographic analysis revealed that rush occurred predominantly at lower elevations (114–158 m) and on gentle slopes ($<8^\circ$), where hydrological conditions favour persistence. Current grazing pressures showed no significant relationship with rush distribution, suggesting that grazing alone could not explain recent expansion patterns in the reserve. This study demonstrates that CNN-based segmentation provides a powerful framework for fine-scale vegetation mapping and ecological assessment. The results highlight the need for integrated management strategies that combine grazing, hydrological, and topographic considerations to control rush encroachment effectively. More broadly, the approach offers a transferable tool for conservation practitioners and policymakers to monitor invasive or encroaching species in wet grasslands and other sensitive habitats, supporting evidence-based management and enhancing biodiversity conservation at a landscape scale.

This project was supported operationally by Dorset Wildlife Trust (led by Steve Masters) and sponsored by Professor Mark Kibblewhite via MK Soil Science Ltd.

Keywords:

Wet grasslands, Convolutional Neural Network, Semantic segmentation, Conservation management, Habitat mapping, Remote sensing

Acknowledgements

First and foremost, I thank God Almighty for the gift of life, strength, and guidance throughout this journey. Without his grace, this work would not have been possible.

I am sincerely grateful to my supervisor, Dr Daniel Simms, for his invaluable guidance, encouragement, and constructive feedback, which have been central to the success of this research.

I would like to extend my deep appreciation to the Dorset Wildlife Trust, particularly Steve Masters, for providing operational support, data, and facilitating fieldwork. I am also grateful to Professor Mark Kibblewhite for his sponsorship and expert input, which greatly enriched this project.

I am deeply thankful to the Commonwealth Scholarship Commission for granting me the opportunity to pursue my studies at Cranfield University, and for the financial support that made this possible.

Finally, I wish to express my heartfelt gratitude to my family and friends for their unwavering love, prayers, and encouragement, which have given me strength and motivation throughout this period.

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List of Abbreviations

APGB	Aerial Photography Great Britain
CI	Confidence Interval
CNN	Convolutional Neural Network
DSM	Digital Surface Model
GIS	Geographic Information Systems
LC	Land Cover
ML	Machine Learning
PA	Producer's Accuracy
RGB	Red, Green, Blue
UA	User's Accuracy
UAV	Unmanned Aerial Vehicle

Rush Dominance in Wet Pastures: Spatial Analysis, Trajectories and Drivers

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Abstract

Lowland wet pastures are biodiversity-rich ecosystems but are increasingly threatened by the expansion of rush (*Juncus* spp.), which can dominate and displace species of conservation value. This study quantified the spatial extent, temporal dynamics, and key drivers of rush distribution in Kingcombe Meadows Reserve, Dorset, using high-resolution aerial imagery (2005, 2020) and deep learning methods. A pretrained U-Net convolutional neural network (CNN) was trained on randomly selected annotated image samples to produce reserve-wide rush maps, achieving overall accuracies above 91%. Bias-corrected area estimations showed that rush cover increased substantially over the study period, rising from 7.6% in 2005 to 20% in 2020, indicating both localised spread and establishment in previously unoccupied areas. Topographic analysis revealed that rush occurred predominantly at lower elevations (114–158 m) and on gentle slopes ($<8^\circ$), where hydrological conditions favour persistence. Current grazing pressures showed no significant relationship with rush distribution, suggesting that grazing alone could not explain recent expansion patterns in the reserve. This study demonstrates that CNN-based segmentation provides a powerful framework for fine-scale vegetation mapping and ecological assessment. The results highlight the need for integrated management strategies that combine grazing, hydrological, and topographic considerations to control rush encroachment effectively. More broadly, the approach offers a transferable tool for conservation practitioners and policymakers to monitor invasive or encroaching species in wet grasslands and other sensitive habitats, supporting evidence-based management and enhancing biodiversity conservation at a landscape scale.

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Keywords: Wet grasslands, Convolutional Neural Network, Semantic segmentation, Conservation management, Habitat mapping, Remote sensing

1 Introduction

The United Kingdom's (UK) lowland wet grasslands are valued for their biodiversity, supporting many rare and specialised species. However, their area has significantly decreased because of drainage changes, more intensive grazing management, and changes in land use (Jefferson et al., 2014). Between 1960 and 2013, around 47% of semi-natural grassland in England was lost, primarily due to conversion to improved pasture or arable land, while many remaining fragments suffered degradation from agricultural intensification (Ridding et al., 2015). These losses have a serious impact on biodiversity conservation, highlighting the urgent need to protect remaining grasslands and manage pressures such as rush encroachment.

Rushes such as soft rush (*Juncus effusus* L.), compact rush (*Juncus conglomeratus* L.), and hard rush (*Juncus inflexus* L.) are herbaceous, grass-like perennials commonly found in damp or waterlogged soils (McCorry & Renou, 2003). These species reproduce both vegetatively via rhizome networks and sexually through abundant seed production, with seeds capable of persisting in the soil seed bank for decades (Ashby et al., 2020). In lowland wet meadows, soft rush and compact rush form dense tussocks that are tolerant of waterlogging and grazing pressure (McCorry & Renou, 2003). Soft rush in particular has been shown to reduce plant species richness and diversity through competitive exclusion and shading effects (Ervin & Wetzel, 2002).

Encroachment by rush species is often associated with inadequate drainage, excessive grazing, soil compaction (resulting from poaching), and increasingly extreme wetter climate conditions. Yet despite its ecological implications, there is a lack of spatially detailed and temporally extended studies quantifying rush

dynamics in UK 's lowland meadow systems (Ashby et al., 2020). Notably, Ashby et al. (2020) used Google Earth imagery and field surveys to assess rush spread in the West Pennine Moors, observing an 82–174% increase in rush frequency between 2005 and 2018. However, their method relied on manual visual interpretation and lacked automation or fine-scale classification.

Although rush ecology and management have been studied, high-resolution remote sensing techniques have rarely been used to map rush dominance and its drivers over time in the UK's lowland grasslands. Vegetation monitoring in semi-natural grasslands, such as the UK's lowland grasslands, has traditionally relied on field-based surveys and moderate-resolution satellite imagery like Landsat or Sentinel-2, often combined with supervised or rule-based classification methods (Adegun et al., 2023). While these approaches provide valuable land cover (LC) maps crucial for understanding habitat dynamics and guiding conservation planning, they are time-consuming and difficult to scale (Taylor et al., 2000).

Advances in remote sensing have introduced machine learning (ML) classifiers such as Random Forest and Support Vector Machines, which automate LC classification based on visual and spatial patterns. However, these methods often require pre-processing steps like feature engineering or texture analysis to manage within-class variability and improve accuracy (Van der Plas et al., 2023).

More recently, high-resolution remote sensing and deep learning methods like Convolutional Neural Networks (CNNs) have emerged, enabling detailed mapping of vegetation changes at sub-decimeter scales. For example, Kattenborn et al. (2020) applied CNNs to Unmanned Aerial Vehicle (UAV)-derived RGB imagery to predict vegetation cover fractions across diverse ecosystems, including forests, grasslands, and glacier forelands. Their models achieved strong predictive performance, with mean R^2 values ranging from 0.70 to 0.89, demonstrating CNNs' capacity to quantify continuous vegetation structure in high-resolution imagery. Similarly, Horning (2020) highlighted the use of ultra-high-resolution aerial imagery, including RGB and multispectral data, for ecological applications such as detecting individual plant species, cryptogamic

biocrusts, and fine-scale habitat structure. The study also underscored the growing role of machine learning, including deep learning, in automating such detailed classifications.

Additionally, Van der Plas et al. (2023) used CNN-based semantic segmentation on 12.5 cm aerial imagery across the Peak District to map habitat fragmentation and achieved over 90% accuracy. Their approach confirmed that CNN-based segmentation methods can produce high-resolution, repeatable land cover maps suitable for informing conservation decisions. While CNNs have been applied to habitat fragmentation, few studies have used them to monitor encroaching species like rush in species-rich wet pastures, especially over time (Zaka & Samat, 2024).

Kingcombe Meadows Reserve in Dorset represents a nationally significant, species-rich agro-grassland. Although rush occurs naturally at Kingcombe, recent observations suggest that its spread compromises other valuable species. However, no previous study has assessed the spatial or temporal dynamics of rush dominance within the reserve.

This research aimed to develop and apply a method for analysing the patterns and trajectories of *Juncus spp.* dominance at Kingcombe Meadows, using a combination of high-resolution aerial imagery, field observations, and environmental data. The approach generated detailed maps of rush distribution and change over time, alongside insights into associated environmental and management factors. Understanding the spatial extent and drivers of rush encroachment will help land managers implement targeted interventions and prioritise conservation actions. The method will support Dorset Wildlife Trust's conservation goals and offer a transferable framework for similar wet grassland systems under pressure from climate and land-use change.

1.1 Aim and Objectives

This project aimed to develop and apply a method for gathering and interpreting data on the historic and current extent and patterns of rush (*Juncus spp.*) growth

within targeted meadows by analysing aerial photographs. The specific objectives were:

- i. To analyse the current spatial distribution of rush (*Juncus spp.*) in Kingcombe Meadows Reserve using aerial imagery to understand its ecological context and spatial associations.
- ii. To develop and apply a method for mapping and quantifying rush (*Juncus spp.*) expansion patterns over time using historical and recent aerial imagery.
- iii. To evaluate environmental and management drivers associated with the dominance of rush (*Juncus spp.*).

2 Method and Materials

2.1 Study area

This study was conducted in Kingcombe Meadows Reserve, situated in West Dorset, southwest England (Figure 1). Covering approximately 212 hectares, Kingcombe was designated a National Nature Reserve in 2021 alongside Powerstock Common and is managed by Dorset Wildlife Trust (Dorset Wildlife Trust, 2024).

The reserve comprises a diverse combination of unimproved hay meadows, wet pastures, species-rich hedgerows, and ancient field boundaries. It represents a lowland agricultural landscape with minimal modern intervention, supporting a rich array of flora and fauna, including wetland species sensitive to soil moisture and grazing regimes (Dorset Wildlife Trust, 2024).

