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Assessment of environmental water strategies for improving fringing vegetation health by modelling vegetation condition in a connected floodplain lakes system

Chunying Wu[1,2,3,4] | J. Angus Webb[1] | Michael J. Stewardson[1]

[1]Department of Infrastructure Engineering, Faculty of Engineering and IT, The University of Melbourne, Melbourne, Victoria, Australia

[2]Australian-German Climate & Energy College, The University of Melbourne, Melbourne, Victoria, Australia

[3]Institute of Applied Geosciences, Karlsruhe Institute of Technology, Karlsruhe, Germany

[4]Institute of Environmental Sciences and Geography, Chair of Soil Sciences and Geoecology, University of Potsdam, Potsdam, Germany

Correspondence
Chunying Wu, Department of Infrastructure Engineering, Faculty of Engineering and IT, The University of Melbourne, Melbourne, Victoria, Australia.
Email: chunyingw@student.unimelb.edu.au

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Abstract

Across the globe, environmental water has been allocated with the purpose of preserving the health and vitality of floodplain vegetation. However, the influences of environmental water volume and environmental water delivery strategies have not been studied widely because of shortage of on-ground monitoring data. Remotely sensed data can bridge this gap by providing long-term and continuous information; Landsat imagery from 1988 to 2020 was used in this research. We used the normalized difference vegetation index (NDVI) as an indicator of physiological condition of lake-fringing trees on the Hattah Lakes floodplain, south-east Australia. We employed the random forest (RF) regression method to model the relationship between NDVI and various climate and hydrological factors, such as the volume of water delivered to the connected lakes system as environmental water allocations or natural floods. The RF models performed well overall, with a mean R^2 value of 0.73. The analysis identified the monthly total of environmental water delivered 3 months prior to the Landsat image date as a more crucial factor than natural floods over the same period for driving vegetation condition. Environmental water from 3 months previously exerts a positive influence on NDVI until the volume reaches a specific threshold. We have observed significant improvements in floodplain vegetation through the current environmental water strategy, particularly since the construction of pumping infrastructure in 2013. We suggest that managers aim to inundate the lake fringing area every 3 years, specifically from August to September, by delivering environmental water up to the modelled threshold volume. Finally, the use of infrastructure has proven to be an effective and efficient method for irrigating floodplain lakes, leading to improvements in vegetation condition while conserving water resources.

KEYWORDS
environmental water strategies, fringing vegetation of lakes, Landsat dataset, machine learning explanation methods, random forest regression

1 | INTRODUCTION

Known as Earth's kidneys, wetlands are one of the world's most significant ecosystems. They provide ecosystem services in the form of flood control, water purification, and habitat (Wu et al., 2022; Wu & Chen, 2020; Xi et al., 2020). However, they have suffered extensive damage over recent decades because of climate change and human activities (Steinfeld & Kingsford, 2013).

Floodplain lakes are one type of wetland. In the context of disruption by dams and river regulation, there is growing recognition of the importance of conserving floodplains and river–floodplain connections (Steinfeld & Kingsford, 2013). Rivers across the globe have undergone regulation for diverse purposes such as public water supply, irrigation, electricity generation, and flood mitigation (Kuiper et al., 2014). More than 60% of river systems worldwide have experienced changes in stream flows (Kuiper et al., 2014). River regulation influences various hydro-geomorphic processes, resulting in a significant reduction in the occurrences of small and moderate floods (Netsvetov et al., 2019; Peake et al., 2011; Souter et al., 2014). As a result, river regulation has detrimental effects on the growth of floodplain trees, the density of forest stands, and the overall structure of floodplain ecosystems (Netsvetov et al., 2019). Deaths of floodplain forests and woodlands are occurring globally (Zhang et al., 2021). Therefore, appropriate measures and policies to address conflicting water demands for human and environmental uses are urgently needed to maintain floodplain ecosystems (Doody et al., 2015; Steinfeld & Kingsford, 2013). In response, many countries have implemented environmental water delivery programmes to provide water to floodplain ecosystems (Doody et al., 2015; Stewardson & Guarino, 2018; Wu et al., 2022).

Restoring and maintaining floodplain vegetation is often a primary objective when supplying environmental water into floodplain systems. Floodplain vegetation in regulated rivers often undergoes changes as a direct consequence of altered timing and reduced magnitude and duration of floods (Reid & Brooks, 2000). This has occurred in many regulated rivers around the world (Catelotti et al., 2015). Floodplain vegetation is also vulnerable to climate change, especially in semi-arid and arid regions (Nilsson et al., 2005; Tockner & Stanford, 2002). The effects of river regulation and climate change are pronounced in dominant perennial species of floodplain vegetation of south-east Australia, particularly black box (*Eucalyptus largiflorens*) and river red gum (*Eucalyptus camaldulensis*) (Jensen & Walker, 2017).

Many studies have been conducted to determine floodplain vegetation water requirements and environmental water effects on vegetation (Merritt et al., 2010; Morrison & Stone, 2015; Moxham et al., 2019; Whitaker et al., 2015). In Australia, river red gum trees have often been monitored using field-based methods during environmental water delivery. After summer watering, tree physiological condition has been observed to increase (Jensen & Walker, 2017). However, field-based monitoring data are spatially sparse and can only ever cover a fraction of a floodplain's area. Meanwhile, they demand significant manpower and material resources and are time-consuming. To compensate for the shortcoming of field-based methods, remote sensing imagery has been used to study long-term vegetation condition since the 1990s (Broich et al., 2018). As a convenient method, remote sensing techniques have gained recognition for acquisition of continuous data across various spatial resolutions (Norman et al., 2014). These data have been increasingly employed in the study of fluvial environments and demonstrate excellent results (Pace et al., 2021; Sims & Colloff, 2012; Wu et al., 2022; Xue et al., 2022).

Different vegetation types have varying responses to environmental water in terms of lag time. This is especially the case in the fringing areas of lakes surrounded by stands of river red gum and black box (Wu et al., 2022). However, studies related to the influence of environmental water volume and timing in floodplain vegetation remain scarce, mainly because of limited monitoring data and computational difficulties (Canham et al., 2021; Jensen et al., 2007; Wu et al., 2022).