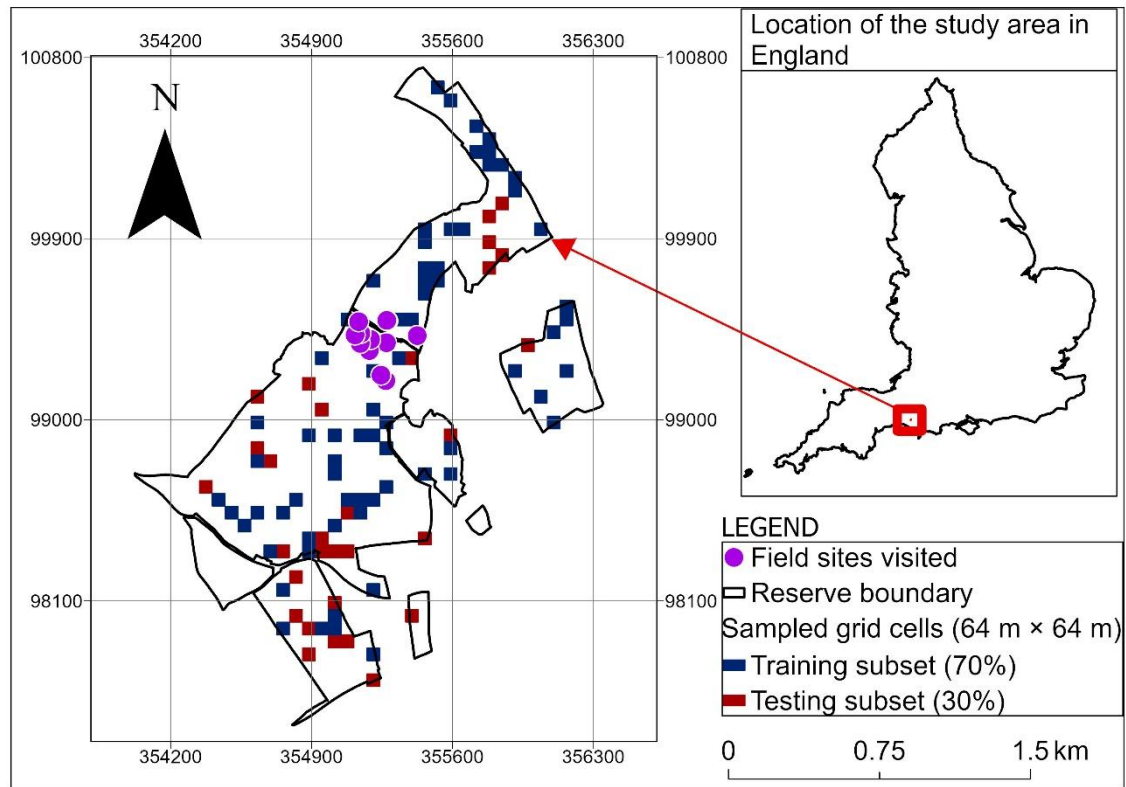


Figure 1. Map showing the spatial distribution of randomly selected grid cells and field survey sites visited in Kingcombe Meadows Reserve, Dorset. The inset map shows the reserve’s location within England.

2.2 Image Data

Orthorectified aerial imagery covering Kingcombe Meadows Reserve (Dorset, UK) was obtained through the Aerial Photography Great Britain (APGB) service provided by Bluesky International Ltd. The imagery used in this study consisted of true-colour aerial photography with red, green, and blue (RGB) channels, captured at a spatial resolution of 12.5 cm per pixel. Two time points were selected (2005 and 2020) to enable temporal comparison of rush (*Juncus spp.*) expansion.

Image availability, cloud-free conditions, and seasonality guided the selection of these years. The 2005 imagery was acquired in June during peak vegetation growth, while the 2020 imagery was captured in April, during early spring when rush tussocks remain visually distinguishable from surrounding vegetation. Both timing periods provided optimal phenological conditions for visually distinguishing

between rush and non-rush areas (Berra et al., 2019). All images independently covered the full extent of the study area and were suitable for semantic segmentation using Convolutional Neural Network (CNN)-based classification models. The images were provided in Virtual Raster (VRT) format, which is a lightweight metadata file that references the actual raster data without duplicating it, allowing efficient handling of large aerial imagery datasets. The VRTs were imported into ArcGIS Pro for subsequent pre-processing steps.

2.3 Convolutional Neural Network

CNNs are deep learning architectures widely used in image analysis because of their ability to automatically extract and learn hierarchical spatial features from image data. They work by applying mathematical filters called "convolutions" across an image to detect patterns such as edges, textures, and shapes. CNNs automatically learn which image characteristics are most important for classification through a training process using labelled examples. In remote sensing and ecology, CNNs have become especially useful for tasks such as vegetation classification, habitat mapping, and object detection (Van der Plas et al., 2023).

The model learns through "epochs", which refers to complete passes through all training data, with each "batch" representing a subset of images processed simultaneously. The learning process is guided by a "loss function" such as cross-entropy loss, which measures prediction accuracy and guides parameter adjustments. Training progress can be monitored using visualisation tools like "TensorBoard" to track performance metrics throughout the learning process.

In this study, a semantic segmentation approach was adopted to classify each pixel in the input aerial imagery into one of two land cover classes: rush and other. CNNs are particularly well-suited for this task. Therefore, a specialised CNN architecture designed to handle such tasks, called U-Net, was selected (Van der Plas et al., 2023).

The U-Net architecture was selected because of its proven effectiveness in remote sensing and ecological contexts. The model (Figure 2) follows a U-shaped

design where a sequence of encoder layers captures essential spatial features by progressively reducing image resolution, and corresponding decoder layers reconstruct pixel-wise predictions by gradually returning to the original image resolution. Skip connections directly link the encoder (left layers) and decoder layers (right layers), ensuring the retention of precise spatial patterns crucial for accurate vegetation boundary detection (Kislov et al., 2021).

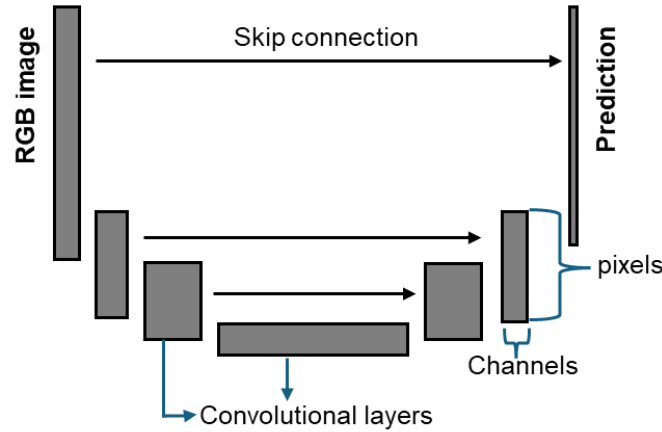


Figure 2. U-Net network convolutional blocks and skip connections enabling effective spatial feature learning (Adapted from Van der Plas et al., (2023). The grey blocks represent processing layers that transform the image data, with the network learning increasingly complex patterns as data flows from input to prediction.

The U-Net model used was adapted from the implementation by Iakubovskii, (2019), which is pretrained on the ImageNet dataset. The specific code implementation followed Van der Plas et al., (2023) (the code is available at: <https://github.com/pdnpa/cnn-land-cover>). Using pretrained weights helped accelerate convergence and reduce the amount of training data required, a crucial benefit given the limited available labelled samples in this study. The classifier maintained the same architecture and training parameters throughout (Van der Plas et al., 2023).

2.4 Sampling and Annotations

To prepare training data for semantic segmentation, a random sampling approach was applied within a systematic spatial framework. A regular 64×64

m grid was generated across the 3 km × 4 km image extent, and cells intersecting with the Kingcombe Meadows Reserve boundary were selected, producing 678 grid cells within the study area. From these, 20% (136 cells) were randomly selected. Grid cells with more than 50% of their area falling outside the reserve boundary were excluded, resulting in 100 grid cells spatially distributed across the reserve (Figure 1).

Within these selected cells, rush (*Juncus* spp.) areas were manually annotated through on-screen digitising, based on the interpretation of aerial imagery from 2005 and 2020. This process produced two separate annotation datasets (one for each year) based on the same sampled cells. Areas containing rush were assigned class label “1”, while all other land cover types were assigned class label “0” (other). Identification of rush was guided by visual interpretation criteria, supported by field observations conducted at Kingcombe Meadows Reserve on 7th July 2025 (Figure 3) and expert input from Dorset Wildlife Trust staff. Additional field photographs are provided in Figure B-1, Appendix B.



Figure 3. Representative field photographs of rush (*Juncus* spp.) at selected sites visited in Kingcombe Meadows Reserve.

A binary classification scheme was therefore adopted, distinguishing "rush" from "other" areas. The 100 annotated samples were randomly split into training (70%) and testing (30%) subsets, with the same grid cell locations used consistently across both years to enable direct comparison of model performance at identical sites. These were used to prepare paired image patches and segmentation masks (512 × 512 pixels) for input to the U-Net convolutional neural network model. Training samples were used to optimise model weights, while testing

samples provided an independent evaluation of model performance at the same geographic locations for both time periods.

2.5 Model Training

The single semantic segmentation model employed a U-Net architecture with a ResNet50 encoder backbone pretrained on ImageNet. This backbone was selected to enhance feature extraction and accelerate convergence, given the limited training samples (Van der Plas et al., 2023). A single network was trained using annotated image patches from both 2005 and 2020, with a batch size of 30 and 50 training epochs. The cross-entropy loss function guided the optimisation process. Training progress and performance metrics were logged via TensorBoard for monitoring.

2.6 Model Evaluation

Model evaluation used a hold-out test set consisting of 30% of the randomly selected annotated patches, allowing assessment of generalisation to data not used during training. Model predictions were compared pixel-wise against the manually annotated reference data to assess classification accuracy. Performance metrics were summarised using confusion matrices to quantify the model's ability to distinguish between rush and other classes. The evaluation metrics used included: TP = true positive, FP = false positive, and FN = false negative predicted pixels in the following equations:

$$\text{sensitivity} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \quad \text{Equation 1}$$

$$\text{precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \quad \text{Equation 2}$$

$$\text{overall accuracy} = \frac{\text{TP} + \text{TN}}{(\text{TP} + \text{FP} + \text{FN} + \text{TN})} \quad \text{Equation 3}$$

Where TP represents correctly identified rush pixels, FP are non-rush pixels incorrectly classified as rush, FN are rush pixels missed by the model, and TN are correctly identified non-rush pixels.