To improve vegetation outcomes and achieve the objective of maintaining vegetation health through environmental water allocation, it is essential to assist water managers in comprehending the collective effects of environmental water and other factors on riparian vegetation condition (Capon et al., 2017). An environmental water strategy evaluation model is needed to examine efficiency of past and ongoing environmental watering strategies. In this study, random forest regression models and machine learning explanation methods have been applied to a 30-year Landsat dataset to model response of vegetation condition (NDVI) to environmental water volume and climate factors in a connected floodplain lakes system.

2 | METHODS

2.1 | Study area

Lying in north-western Victoria, south-eastern Australia, on the banks of the River Murray, the Hattah Lakes floodplain system comprises more than 20 permanent and semipermanent freshwater lakes with associated floodplains and waterways (Figure 1). As a semi-arid environment with hot dry summers and cooler winters, the floodplain has greater rainfall in the winter (Butcher & Hale, 2011). However, rainfall occurs all year with an average annual rainfall of about 250 mm (Wu et al., 2022).

The Hattah Lakes floodplain provides high biodiversity and habitat values, including vegetation communities such as black box and river red gum woodlands. These vegetation communities provide habitat for more than 47 waterbird species and other fauna (MDBA, 2012). As a national park, the Hattah Lakes floodplain is important for social and cultural activities. Therefore, based on its many values, the Hattah Lakes floodplain was designated as an 'icon site' in The Living Murray programme—Australia's first major river restoration programme (Wood et al., 2016). Fringing trees are targeted for preservation by the environmental water programme (MDBA, 2012). Therefore, the study area of this research is focussed on the fringing vegetation areas (green shaded areas in Figure 1) around nine selected Ramsar-listed lakes (Table 1).

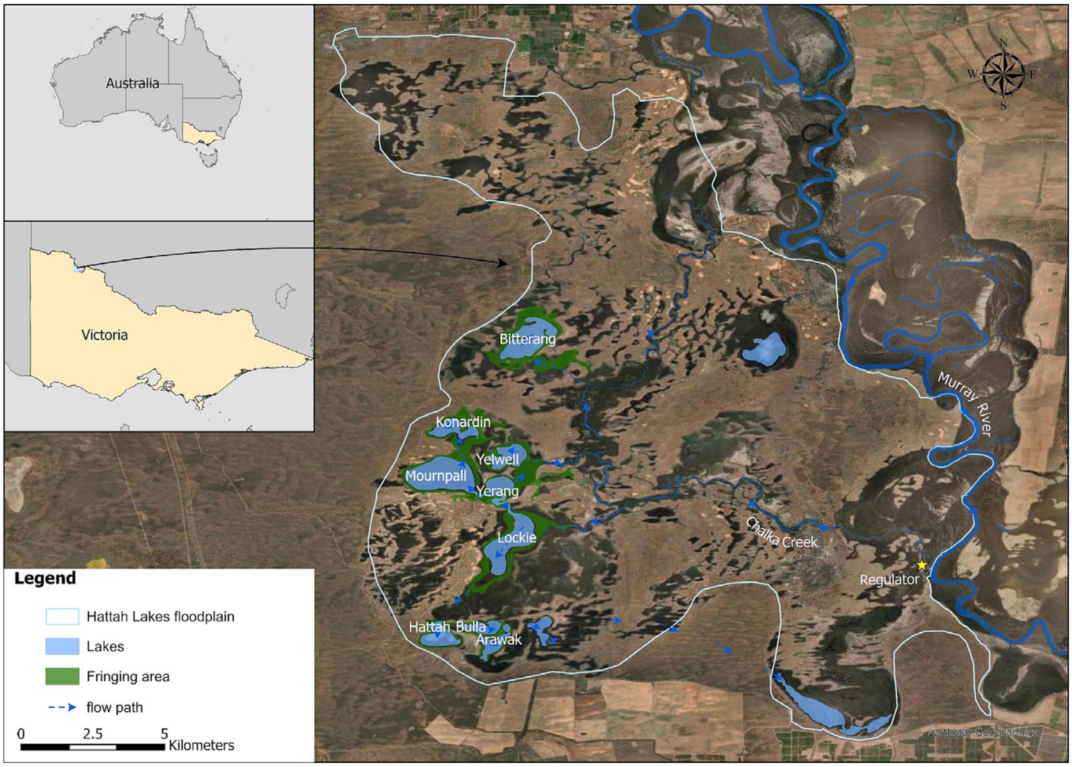

FIGURE 1 Location and lake distribution of study area: the Hattah Lakes.

TABLE 1 Description of nine lakes selected.

Lake name	Lake area (ha)	Lake depth (m)	Permanent/ semipermanent	Flows at Euston for lake to fill naturally (ML/day)	Area of fringing area (ha)
Lake Lockie	123	1.0	Permanent	40,000	140
Lake Hattah	52	3.1	Semipermanent	40,000	33
Lake Bulla	32	2.5	Permanent	55,000	24
Lake Mournpall	181	3.2	Semipermanent	40,000	92
Lake Yerang	43	1.5	Permanent	40,000	66
Lake Arawak	37	2.4	Semipermanent	55,000	29
Lake Yelwell	55	1.3	Permanent	55,000	103
Lake Konardin	57	1.7	Permanent	70,000	105
Lake Bitterang	109	2.4	Permanent	70,000	190

Because the River Murray and its floodplains are highly regulated, the Hattah Lakes ecosystem has been damaged by the loss of natural connectivity to the river over many decades (Cunningham et al., 2009). Floodplain vegetation requires periodic flooding to maintain ecological condition. To partly restore the floodplain lakes system, the flooding regime of the Hattah Lakes has been managed with environmental water since 2005 (MDBA, 2012). Environmental water is pumped through Chalka Creek and fills the lakes one by one (Figure 2). Lake Lockie is the first to be filled when environmental water is delivered, and then, water flows towards Lake Hattah and on to a sequence of lakes in the south (starting with Little Lake Hattah and ending with Lake Nip Nip). Meanwhile, water moves from Lake Lockie to Lake Yerang and feeds the northern lakes. The use of pumping allows lakes to be filled with environmental water at flows that are feasible to deliver along the River Murray. Elevating River Murray flows to thresholds for natural filling (Table 1) using environmental water is not possible because of (i) limits on the total amount of environmental water available, (ii) limited release capabilities from upstream dams, and (iii) operational constraints on the river designed to avoid flood impacts on riparian landholders and infrastructure.

2.2 | Dataset and preprocessing

In this study, multiple types of data have been used, including Landsat imageries with 16-day intervals and 30-m resolution, historical climate data, and hydrological records.

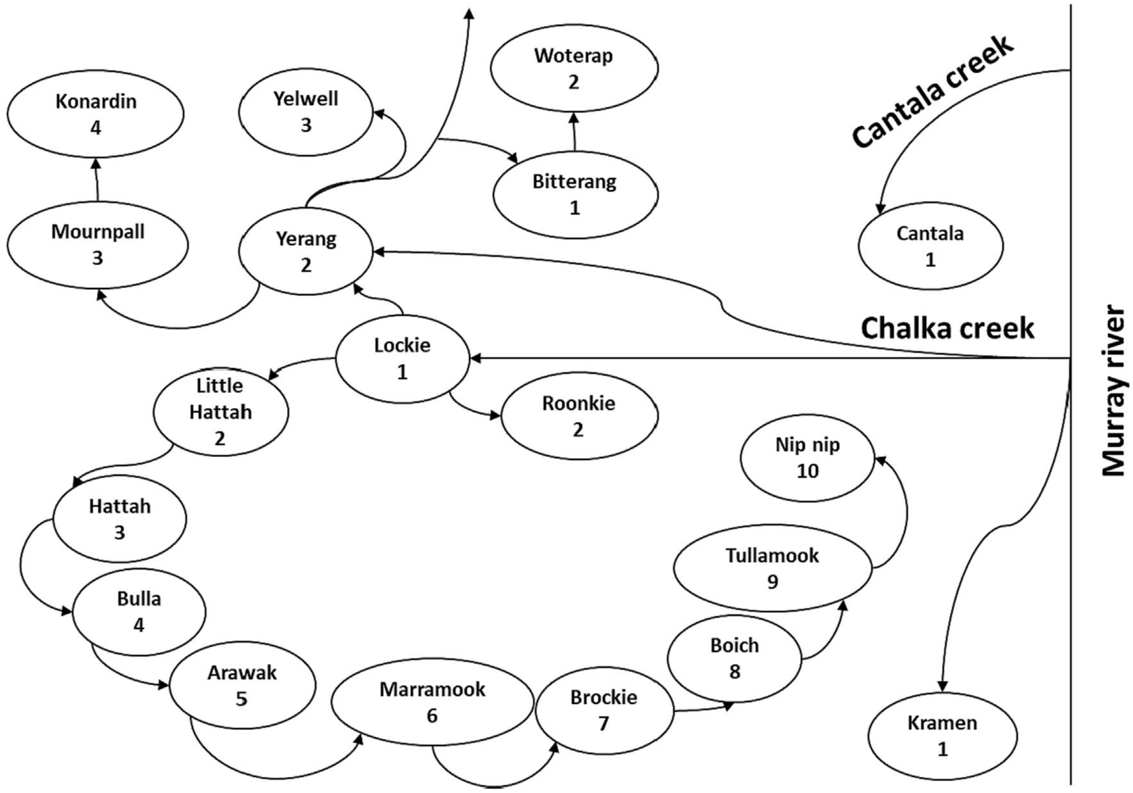

FIGURE 2 Environmental water flow path diagram and filling pattern of the Hattah Lakes system redrawn from Wijesuriya (2022).

2.2.1 | Remote sensing imageries

Landsat 5, 7, and 8 collection 1 datasets (USGS Landsat 5/7/8 Level 2, Collection 2, Tier 1, surface reflectance products) from 1988 to 2020 were used in this study, with the data being processed in Google Earth Engine (GEE). Clouds and cloud shadows were removed and filled using the mean of the values of images 1.5 months before and after the image with missing values. Poor-quality images were identified by counting the gap pixels and removed from the dataset. Landsat 7 Scan Line Corrector (SLC)-off gap was repaired by applying the morphological mean filter in GEE. To deal with the differences between the spectral characteristics of Landsat OLI and TM/ETM+ (Roy et al., 2016), the Landsat TM/ETM+ to OLI Harmonization function developed by GEE was applied to the imagery (https://developers.google.com/earth-engine/guides).

We used the normalized difference vegetation index (NDVI) as a measure of tree physiological condition in the lake fringing areas (Anyamba & Tucker, 2005; Zhang et al., 2013). In these areas, there is little to no understorey vegetation (J.A. Webb, personal observation), and so, NDVI captures the 'greenness' of the fringing river red gum and black box trees. NDVI varies in Hattah Lakes among and within years (Wu et al., 2022) and thus can be used as an indicator of tree condition or 'health'. Hereafter, we use the word 'condition' to describe physiological condition or greenness as measured by NDVI. NDVI is calculated by the following formula:

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED}, \tag{1}$$

where ρNIR is the reflectance value of the near infrared band and ρRED is the reflectance value of red band. Greater values of NDVI are indicative of better vegetation condition.

2.2.2 | Climate data

Climate data, including daily precipitation, maximum temperature, and vapour pressure, were extracted from the Australian Water Availability Project (AWAP), which is a high-quality dataset of historical and ongoing climate analyses for Australia with a spatial resolution of 5 km (Jones et al., 2009). To match the Landsat data acquisition date, we calculated monthly accumulated precipitation, mean maximum temperature, and mean vapour pressure with different lag periods (see below).

2.2.3 | Hydrological data

Between 2005 and 2010, environmental water was delivered to the Hattah Lakes from the River Murray through transportable pumps (Wood et al., 2018). In October 2013, a permanent pumping station—the Chalka Creek regulator—was built on the Hattah Lakes floodplain

(Butcher & Hale, 2011), and environmental water has been delivered by that regulator since then.

Natural floods occur and flow through Chalka Creek into Hattah Lakes when discharges at Euston Weir (~70-km upstream of Hattah Lakes) exceed the commence-to-flow (CTF) threshold (36,700 ML/day prior to October 2013 and 25,000 ML/day thereafter). To quantitatively calculate natural flood volume flowing into Hattah Lakes, we constructed a linear function between discharge at the Chalka Creek regulator and discharge at Euston Weir in excess of the CTF threshold during the natural flooding period between August 2016 and December 2016 (Figure 3). The relationship and linear function were applied to long-term discharge records at Euston Weir.