Sensitivity, also known as Producer's Accuracy, represents the probability that an actual rush pixel is correctly identified as rush, while Precision, also known as User's Accuracy, represents the probability that a pixel classified as rush is actually rush. Overall Accuracy represents the proportion of all pixels (both rush and other) that were correctly classified by the model. These metrics provided insight into the model's precision, supporting an assessment of its suitability for mapping rush distribution and expansion.

2.7 Temporal Change Detection and Area Estimation

A pixel-level change map was generated by overlaying the 2005 and 2020 classification maps, producing four strata: No Change, Rush Lost, Stable Rush, and Rush Gained.

According to Stehman (2012) Classification maps contain systematic omission and commission errors, and therefore, direct pixel counting produces biased area estimates. To obtain unbiased estimates, a stratified random sampling approach was applied, using the independent reference labels from 30 validation patches (512 × 512 pixels each) for both years. Test patches were stratified into the four map-based change classes, and error matrices were constructed by comparing model predictions against reference labels. Area estimates were computed using Stehman (2012) design-based estimator:

$$\hat{A}_j = A \times \sum (W_i \times p_{ij}) \quad \text{Equation 4}$$

Where:

$\hat{A}_j$ = unbiased area estimate for reference class j

A = total study area (212.13 ha)

W_i = proportion of study area in map stratum i

p_{ij} = sample proportion of reference class j within map stratum i

Standard errors were computed as:

$$SE(\hat{A}_j) = A \times \sqrt{\left[\sum (W_i^2 \times p_{ij})(1 - p_{ij})/n_i \right]} \quad \text{Equation 5}$$

Where n_i is the sample size in stratum i.

Confidence intervals (95%) were calculated as the estimate $\pm 1.96 \times SE$. Statistical significance of change was indicated by non-overlapping confidence intervals between time periods.

2.8 Topographic Analysis

Environmental drivers of rush distribution were analysed using topographic variables derived from a 2-meter resolution Digital Surface Model (DSM) obtained from the APGB service, provided by Bluesky International Ltd. The DSM was captured on May 23, 2023. Slope and elevation analyses were conducted to examine relationships between terrain characteristics and rush occurrence patterns identified in the 2020 CNN predictions.

Slope values in degrees were calculated from the DSM using the ArcGIS Pro's slope tool that measures the maximum rate of elevation change between each pixel and its eight surrounding neighbours, with rush and non-rush areas compared using zonal statistics to determine mean and median values. Slope data were reclassified into four categories based on the range of terrain variability observed (Low: 0-8.2°, Gentle: 8.2-25.56°, Steep: 25.56-47.33°, Very Steep: 47.33-80.45°), and the percentage of each slope class occupied by rush was calculated.

Elevation values were extracted for rush and non-rush areas to compare the mean and median characteristics between vegetation types. Descriptive statistics were calculated for both variables, with results presented as means and medians to account for potential data skewness.

2.9 Management Analysis

Grazing data were obtained from reserve management records covering 2018-2024, providing daily grazing pressure measurements (livestock units per hectare, LU/ha) across compartments. The average grazing pressure was calculated for each compartment over the entire monitoring period to represent the typical grazing intensity. Rush coverage data from the 2020 CNN classification were matched with corresponding grazing compartments, with rush coverage calculated as the percentage of total compartment area occupied by rush vegetation. 38 out of 103 compartments had both rush coverage and complete grazing pressure data available for analysis.

Compartments were classified into four grazing intensity categories using natural breaks (Jenks) classification in ArcGIS Pro to identify meaningful breaks in the livestock density distribution: Low (<2.0 LU/ha), Moderate (2.0-3.0 LU/ha), High (3.0-4.0 LU/ha), and Very High (>4.0 LU/ha). Statistical analysis included Pearson correlation to assess the relationship between grazing pressure and rush coverage.

2.10 Tools Used

Statistical analysis and model development utilised multiple software platforms. Python 3.7 with PyTorch was employed for deep learning model implementation and automatic differentiation (Van der Plas et al., 2023; Paszke et al., 2019). Spatial data processing, sampling design, and map preparation were conducted in ArcGIS Pro 3.1.2. Statistical analysis of the livestock density relationships was performed using R version 4.4.1

3 Results

3.1 Model Training and Convergence

Both models (2005 and 2020) demonstrated successful convergence within 50 epochs, with training and validation losses decreasing smoothly and only a small gap between them. The 2005 model converged slightly better than the 2020

model, achieving a lower overall loss, as illustrated in Figure 4. This successful performance was facilitated by transfer learning, where the pre-trained ResNet50 backbone was fine-tuned on the rush classification dataset, allowing ImageNet-learned features to adapt to the specific characteristics of rush vegetation in aerial imagery.

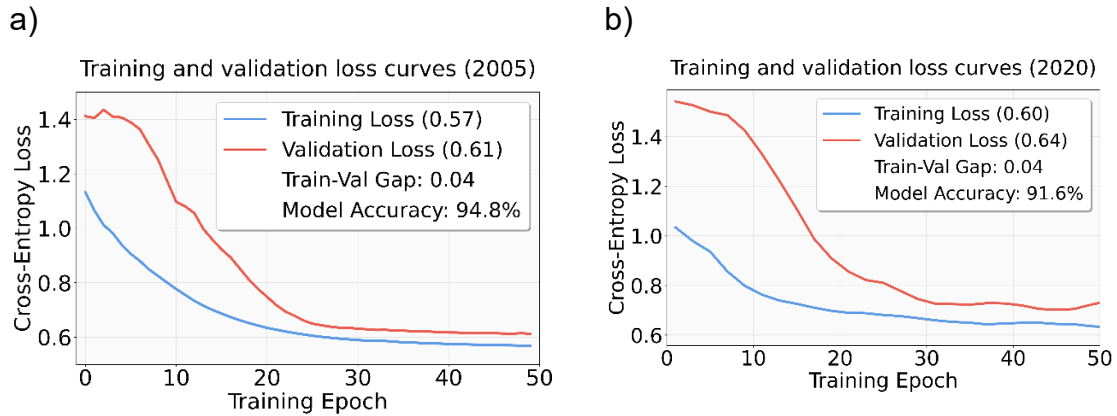


Figure 4 Training and validation loss curves for the U-Net model using (a) the 2005 dataset and (b) the 2020 dataset. The 2005 model achieved final training and validation losses of 0.57 and 0.61, respectively, with an accuracy of 94.8%. The 2020 model achieved training and validation losses of 0.60 and 0.64, respectively, with an accuracy of 91.6%. Both models showed successful convergence with a small training-validation gap of 0.04.

3.2 Class Distribution

The training and testing datasets showed notable differences in class distributions between 2005 and 2020, reflecting ecological changes in the study area. In 2005, rush accounted for approximately 11 % of the training and the testing data, with the remaining ~89 % belonging to the “other” class, indicating imbalanced class representation across the dataset. By 2020, rush coverage had increased substantially, comprising ~32 % of the training set and ~23 % of the testing set, while the “other” class decreased to 67.8% and 76.9%, respectively, highlighting significant rush expansion over the 15 years Figure 5. The similar distributions between training and testing sets within each year confirmed that the data split was representative and suitable for model evaluation.

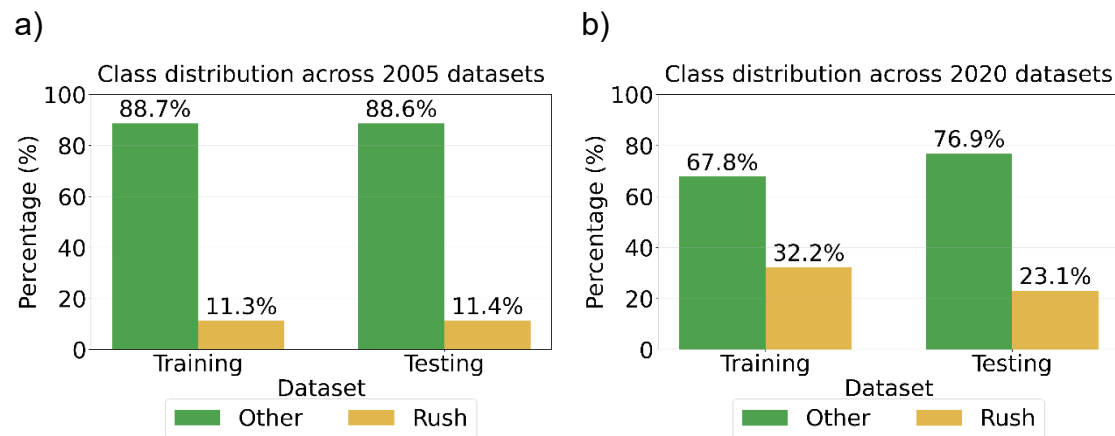


Figure 5 Class distribution across training and testing datasets for (a) 2005 and (b) 2020. The 2020 dataset shows substantially higher rush representation (23.1–32.2%) compared to 2005 (11.3–11.4%), reflecting rush expansion over the study period.

3.3 Classification Accuracy Assessment

Model evaluation on the independent test datasets demonstrated high classification accuracy for both time points. The confusion matrices (Figure 6) show that both models demonstrated strong discriminatory ability, though their error patterns differed. The 2020 model achieved higher rush sensitivity (93.6% vs. 76.5%) and was more effective at minimising false negatives/omission errors (6.4% vs. 23.5%), but at the cost of increased false positives/commission errors (9.0% vs. 2.8%).