2.3 | Random forest regression

2.3.1 | Explanatory variables

Explanatory variables for our models of vegetation condition are listed in Table 2. Our previous work found that a positive influence on floodplain vegetation in Hattah Lakes can be detected 1 to 3 months after inundation with environmental water (Wu et al., 2022). With this in mind, we selected accumulated environmental water volume with 1-, 2-, and 3-month lags as independent variables. We also tested whether precipitation within 3 months and natural floods within 3 months affect fringing vegetation condition.

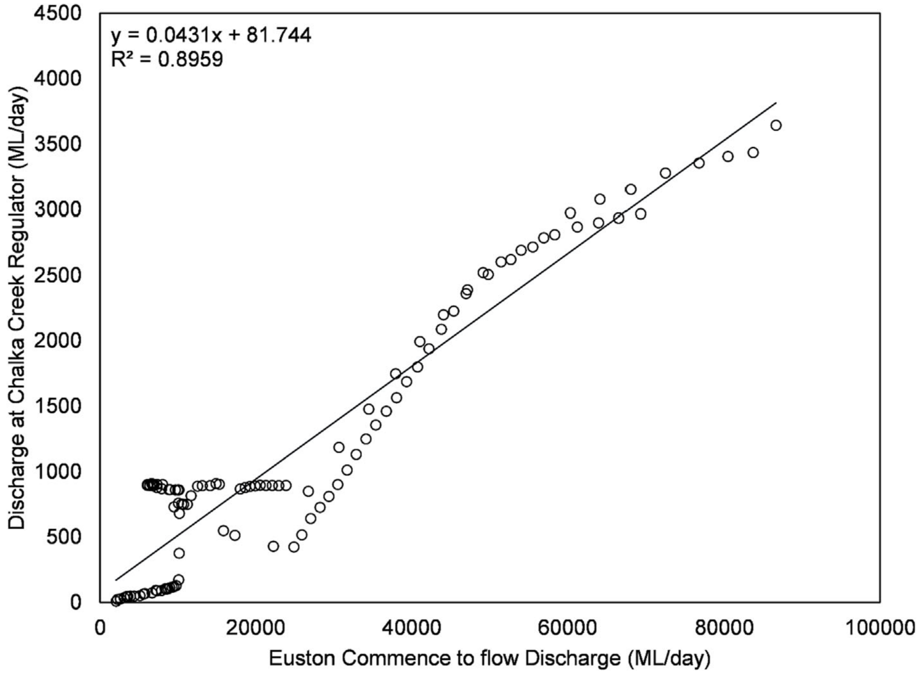

FIGURE 3 Relationship between discharge at the Chalka creek regulator and difference between the discharge at Euston weir and CTF threshold (25,000 ML/day).

TABLE 2 Description of features (explanatory variables).

Abbreviation	Feature	Unit	Rationale
tempmax_1m	Monthly mean max temperature	deg. Celsius	Temperature and precipitation are prerequisite climatic factor for vegetation growth (Ren et al., 2022). Atmospheric water demand for plants is strongly influenced by vapour pressure deficit (VPD) (Yuan et al., 2019).
vapourpre_1m	Monthly mean vapour pressure	hPa	
prec_1m	Accumulated precipitation 1 month prior	mm	
prec_2m	Accumulated precipitation 2 months prior	mm	
prec_3m	Accumulated precipitation 3 months prior	mm	
envwater_1m	Accumulated environmental water 1 month prior	ML	Vegetation exhibits favourable responses to environmental water typically within a period of 1 to 3 months following inundation (Wu et al., 2022).
envwater_2m	Accumulated environmental water 2 months prior	ML	
envwater_3m	Accumulated environmental water 3 months prior	ML	
natflood_1m	Accumulated natural floods 1 month prior	ML	The dynamics of floodplain vegetation are impacted by flooding, which serves as a crucial driving factor (Broich et al., 2018).
natflood_2m	Accumulated environmental water 2 months prior	ML	
natflood_3m	Accumulated environmental water 3 months prior	ML	
season	Season of current date	NA	We assume that coupled with season variable, influence of variables above shows different patterns.

2.3.2 | Model description

Random forests (RF) modelling is a machine-learning approach for identifying complex and non-linear relationships between a dependent variable and potential explanatory variables (Breiman, 2001). This nonparametric machine learning method is composed of an ensemble of decision trees that predict the outcome measure. In the random forest (RF) algorithm, a decision tree is constructed using a bootstrapped dataset and this process is repeated multiple times to create a forest of trees. The final prediction is calculated by taking the average of the predictions made by all the trees in the forest. RF is a regression and classification method (Singh et al., 2017), but this study used RF regression.

We had previously compared RFs with support vector machine and long-short-term memory network models and found that RFs have the best predictive performance for data in the Hattah Lakes system (C. Wu, unpublished data).

The model was implemented using *sklearn*'s random forest regressor function (Pedregosa et al., 2011) in Python. The dataset was divided into training (90%) and test (10%) sets. The training set was used in model fitting and the model was tuned by grid search with fivefold cross-validation to find the optimal set of hyperparameters. The *bootstrap sample* function was used when building the trees to randomly split the dataset into homogeneous subsets. The training set was shuffled during cross validation, which makes each split comparable with our dataset. The model was evaluated by the coefficient of determination (R^2).

2.4 | Model explanation methods

As a 'Black Box' model, the RF regression model cannot be understood by looking at its parameters (Molnar, 2019). In this study, we use model explanation methods to extract relationships between NDVI and the explanatory variables.

Feature importance, as the name suggests, compares the importance of different explanatory variables for explaining the dependent variable (Breiman, 2001). They are normalized values and represent relative importance across all features. It calculates a score for each feature of each tree in the random forest and then takes an average across trees to assess the feature's contribution to the prediction. Feature importance is implemented in Python using the *scikit-learn* random forest regression function.

Individual conditional expectation (ICE) plots illustrate the prediction changes for each dependent variable by displaying a distinct line for every instance, showcasing the impact of feature variations on the predictions (one line per instance) (Molnar, 2019). This study employs centred ICE plots, which centre the curves at a specific point in the feature and visualize the variation in predictions relative to this point. The partial dependence plot (PDP) displays only the average relationship between the feature and the prediction, shown as a single line across all instances. The PDP shows the marginal effect of one or two independent variables in the RF model on the predicted outcome of the fitted model (Jiang et al., 2022). In this study, we used the two-dimensional (2D) PDP to see the interaction between pairs of features.

To avoid the issues with extrapolation when features are highly correlated, we used the accumulated local effect (ALE) plot to describe how different variables affect the prediction (Apley & Zhu, 2020). The features are initially divided into intervals, and the prediction difference is computed by replacing the feature with the upper and lower limits of each interval. These differences are subsequently aggregated and centred, ultimately yielding the ALE curve (Molnar, 2019). For this study, ALE plots of 1D and 2D were implemented using Python package *PyALE*.

In this study, the PDPs give an overall idea of the impact of each feature, while the ALE plots were used to examine if the slopes seen in the PDPs could be an artefact caused by extrapolation problems.

3 | RESULTS

3.1 | Model performance

The RF regression model shows good overall performance for modelling NDVI. The model showed different performance among the nine lakes (Figure 4). The R^2 of test for Lake Kondardin is the highest with a value of 0.82, while the mean R^2 of test for nine lakes is 0.73.

The model performances for lakes in the northern area are better than those of lakes in the southern area (Figure 4). The bar plot illustrates the percentage of boundary pixels in the fringing area for each lake, where boundary pixels are defined as pixels with mixed land use types. They reveal that lakes with greater percentages of boundary pixels have lower R^2 values than others (Figure 4). This indicates that the presence of mixed land use influences the precision of the model predictions.

3.2 | Feature importance

The most important features for predicting NDVI are very similar among lakes (Figure 5). Monthly mean max temperature (*Tempmax_1m*) is the most important feature for NDVI modelling for all lakes, followed by accumulated precipitation 3 month prior (*prec_3m*) for most of the lakes and then accumulated environmental water for the 3 months prior (*envwater_3m*) for the four southern lakes.

There are some order differences in variable importance among lakes. Focussing on accumulated environmental water 3 month prior (*envwater_3m*), it is more important for vegetation around Lake Lockie, Lake Hattah, Lake Bulla, and Lake Arawak than the other five lakes (Figure 5). Conversely, temperature accounts for almost 50% of the variation for the five lakes in northern area, while environmental water has a lower value of importance.

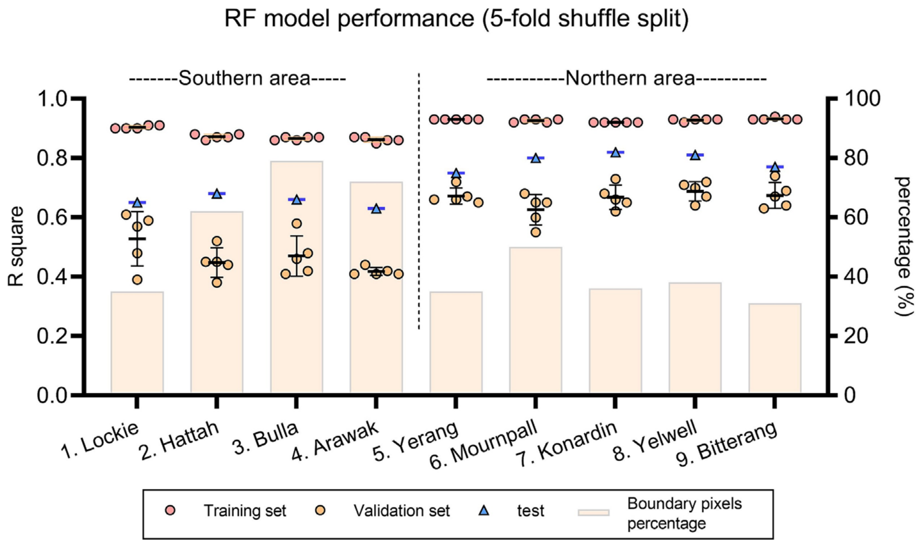

FIGURE 4 Random forest model performance (the bar plot shows percentage of boundary pixels for each lake pixels. Boundary pixels refer to pixel with mixed land use type). Variability in performance for the training and validation sets is summarized by error bar of one *SD*.