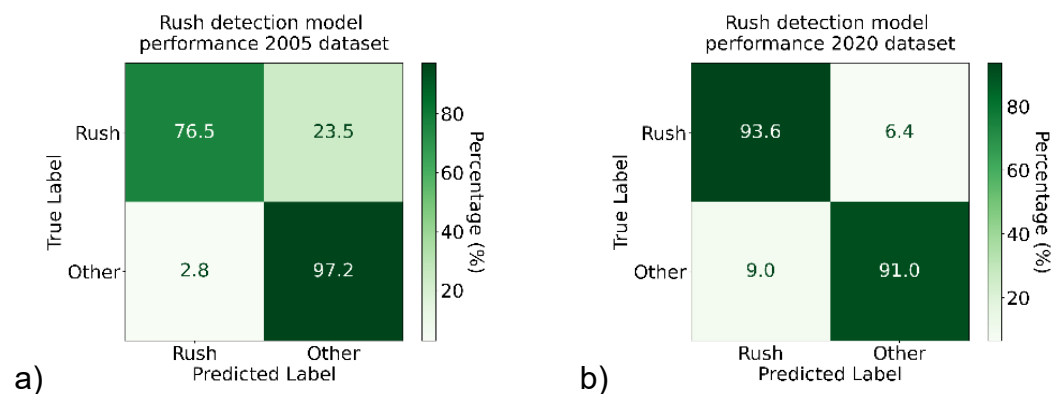


Figure 6 Confusion matrices showing classification performance for (a) the 2005 model and (b) the 2020 model on their respective test datasets. Values represent percentages of true label against predicted label classifications.

The producer's accuracy (PA) and user's accuracy (UA) for each class are illustrated in Table 1. The results highlighted that the 2005 model achieved higher accuracy in mapping non-rush areas (Other PA = 97.2%, Other UA = 97.0%) and demonstrated better precision when classifying rush pixels (Rush UA = 77.8%), while the 2020 model performed better at detecting rush where it was present (Rush PA = 93.6%). However, the 2020 model showed lower precision for rush classification (Rush UA = 75.7%), indicating more false positives compared to the 2005 model. Both models demonstrated high reliability for non-rush classifications.

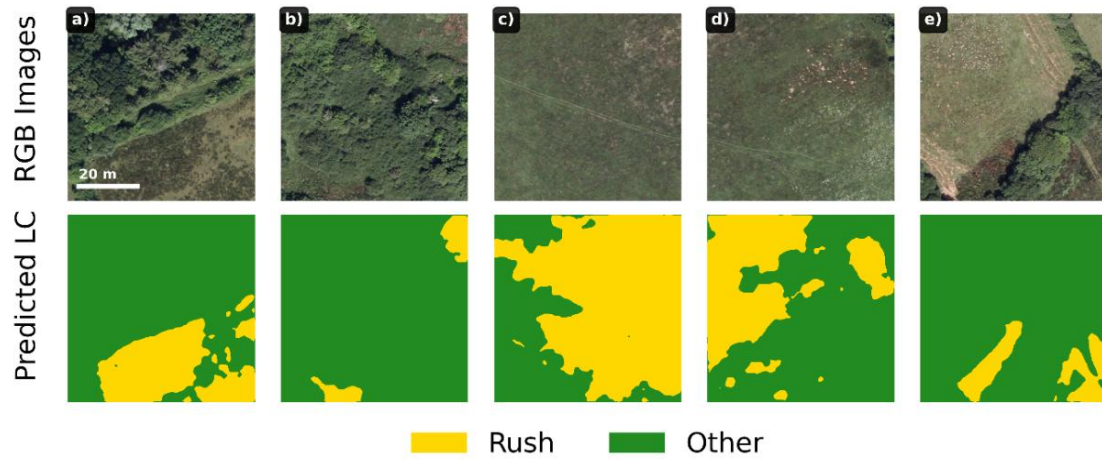
Table 1 Accuracy assessment metrics for the 2005 and 2020 models, including overall accuracy, producer's accuracy (PA), and user's accuracy (UA) for rush and non-rush classes.

Year	Overall accuracy	Rush PA	Rush UA	Other PA	Other UA
2005	94.8	76.5	77.8	97.2	97.0
2020	91.6	93.6	75.7	91.0	97.9

3.4 Sample Predictions

Visual examination of model predictions on sample patches demonstrated the models' ability to effectively mark rush boundaries and identify spatial patterns across diverse landscapes. Representative examples from both temporal periods showed successful rush detection across varying coverage densities, from sparse patches to dense coverage areas (Figure 7). The models effectively captured fine-scale spatial details, including fragmented distributions and complex boundary transitions between rush and other vegetation types.

i)



ii)

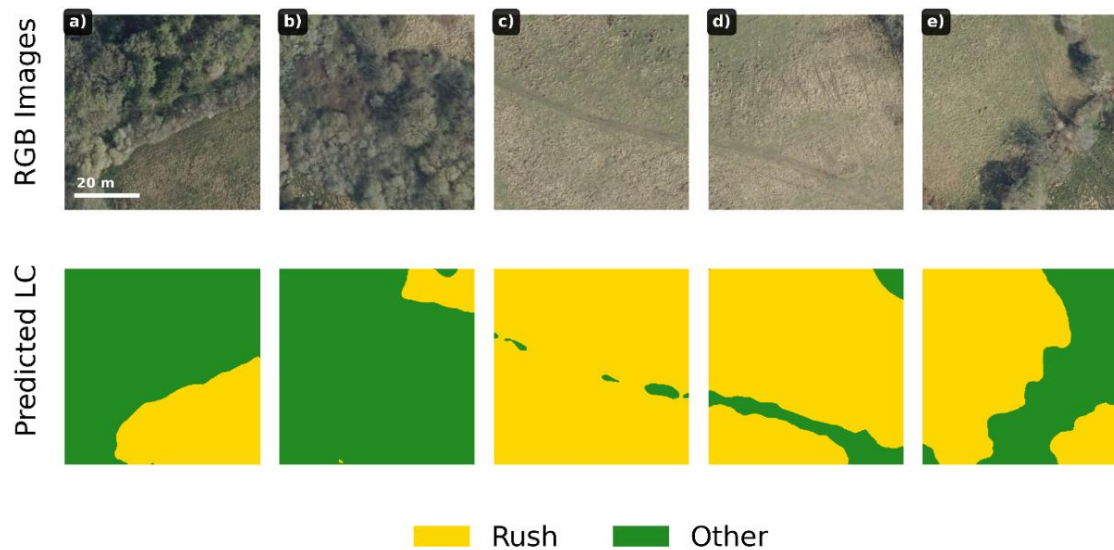
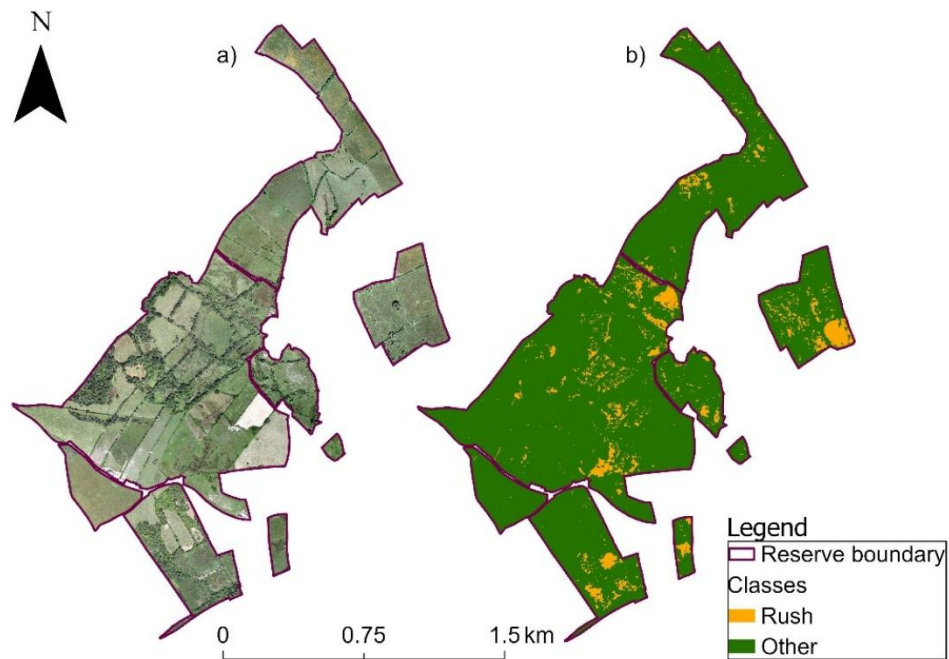


Figure 7 Temporal comparison of model predictions on identical landscape patches from (i) 2005 and (ii) 2020. Examples show both model accuracy and evidence of rush expansion over the 15 years, particularly visible in patches (a), (c), (d) and (e)

Model predictions across the entire study area gave the outputs illustrated in Figure 8

i) 2005



ii) 2020

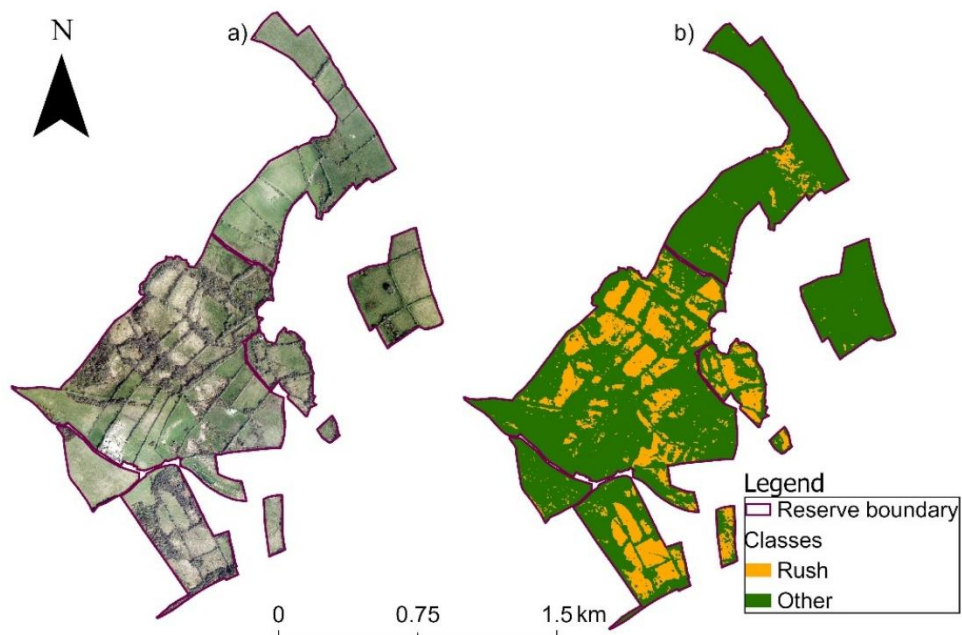


Figure 8 CNN model predictions of rush distribution across Kingcombe Meadows Reserve. Model outputs for i) 2005 and ii) 2020, showing original aerial imagery (a) and corresponding classification results (b). Orange areas represent predicted rush coverage, green areas represent other LC types

3.5 Rush Distribution and Spatial Patterns

Map-based classification suggested rush occupied 14.35 ha (6.8%) in 2005 and 40.93 ha (19.3%) in 2020. However, such estimates were biased due to classification errors (Stehman, 2012). Therefore, error-corrected estimates derived from stratified area estimation were calculated (Table 2).

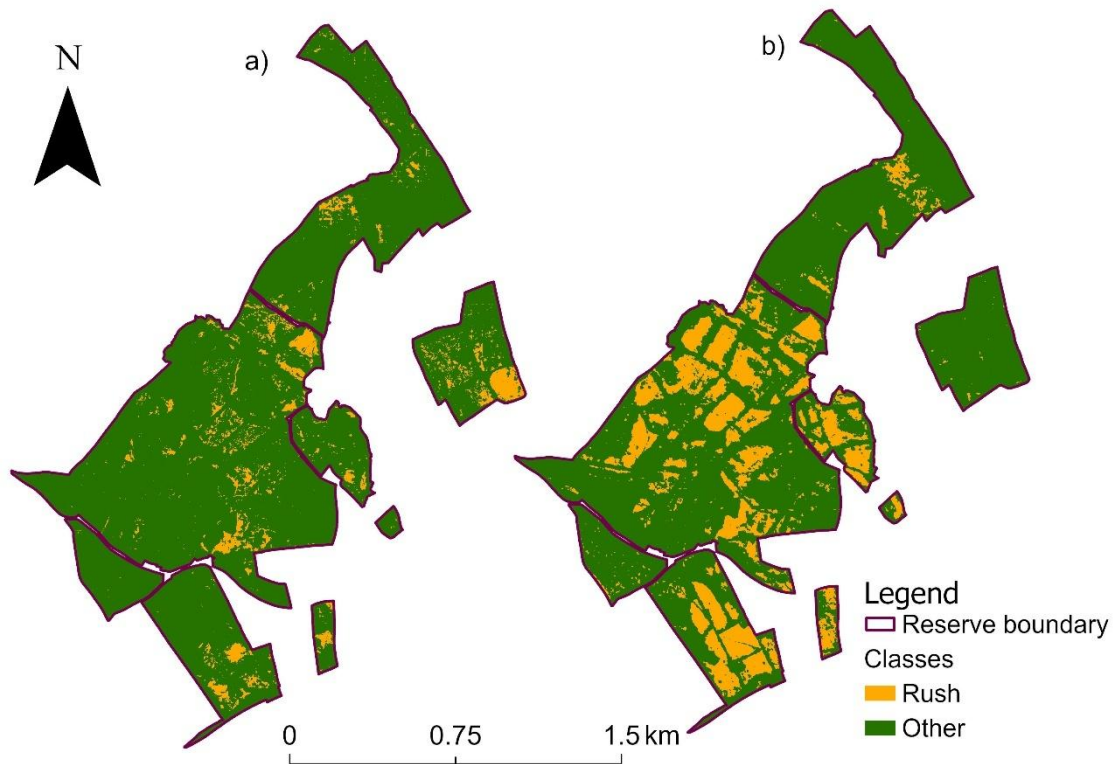


Figure 9 Rush distribution predictions showing: (a) 2005 and (b) 2020. Model predictions reveal substantial rush expansion across the reserve, particularly in the central and southern regions, over the 15 years.

Error-corrected area estimates revealed that rush coverage across Kingcombe Meadows Reserve increased dramatically over the 15 years, expanding from 16.2 ha (7.6%) in 2005 to 42.5 ha (20%) in 2020. This represented nearly a threefold increase in rush extent, with the total area affected expanding by 26.3 ha over the study period (Table 2).

Spatial analysis indicated that this expansion was most pronounced in the central and southern regions of the reserve, where extensive new colonisation occurred in areas that previously contained little or no rush (Figure 9). The temporal

comparison highlighted both the densification of existing rush patches and the establishment of new ones.

Table 2 Error-corrected area estimates of rush and “other” classes in Kingcombe Meadows Reserve in 2005 and 2020, derived using stratified sampling-based estimation (Stehman, 2012).

Years	2005		2020	
Classification	Area (ha)	Area (%)	Area (ha)	Area (%)
Rush	16.2	7.6	42.5	20
Other	195.8	92.4	169.5	80
Total reserve	212	100	212	100
95% CI	±0.05		±0.08	

3.6 Spatial Patterns of Change

Figure 10 demonstrated that while some existing rush areas were lost, these losses were substantially outweighed by new rush establishment. The spatial distribution of changes showed that rush expansion was not simply the enlargement of existing patches, but involved colonisation of previously rush-free areas, particularly in the central and southern regions of the reserve.

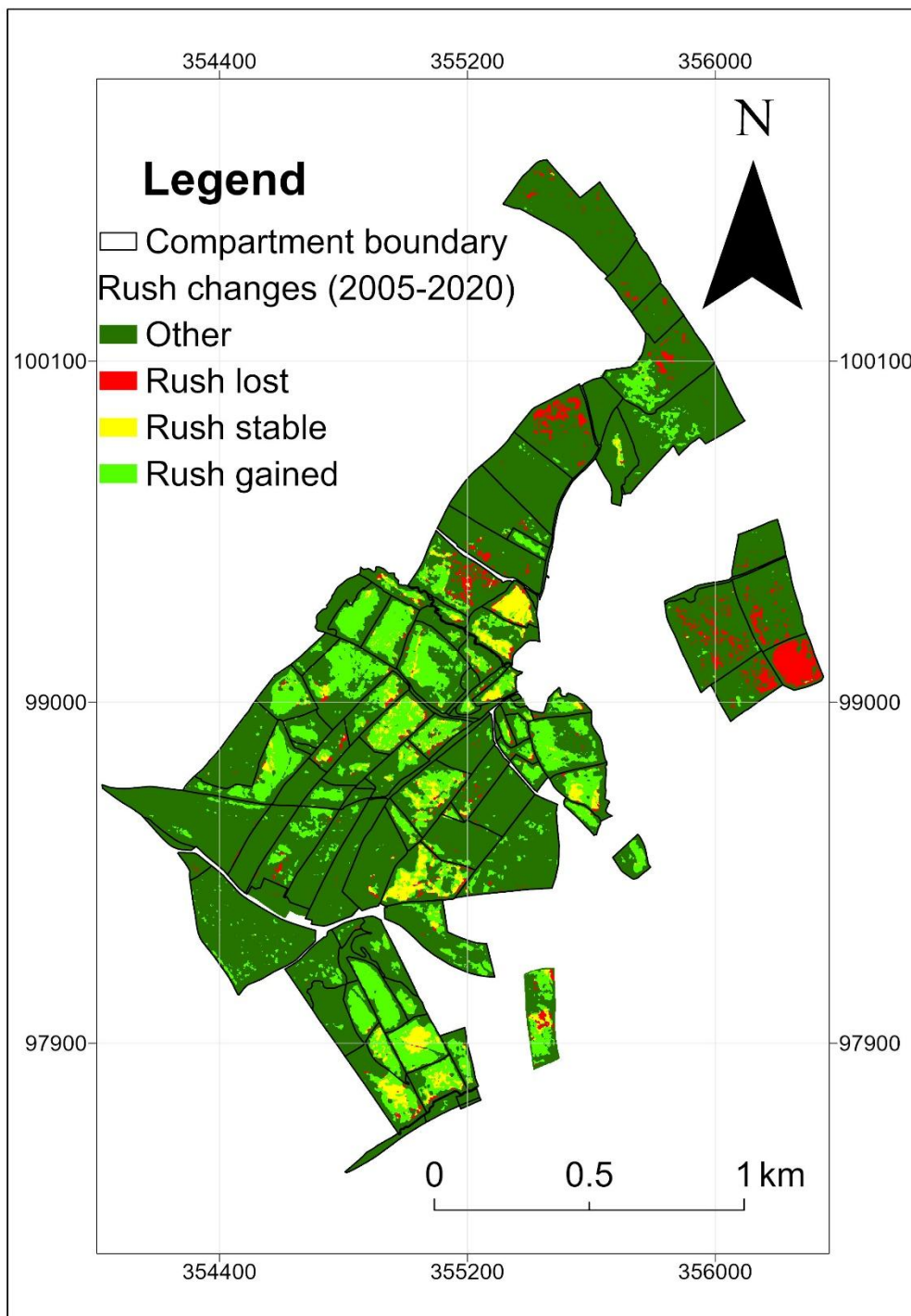


Figure 10 The map shows areas where rush coverage remained stable (yellow), was gained (light green), was lost (red) and Other LC between 2005 and 2020 predictions. Black lines delineate compartment boundaries in Kingcombe Meadows Reserve.

3.7 Topographic Analysis

To understand environmental factors influencing rush distribution patterns, topographic analysis was conducted using the 2020 rush predictions overlaid with terrain variables derived from the DSM. Rush demonstrated distinct preferences for specific topographic conditions that aligned with its ecological requirements for poorly drained habitats.