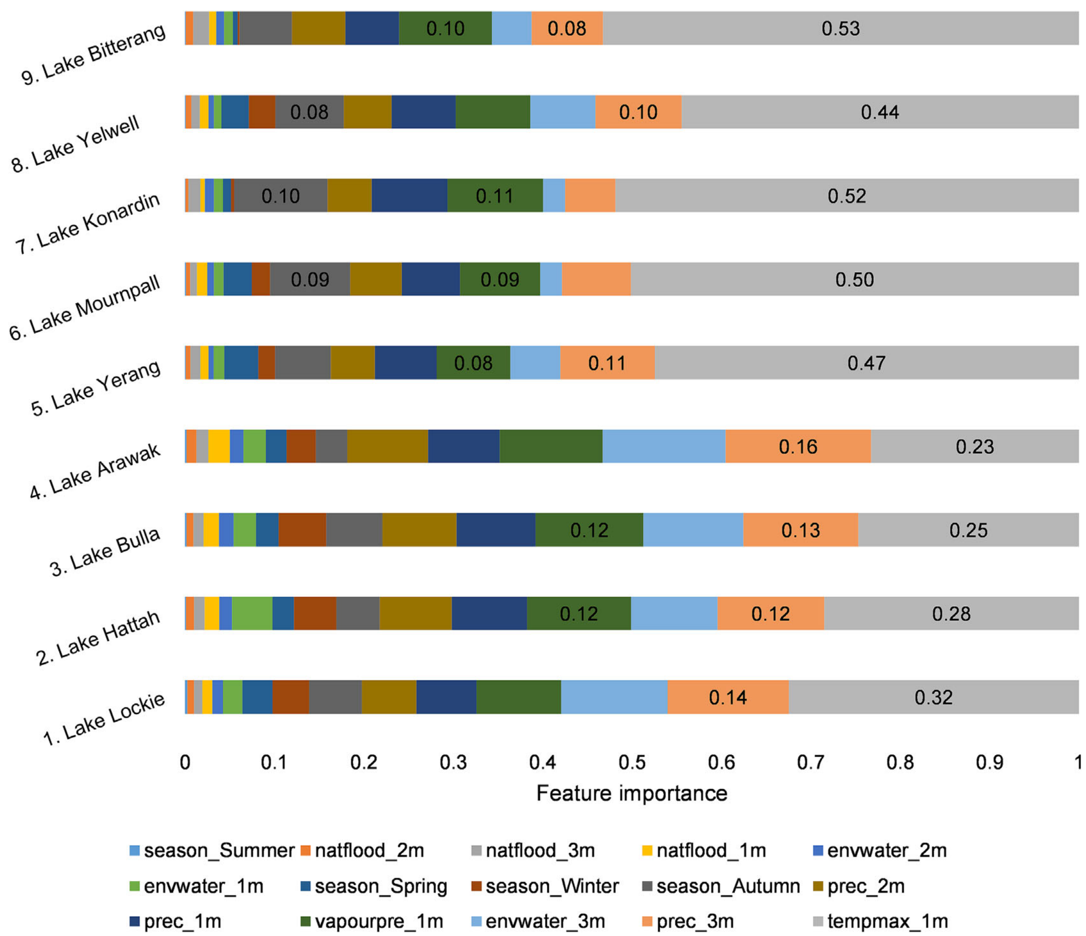

FIGURE 5 Stacked bar plot of feature importance for each lake.

3.3 | Influence of environmental water on NDVI and environmental water delivery strategies evaluation

Accumulated environmental water 3 month prior (*envwater_3m*) is more important to NDVI response than accumulated environmental water 1 month prior (*envwater_1m*) and 2 months prior (*envwater_2m*) (Figure 5). Lake Lockie, Lake Hattah, Lake Bulla, and Lake Arawak show similar influence curves, with partial dependence of NDVI increasing by almost 0.1 when environmental water volume reaches 7000 ML before levelling off (Figure 6a–d). For the other five lakes, the effect of environmental water is small but also levels off when environmental water 3 months prior reaches a high volume. Environmental water also has a greater effect than natural floods (Table 3). This is especially the case at the 3-month lag time, where the environmental water effect (*envwater_3m*) is approximately an order of magnitude greater than the equivalent effect for natural floods (*natflood_3m*).

To evaluate the current environmental watering strategy, differences between modelled NDVI calculated both with and without environmental water delivery were calculated (Figure 7) for the fringing areas of Lake Lockie and Lake Bitterang. These two lakes were chosen as examples of the different groups of results for the southern and northern lakes, respectively. For both lakes, modelled NDVI with environmental water is greater than modelled NDVI without environmental water delivery (especially for environmental water delivery after 2010).

3.4 | Interacting influences of environmental water and precipitation on vegetation

The 2D PDP plot shows the dependence of NDVI on the joint value of *accumulated environmental water 3 month prior* and *accumulated*

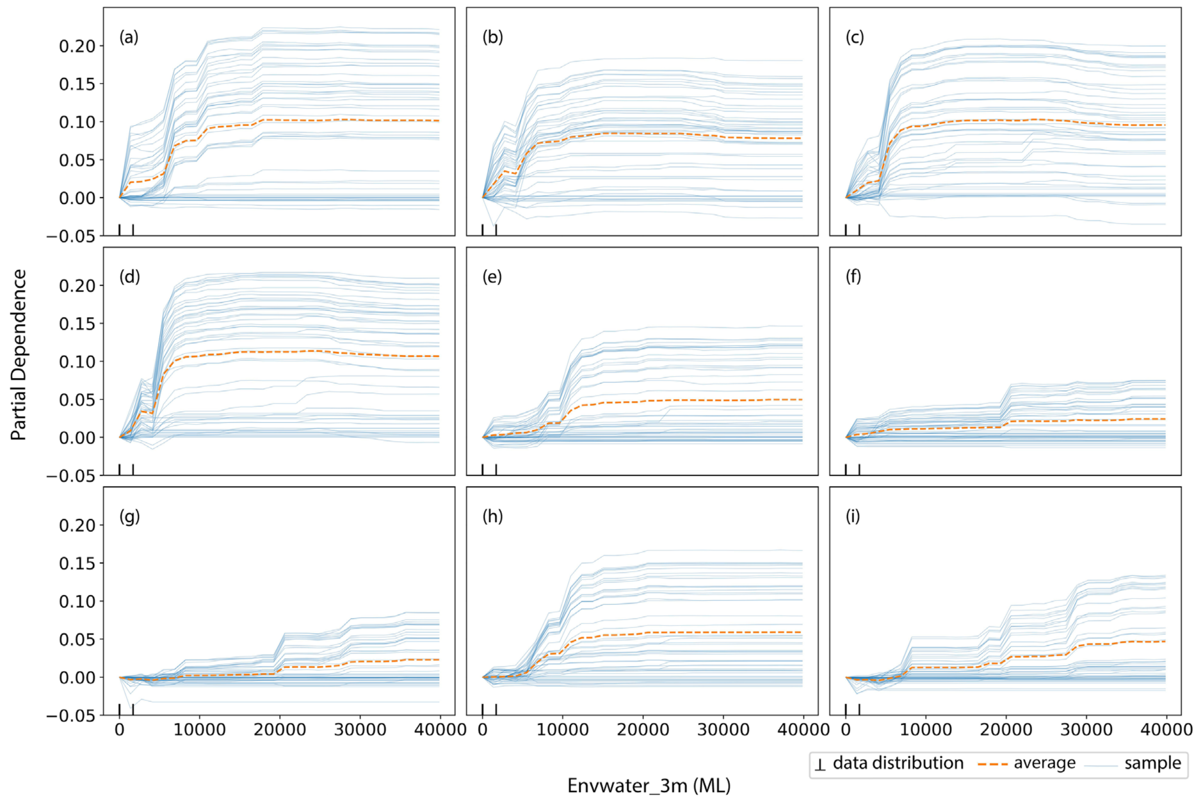

FIGURE 6 Centred ICE plot of the effect of environmental water 3 months prior among nine lakes: (a) Lake Lockie (the first connected lake); (b) Lake Hattah; (c) Lake Bulla; (d) Lake Arawak; (e) Lake Yerang; (f) Lake Mournpall; (g) Lake Konardin; (h) Lake Yelwell; and (i) Lake Bitterang. The orange dotted line represents the average PDP line, while the blue lines depict the individual ICE lines for each instance. The partial dependence refers to the change in the predicted NDVI.