3.7.1 Elevation Analysis

Elevation analysis revealed that rush occurred at significantly lower elevations (mean=140.1 m, median=136 m) compared to non-rush areas (mean 164.3 m, median=163 m), representing an average difference of 24 m (Table 3)

Table 3 Mean and median elevation of rush and the “Other” class

Classes	Mean (m)	Median (m)
Rush	140.1	136
Other	164.3	163

Rush was concentrated within the lowest elevation zones (114–158 m), corresponding to valley bottoms and flatter areas prone to water accumulation (Figure 11)

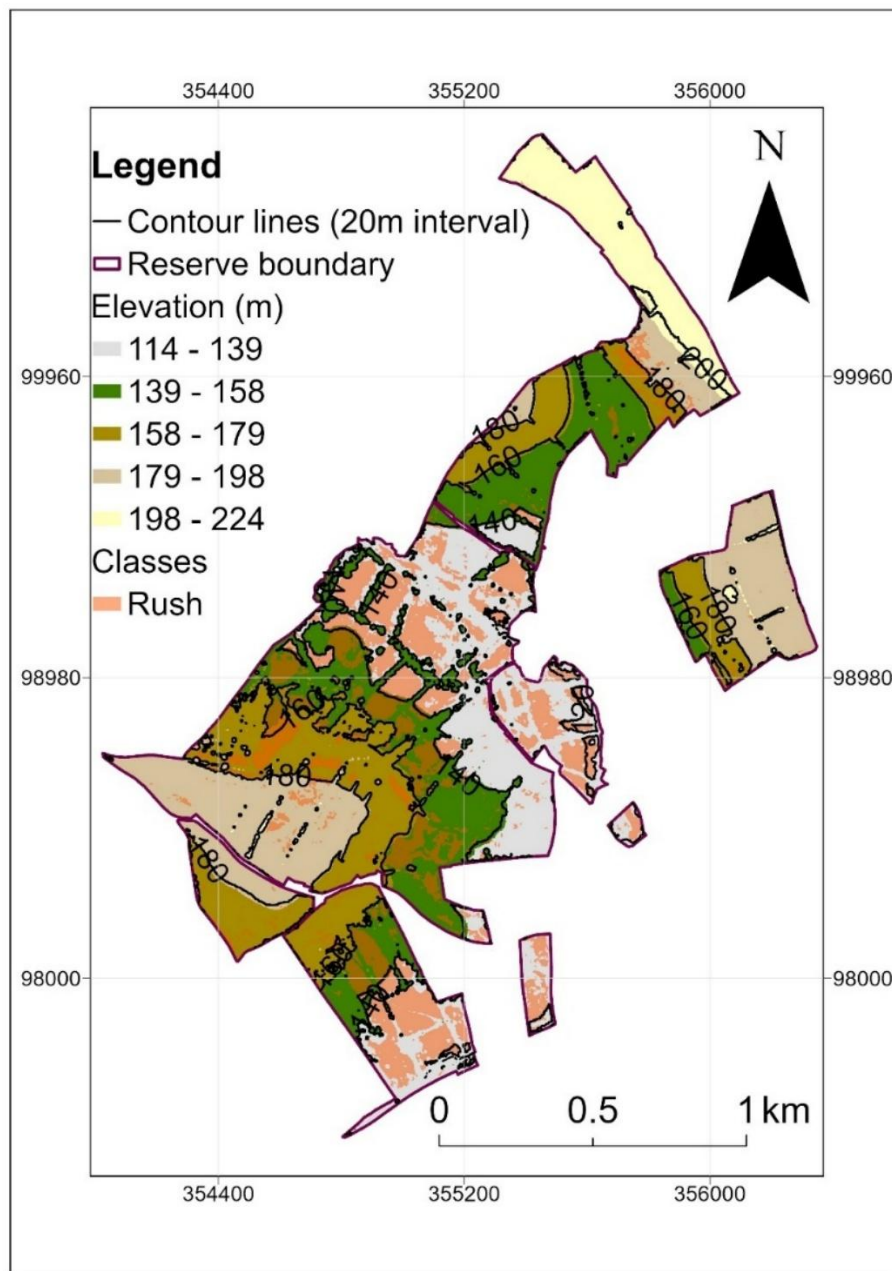


Figure 11 Elevation distribution and rush occurrence across Kingcombe Meadows Reserve. Rush vegetation is concentrated in lower elevation zones (114–158 m). Contour lines (20m intervals) illustrate topographic detail.

3.7.2 Slope Analysis

Slope analysis demonstrated an inverse relationship between slope steepness and rush occurrence. Rush areas averaged 8.3° (median 5.1°), whereas “Other” were more than twice as steep, averaging 18.3° (median 14.0°; Table 4).

Table 4 Mean and median slope characteristics of rush and the “Other” class

Classes	Mean (°)	Median (°)
Rush	8.3	5.1
Other	18.3	14.0

Analysis of rush distribution across slope categories revealed strong habitat selectivity. 28.3% (25.03 ha) of all low slope terrain (0–8.2°) was occupied by rush, compared to only 4.3% (0.87 ha) on very steep slopes (>47.3°; Table 5). Rush distribution patterns showed clear topographic preferences, with higher occurrence on gentler terrain and declining presence on steeper slopes.

Table 5 Rush distribution across slope classes. Percentages represent the proportion of each slope class occupied by rush vegetation

Slope Class	Slope Range (°)	Rush Area (%)	Rush Area (ha)
Low	0-8.2	28.3%	25.03
Gentle	8.2-25.56	18.7%	13.64
Steep	25.56-47.33	4.9%	1.34
Very Steep	47.33-80.45	4.3%	0.87

3.8 Management Drivers

To assess whether current grazing management influences rush distribution, the relationship between grazing pressure and rush coverage was analysed.

Analysis of the relationship between grazing pressure and rush coverage revealed no significant correlation ($r = -0.017$, $n = 38$, $p > 0.05$). Rush coverage varied widely across all grazing categories, ranging from 0% to 56.3% regardless of grazing intensity. Compartments under low grazing pressure (<2.0 LU/ha) exhibited substantial variability in rush coverage (0-51.5%), with areas under very high grazing pressure (>4.0 LU/ha) displaying comparable variability (0.2-53.5%) as illustrated in Figure 12

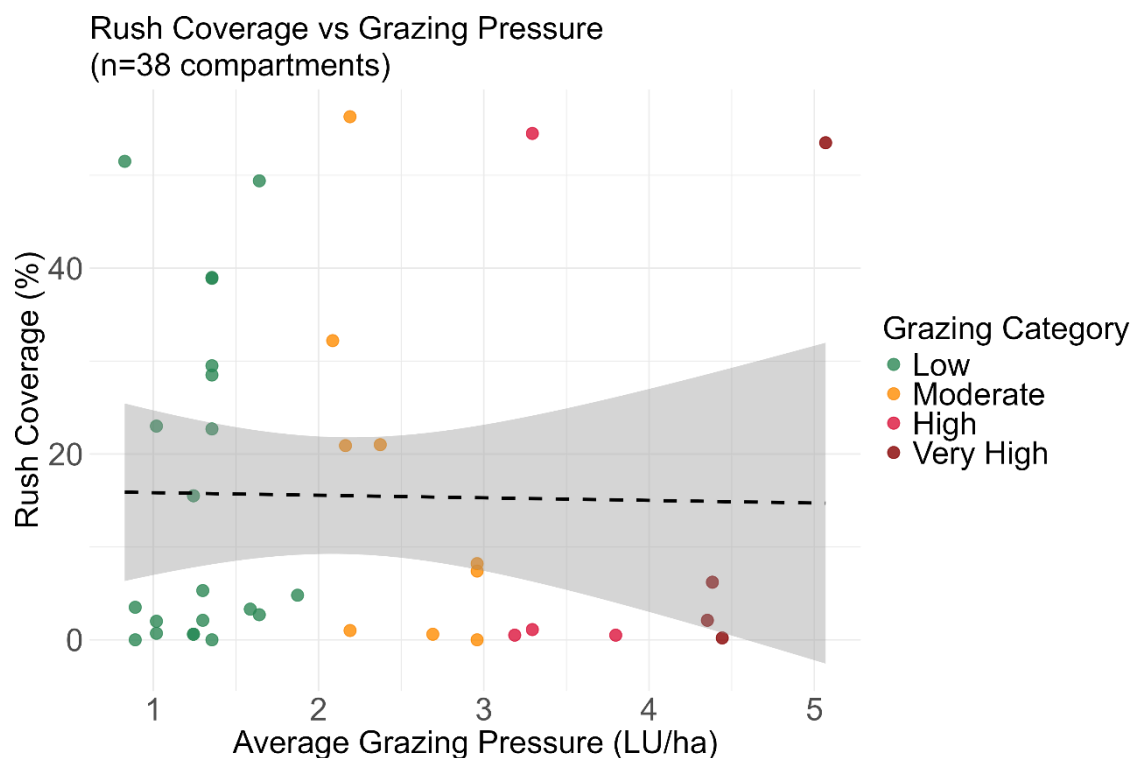


Figure 12 Relationship between grazing pressure and rush coverage across compartments at Kingcombe Meadows Reserve. Rush coverage (%) plotted against average grazing pressure (LU/ha) for 38 compartments, based on 2018-2024 grazing records and 2020 rush distribution data. Points are colored by grazing intensity categories: Low (<2.0 LU/ha), Moderate (2.0-3.0 LU/ha), High (3.0-4.0 LU/ha), and Very High (>4.0 LU/ha). The dashed line represents the linear trend ($r = -0.017$, $p > 0.05$), indicating no significant correlation.

Given that topographic analysis revealed strong elevation constraints on rush distribution, the grazing analysis was repeated using only compartments within suitable elevation zones ($\leq 158\text{m}$, $n=19$) to test whether habitat unsuitability was masking potential grazing effects. This subset analysis revealed a stronger negative correlation ($r = -0.495$, $p = 0.626$), suggesting that within topographically suitable areas, grazing pressure may influence rush establishment patterns (Figure 4-10). The analysis showed a moderate negative correlation that approaches but does not reach statistical significance.