TABLE 3 Feature importance of features related to environmental water and natural floods.

	natflood_1m	*natflood_2m*	*natflood_3m*	*envwater_1m*	*envwater_2m*	*envwater_3m*
1. Lake Lockie	0.011	0.007	0.009	0.022	0.012	0.119
2. Lake Hattah	0.017	0.009	0.012	0.045	0.014	0.097
3. Lake Bulla	0.017	0.008	0.011	0.025	0.017	0.112
4. Lake Arawak	0.024	0.011	0.014	0.025	0.015	0.138
5. Lake Yerang	0.009	0.005	0.011	0.012	0.006	0.056
6. Lake Mournpall	0.012	0.005	0.007	0.010	0.008	0.024
7. Lake Konardin	0.005	0.003	0.013	0.010	0.010	0.025
8. Lake Yelwell	0.010	0.006	0.010	0.008	0.006	0.073
9. Lake Bitterang	0.008	0.008	0.018	0.010	0.008	0.044

precipitation 1 month prior (Figure 8). For Lake Lockie, environmental water has a strong impact on NDVI when environmental water 3 months prior volume is less than 10,000 ML (for Lake Hattah, Lake Bulla, and Lake Arawak, this number is about 7000 ML). For Lake Mournpall, Lake Konardin, and Lake Bitterang, both precipitation and environmental water have an impact on NDVI when precipitation

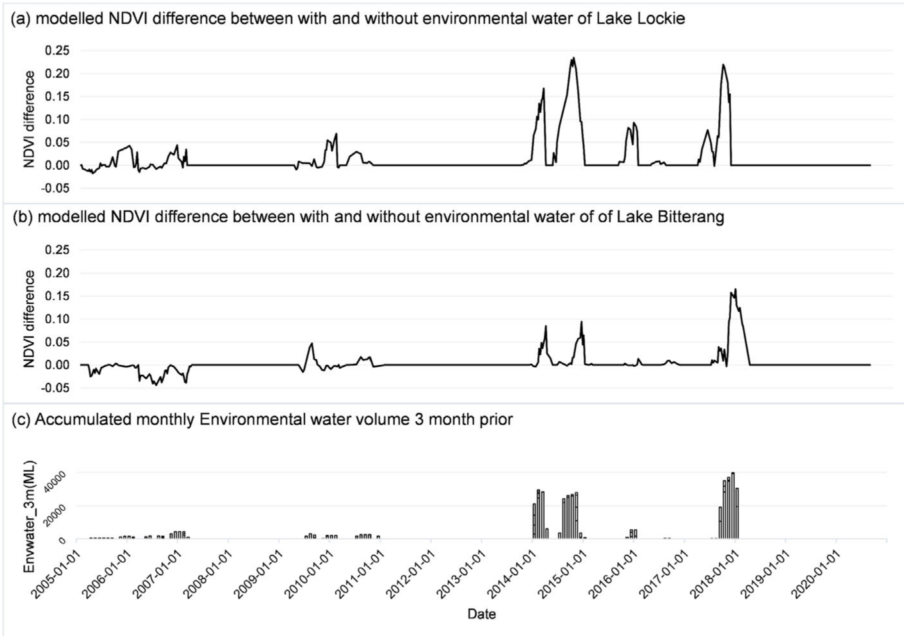

FIGURE 7 Modelled NDVI difference in situation of with and without environmental water for (a) Lake Lockie and (b) Lake Bitterang. (c) The amount of environmental water delivered over time.