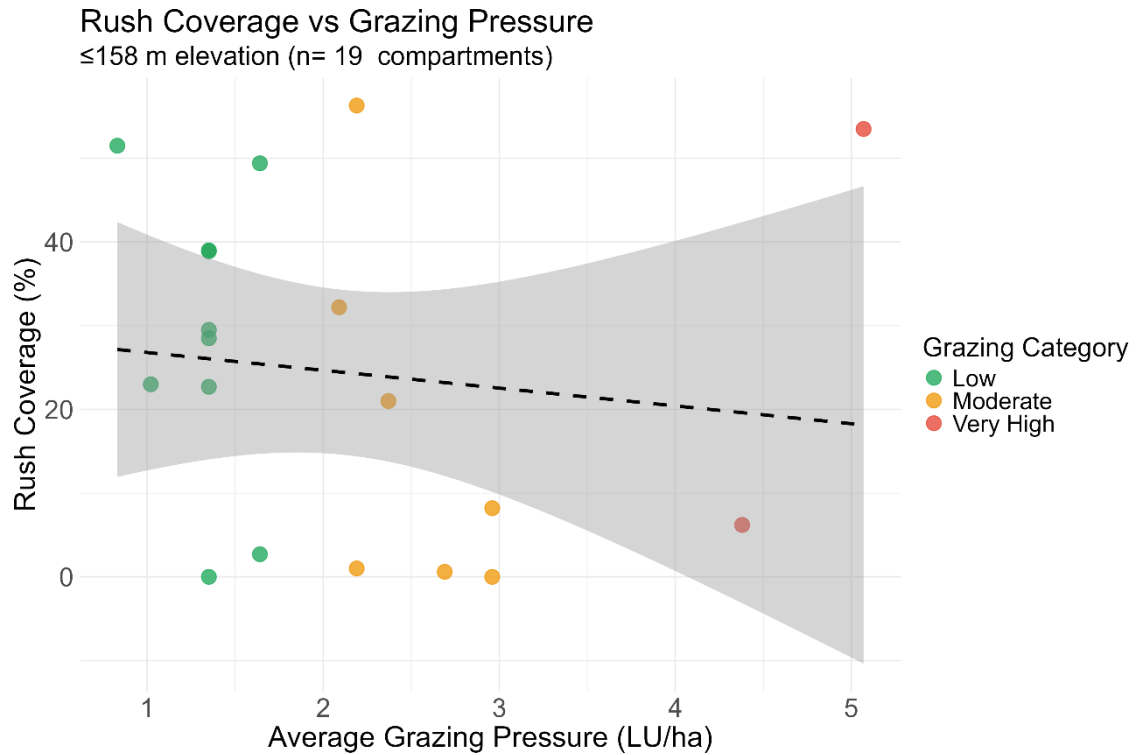


Figure 13 Relationship between grazing pressure and rush coverage for compartments at suitable elevations at Kingcombe Meadows Reserve. Rush coverage (%) plotted against average grazing pressure (LU/ha) for 19 compartments at elevations ≤ 158 m, based on 2018-2024 grazing records and 2020 rush distribution data. Points are colored by grazing intensity categories: Low (< 2.0 LU/ha), Moderate (2.0-3.0 LU/ha), and Very High (> 4.0 LU/ha). The dashed line represents the linear trend ($r = -0.495$, $p = 0.626$).

4 Discussion

4.1 Model Performance

The U-Net model trained on the 2005 and 2020 datasets both demonstrated successful convergence within 50 epochs, with steadily decreasing training and validation losses and only a small train-validation gap (Figure 4). This pattern indicated minimal overfitting and strong generalisation capacity, suggesting that the models effectively learned relevant spatial features associated with rush presence. The high classification accuracies (94.8% for 2005 and 91.6% for 2020) are consistent with other U-Net applications in remote sensing. For

instance, Van der Plas et al. (2023) reached up to 95% accuracy for main land-cover classes, while Boston et al. (2024) reported 93% accuracy in multi-class vegetation mapping, outperforming a traditional random forest model (87%). These comparable results supported the reliability of the model performance in capturing rush vegetation with high accuracy.

The slightly better performance of the 2005 model likely reflected higher image quality or more distinct visual separation between rush and surrounding vegetation in that year. This difference could have stemmed from several factors: firstly, sensor calibration and atmospheric correction procedures may have evolved between acquisition dates, potentially affecting image quality (Maxwell et al., 2018). Secondly, environmental conditions during image acquisition, such as soil moisture content or atmospheric haze, could have significantly influenced vegetation reflectance patterns (Belgiu & Drăguț, 2016). Additionally, the 15-year interval may have introduced genuine ecological changes in the vegetation community composition, such as shifts in species dominance or growth patterns, potentially reducing the visual differences between rush patches and background vegetation (Dronova & Taddeo, 2022).

Despite the strong performance, the small train–validation gap suggested that the models remained sensitive to dataset-specific conditions. Variations in illumination, seasonal phenology, or sensor specifications between 2005 and 2020 may have introduced visual variability that affected generalisation in the later dataset (Maxwell et al., 2018; (Belgiu & Drăguț, 2016). The binary classification scheme (rush vs. other) simplified the landscape into two categories and may have reduced finer ecological patterns.

4.2 Class Distribution

In 2005, rush vegetation comprised about 11% of the training and testing datasets, respectively, while the remainder consisted of other LC types. By 2020, rush coverage had expanded dramatically to 23.1–32.2% (testing and training datasets, respectively (Figure 5).

The 2005 dataset was highly imbalanced ($\approx 89:11$), while the 2020 dataset was more moderate ($\approx 3:1$ to $2:1$). Class imbalance is a well-recognised challenge in remote sensing classification, as minority classes are often underrepresented and prone to misclassification (Deng et al., 2025). In this study, the severe imbalance in the 2005 dataset likely increased the risk of underestimating rush coverage. The 2020 dataset's more balanced distribution, though still imperfect, provided a better foundation for training.

The similar class distributions between training and testing sets within each year confirmed that the splitting strategy preserved representative sampling across classes. Such consistency is crucial for robust evaluation, as disparities between training and testing distributions can yield overly optimistic accuracy estimates (Deng et al., 2025). The slight variation in the 2020 dataset likely reflected natural spatial heterogeneity rather than systematic sampling bias.

4.3 Classification Performance Assessment

The confusion matrices (Figure 6) highlighted clear differences in model behaviour between 2005 and 2020, reflecting the underlying trade-offs between sensitivity and precision in binary remote sensing classification.

The 2020 model demonstrated significantly higher sensitivity for rush detection (93.6% vs. 76.5%), meaning it correctly identified a greater proportion of actual rush pixels. This high sensitivity translated to fewer false negatives (6.4% vs. 23.5%), indicating that the 2020 model was less likely to miss rush vegetation where it was present. However, this aggressive approach came with increased false positives (9.0% vs. 2.8%), resulting in lower precision for rush detection (75.7% vs. 77.8%). The higher class representation in the 2020 training data (Figure 5) likely contributed to this more comprehensive but less precise detection behaviour.

In contrast, the 2005 model demonstrated conservative detection characteristics, with lower false positive rates (2.8% vs. 9.0%) but at the cost of missing substantial rush areas (76.5% sensitivity; Table 1). This conservative approach resulted in slightly better precision when identifying rush pixels (77.8% vs.

75.7%), meaning that when the model classified a pixel as rush, it was marginally more reliable. Both models demonstrated high reliability for non-rush classifications, with user accuracies of 97.0% (2005) and 97.9% (2020), indicating that both models were highly trustworthy when classifying pixels as "other."

These contrasting behaviours create distinct practical implications. The 2020 model's comprehensive detection approach risked overestimating rush coverage but ensured minimal areas are overlooked, making it valuable for biodiversity surveys or early invasion tracking, where complete detection is a priority (Ashby et al., 2020). Conversely, the 2005 model's conservative approach provided marginally more reliable rush identification when positive classifications were made, better suited for precise quantification of confirmed rush populations, though at the risk of underestimating the total extent. This performance difference reflects the classic precision-recall trade-off well established in machine learning (Kattenborn et al., 2020), where training data characteristics significantly influenced each model's detection strategy and subsequent applicability to different monitoring objectives.

To address these model-specific biases in area estimation, overall statistics for rush coverage across the study area were corrected using Stehman (2012) design-based estimator applied to the independent validation data, ensuring that area estimates remained unbiased despite individual model limitations. However, the spatial maps themselves retained these classification errors and should be interpreted with caution. Users should be aware that the 2020 map may overestimate rush extent in specific locations due to higher false positive rates, while the 2005 map may underestimate rush coverage by missing actual rush areas.

Another limitation arose when rush detection was less reliable in sparsely distributed patches compared to dense, well-established stands. Even at 12.5 cm resolution, isolated tussocks often blended visually with the surrounding sward, reducing the separability of rush during digitisation and classification.

4.4 Visual Assessment of Model Predictions and Spatial Patterns

The visual assessment (Figure 7 and Figure 8) confirmed that the U-Net models effectively delineated rush patches ranging from small, fragmented clusters to extensive continuous stands, demonstrating their capacity to capture ecological heterogeneity. The models successfully scaled up predictions from a limited training dataset (70 samples per year) to generate comprehensive rush classifications across the entire 212 ha reserve, illustrating the power of deep learning approaches for landscape-scale ecological monitoring.

Despite differences in lighting, image quality, and seasonal timing between the 2005 and 2020 aerial imagery, predicted rush boundaries remained well-defined and spatially coherent. Classifications showed a clear separation between rush and non-rush areas with minimal noise commonly associated with pixel-based classification approaches. Reliable boundary mapping allowed quantification of fragmentation, connectivity, and landscape change, which indicated reliable performance across imagery types and years.

Such an ability to represent both fine-scale and broad vegetation patterns aligned with findings by Kattenborn et al. (2020), who found that CNNs were effective in predicting the cover of different plant species and communities using UAV imagery, making them highly suitable for ecological monitoring and management applications. The success of the U-Net model in capturing these transitions suggested that the deep learning approach effectively learned to distinguish subtle visual and spatial differences that traditional pixel-based methods often missed and thereby leading to the achievement of objectives i and ii of this study.

4.5 Temporal Change Analysis and Area Estimation

The temporal analysis revealed dramatic rush expansion across Kingcombe Meadows Reserve between 2005 and 2020. Bias-corrected estimates indicated an increase from 16.2 ha (7.6%) to 42.5 ha (20.0%), a 163% rise over 15 years (Table 2). This rapid colonisation was consistent with aggressive wetland species establishing under favourable conditions (Ashby et al., 2020).

The application of stratified area estimation methods following Stehman (2012) protocols provided unbiased estimates of the different class coverage by accounting for classification errors. The error-corrected estimates revealed slightly higher rush coverage than raw map-based calculations, suggesting that the original classification contained omission errors where actual rush patches were misclassified as other LC types (Stehman, 2012).

The concentration of new rush patches in central and southern areas of the reserve, along with scattered colonisation across the landscape (Figure 10), suggested both local spread from established stands and long-distance dispersal, potentially driven by more favourable environmental conditions across the reserve over time. This pattern reflected the dual reproductive and dispersal strategies characteristic of rush expansion: local vegetative growth via rhizomes and broader seed-mediated establishment in new areas. Similar spatial dynamics of rush expansion have been documented in upland grasslands using aerial imagery (Ashby et al., 2020), while remote sensing methods have been recognised as valuable tools for detecting such heterogeneous invasion patterns across landscapes (Crowley & Cardille, 2020).

4.6 Drivers

The analysis revealed a clear relationship between elevation and rush distribution, with rush strongly concentrated in lower-lying areas of Kingcombe Meadows Reserve (Figure 11). Rush occurred at significantly lower elevations (mean = 140.1 m, median = 136 m) compared to non-rush areas (mean = 164.3 m, median = 163 m), giving an average difference of 24 m (Table 3). This separation highlighted the importance of topography as an ecological driver and underscored the role of hydrology in shaping rush patterns.

The highest concentration of rush was observed between 114–158 m, which at Kingcombe Meadows corresponded to low-lying and poorly drained topographic positions. Such areas typically experience greater water retention and a higher frequency of soil saturation, creating conditions favourable for rush establishment (Ashby et al., 2020). Although areas above ~158 m were generally less suitable for rush colonisation due to reduced soil moisture, isolated upland patches

persisted. Their occurrence may have been influenced by site-specific factors such as local soil characteristics, legacy effects of past management, or other micro-environmental conditions that created suitable niches despite the broader unsuitability of higher elevations.

The slope analysis reinforced that rush patches were concentrated on flatter ground and were largely absent from steeper slopes. Mean slopes within rush areas were less than half those of other LC areas, indicating strong habitat selectivity for gently sloping terrain (Table 4). This topographic preference reflects the adaptation of rushes like *Juncus effusus* to waterlogged conditions in low-lying wetland areas, where they tend to dominate the vegetation due to their tolerance for seasonal flooding and poor drainage (Müller et al., 2020).

The initial analysis of grazing pressure (Figure 12), revealed no significant relationship with rush coverage across all 38 compartments ($r = -0.017$, $p > 0.05$). However, when the analysis was restricted to compartments within suitable elevation zones ($\leq 158\text{m}$, $n = 19$; Figure 13), a moderate negative correlation emerged ($r = -0.495$, $p = 0.026$), demonstrating that grazing effects were masked when topographically unsuitable areas were included. This finding illustrated how reduced intensity of grazing can sometimes lead to rapid spread and dominance of soft rush (*Juncus effusus*) in suitable wet grassland habitats (Kaczmarek-Derda et al., 2019).

This subset analysis revealed that within suitable habitats, higher grazing pressure showed a potential negative association with rush coverage, though this relationship was not statistically significant. The weak statistical relationship suggested that current grazing management may have limited direct control over established rush populations, particularly given the strong environmental constraints identified. These findings indicated that effective rush control at Kingcombe Meadows would likely require integrated approaches addressing both habitat modification (drainage, topographic management) and livestock management within suitable areas.

Additionally, the moderate relationship suggested that grazing may play a role in limiting new rush establishment under favourable hydrological conditions, but its

influence is strongly constrained by environmental context. Previous studies have shown that in wet meadow ecosystems, moderate grazing pressures can reduce dominance by competitive plant species and promote biodiversity, suggesting a potential to limit rush encroachment under favourable hydrological conditions (Kulik et al., 2023).

The persistence of established rush populations regardless of current grazing pressure likely reflected the resilient nature of mature rush tussocks and potential legacy effects of historical management practices. Once established, rush communities can persist even under changed management regimes, explaining why high coverage occurred across diverse grazing intensities within suitable areas (Ashby et al., 2020).

5 Conclusions

This study demonstrated the value of convolutional neural network–based semantic segmentation for mapping rush-dominated wet grasslands at high resolution. The developed models achieved strong classification performance (94.8% for 2005 and 91.6% for 2020), successfully capturing both small fragmented clusters and extensive stands. While classification errors were present, error-adjusted area estimation ensured robust and unbiased quantification of rush extent and change.

Rush distribution was strongly shaped by topographic and hydrological gradients. Expansion between 2005 and 2020 reflected a combination of local vegetative spread and longer-distance colonisation.

Contrary to expectations, current grazing intensity in the reserve (2018–2024) showed no significant relationship with rush cover when assessed across all compartments. However, when analysis was restricted to topographically suitable zones, a moderate but non-significant negative trend emerged, suggesting that higher grazing pressure may help suppress new rush establishment under favourable conditions.

Overall, this study highlighted the potential of deep learning methods not only to generate reliable, fine-scale habitat maps but also to provide a repeatable monitoring tool for tracking vegetation dynamics over time. Such approaches enable conservation practitioners to detect encroachment trends, evaluate management effectiveness, and prioritise interventions. For Kingcombe Meadows and similar wet grasslands, the findings emphasise the importance of proactive management in vulnerable low-lying habitats, where integrated strategies addressing both hydrological context and grazing regimes are most likely to prevent further rush expansion and preserve species-rich communities.

References

- Adegun, A. A., Viriri, S., & Tapamo, J.-R. (2023). Review of deep learning methods for remote sensing satellite images classification: experimental survey and comparative analysis. *Journal of Big Data*, 10(1), 93.
- Ashby, M. A., Whyatt, J. D., Rogers, K., Marrs, R. H., & Stevens, C. J. (2020). Quantifying the recent expansion of native invasive rush species in a UK upland environment. *Annals of Applied Biology*, 177(2), 243–255.
- Belgiu, M., & Drăguț, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 114, 24–31.
- Berra, E. F., Gaulton, R., & Barr, S. (2019). Assessing spring phenology of a temperate woodland: A multiscale comparison of ground, unmanned aerial vehicle and Landsat satellite observations. *Remote Sensing of Environment*, 223, 229–242.
- Boston, T., Van Dijk, A., & Thackway, R. (2024). U-Net Convolutional Neural Network for Mapping Natural Vegetation and Forest Types from Landsat Imagery in Southeastern Australia. *Journal of Imaging*, 10(6), 143.
- Crowley, M. A., & Cardille, J. A. (2020). Remote sensing's recent and future contributions to landscape ecology. *Current Landscape Ecology Reports*, 5(3), 45–57.
- Deng, Y., Chen, G., Tang, B., Duan, X., Zuo, L., & Zhao, H. (2025). Study on Class Imbalance in Land Use Classification for Soil Erosion in Dry–Hot Valley Regions. *Remote Sensing*, 17(9), 1628.
- Dorset Wildlife Trust. (2024). Kingcombe Meadows | Dorset Wildlife Trust. [Dorsetwildlifetrust.org.uk. https://www.dorsetwildlifetrust.org.uk/nature-reserves/kingcombe-meadows](https://www.dorsetwildlifetrust.org.uk/nature-reserves/kingcombe-meadows)
- Dronova, I., & Taddeo, S. (2022). Remote sensing of phenology: Towards the comprehensive indicators of plant community dynamics from species to

- regional scales. *Journal of Ecology*, 110(7), 1460–1484.
- Ervin, G. N., & Wetzel, R. G. (2002). Influence of a dominant macrophyte, *Juncus effusus*, on wetland plant species richness, diversity, and community composition. *Oecologia*, 130, 626–636.
- Horning, N. (2020). Land cover mapping with ultra-high-resolution aerial imagery. *Remote Sensing in Ecology and Conservation*, 6(4), 429–430.
- Iakubovskii, P. (2019). Segmentation models pytorch. *GitHub Repository*.
- Jefferson, R. G., Smith, S. L. N., & MacKintosh, E. J. (2014). Lowland grasslands. In *Guidelines for the Selection of Biological SSSIs. Part, 2*.
- Kaczmarek-Derda, W., Østrem, L., Myromslien, M., Brandsæter, L. O., & Netland, J. (2019). Growth pattern of *Juncus effusus* and *Juncus conglomeratus* in response to cutting frequency. *Weed Research*, 59(1), 67–76.
- Kattenborn, T., Eichel, J., Wiser, S., Burrows, L., Fassnacht, F. E., & Schmidtlein, S. (2020). Convolutional Neural Networks accurately predict cover fractions of plant species and communities in Unmanned Aerial Vehicle imagery. *Remote Sensing in Ecology and Conservation*, 6(4), 472–486.
- Kislov, D. E., Korznikov, K. A., Altman, J., Vozmishcheva, A. S., & Krestov, P. V. (2021). Extending deep learning approaches for forest disturbance segmentation on very high-resolution satellite images. *Remote Sensing in Ecology and Conservation*, 7(3), 355–368.
- Kulik, M., Bochniak, A., Chabuz, W., Żółkiewski, P., & Rysiak, A. (2023). Is grazing good for wet meadows? Vegetation changes caused by white-backed cattle. *Agriculture*, 13(2), 261.
- Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine-learning classification in remote sensing: An applied review. *International Journal of Remote Sensing*, 39(9), 2784–2817.

- McCorry, M. J., & Renou, F. (2003). Ecology and management of *Juncus effusus* (soft rush) on cutaway peatlands. *Forest Ecosystem Research Group Report*, 69, 66.
- Müller, J., Jantzen, C., & Wiedow, D. (2020). The energy potential of soft rush (*Juncus effusus* L.) in different conversion routes. *Energy, Sustainability and Society*, 10(1), 26.
- Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., & Antiga, L. (2019). Pytorch: An imperative style, high-performance deep learning library. *Advances in Neural Information Processing Systems*, 32.
- Ridding, L. E., Redhead, J. W., & Pywell, R. F. (2015). Fate of semi-natural grassland in England between 1960 and 2013: A test of national conservation policy. *Global Ecology and Conservation*, 4, 516–525.
- Stehman, S. V. (2012). Impact of sample size allocation when using stratified random sampling to estimate accuracy and area of land-cover change. *Remote Sensing Letters*, 3(2), 111–120.
- Taylor, J. C., Brewer, T. R., & Bird, A. C. (2000). Monitoring landscape change in the National Parks of England and Wales using aerial photo interpretation and GIS. *International Journal of Remote Sensing*, 21(13–14), 2737–2752.
- Van der Plas, T. L., Geikie, S. T., Alexander, D. G., & Simms, D. M. (2023). Multi-stage semantic segmentation quantifies fragmentation of small habitats at a landscape scale. *Remote Sensing*, 15(22), 5277.
- Zaka, M. M., & Samat, A. (2024). Advances in Remote Sensing and Machine Learning Methods for Invasive Plants Study: A Comprehensive Review. *Remote Sensing*, 16(20), 3781.

Appendices

Appendix A : Ethical approval letter



Figure A-1 Cranfield University ethical approval letter for the study.

Appendix B Field Photos



Figure B-1 Site photographs from fieldwork at Kingcombe Meadows Reserve, Dorset.