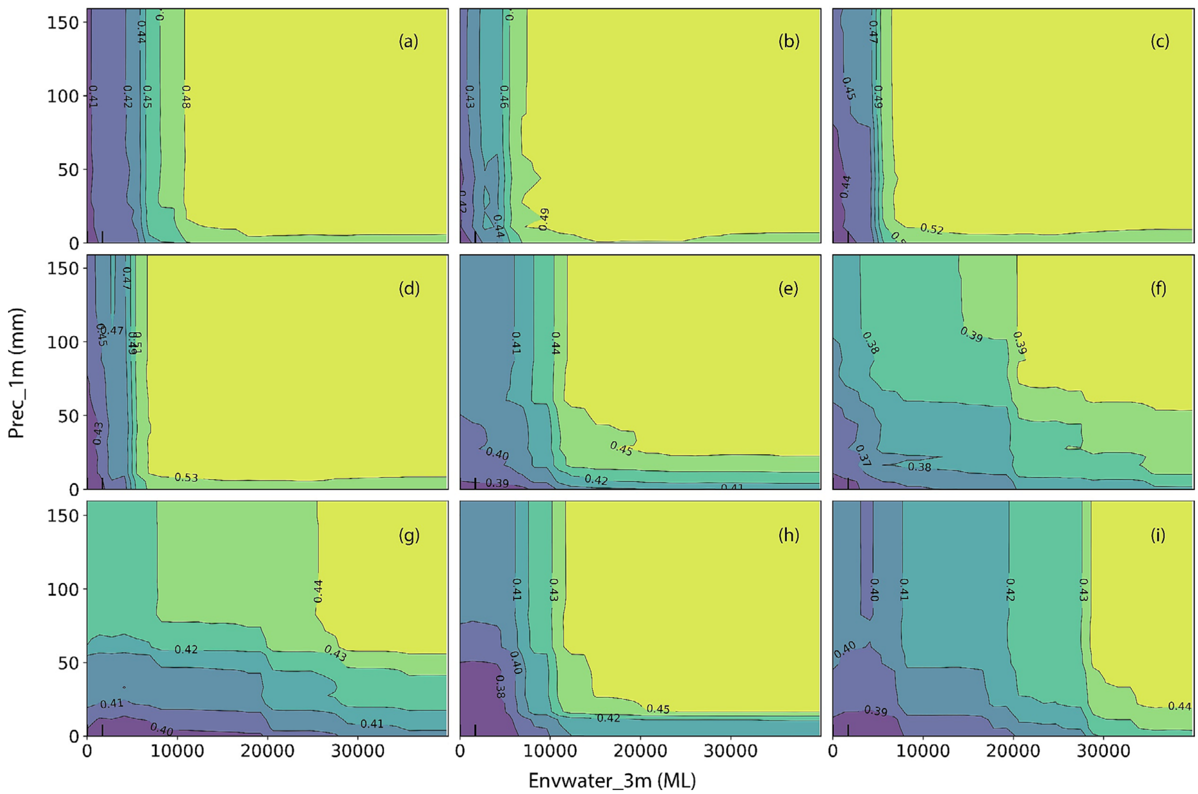

FIGURE 8 2D PDP plot of *envwater_3m* and *prec_1m*: (a) Lake Lockie (the first connected lake); (b) Lake Hattah; (c) Lake Bulla; (d) Lake Arawak; (e) Lake Yerang; (f) Lake Mournpall; (g) Lake Konardin; (h) Lake Yelwell; and (i) Lake Bitterang; the values along the contour lines represent the partial dependence of joint influence, while the colour gradient from purple to yellow indicates the corresponding dependence values, ranging from low to high; (a) to (d) represent the outcomes for southern lakes, while (e) to (i) are the results for northern lakes.

is less than 80 mm (Figure 8). When precipitation is less than 20 mm, environmental water improves NDVI of fringing area of these three lakes.

3.5 | Influence of climate factors on vegetation

Accumulated precipitation 3 month prior has a nonlinear relationship with NDVI (Figure 9). When *prec_3m* is less than 50 mm, the mean dependence of NDVI slightly decreases for Lake Lockie, Lake Hattah, Lake Bulla, and Lake Arawak, while it slightly increases for the other five lakes. For all lakes, the dependence of NDVI increases suddenly when *prec_3m* increases from 50 to 80 mm.

Monthly mean max temperature has a negative influence on NDVI. From the ICE plot (Figure S1), the partial dependence of NDVI decreases when max temperature increases from 18°C to 25°C. The influence of temperature on fringing vegetation is similar for all the lakes.

Monthly mean vapour pressure has a positive relationship with NDVI according to the ICE plot (Figure S2). NDVI remains stable when vapour pressure is less than 8 hPa but improves with increasing vapour pressure when vapour pressure is greater than 8 hPa.

4 | DISCUSSION

Our results indicate that environmental water is more important for fringing vegetation condition than natural floods, especially with a lag time of 3 months. This is a major finding and speaks to the value of managed inundation events delivered to regulated floodplains. Additionally, these results suggest that the current environmental water strategy is beneficial for enhancing fringing vegetation. Together, these results emphasize the significance of environmental water as a critical factor in floodplain lake management to support vegetation health. The findings can provide valuable insights for decision-makers regarding the effective utilization of environmental water to enhance the fringing areas of lakes.

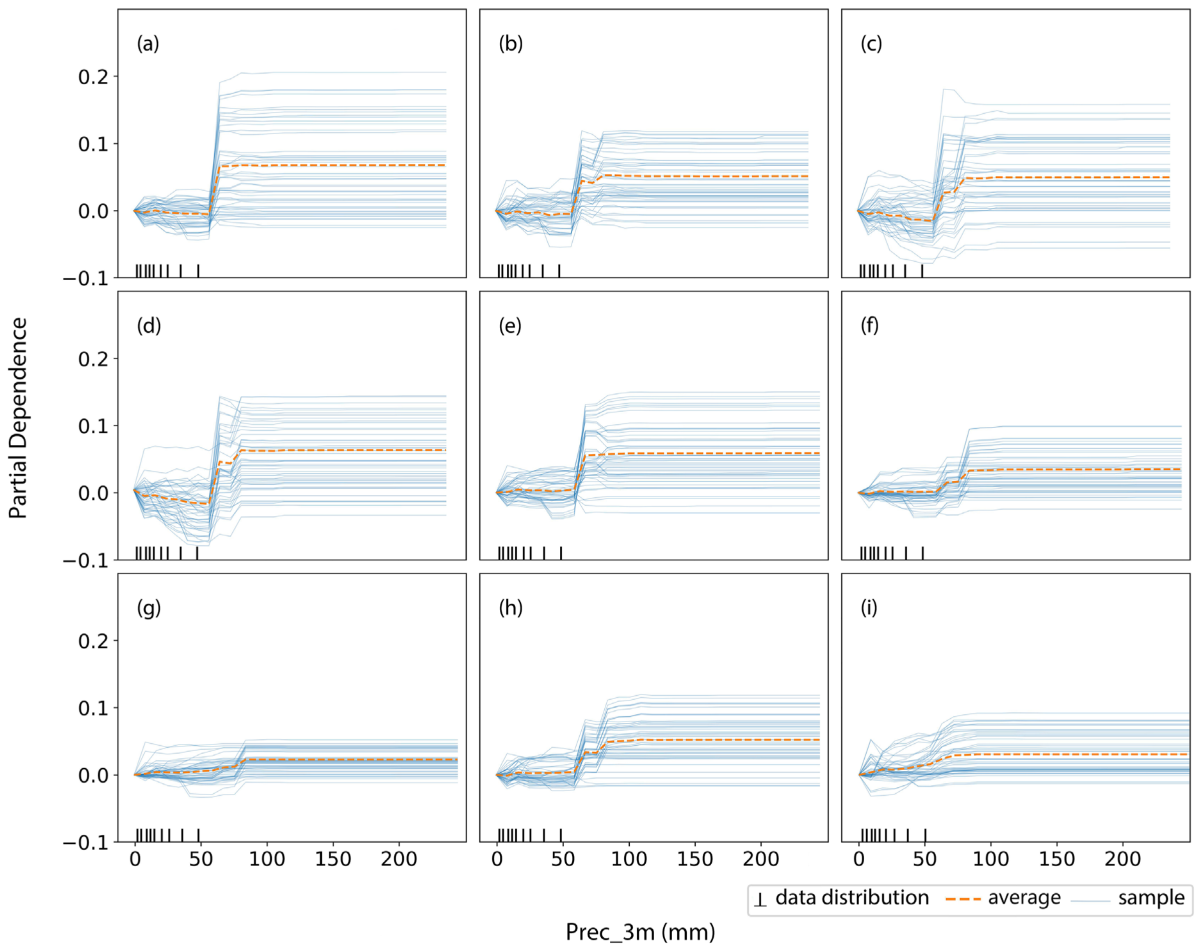

FIGURE 9 Centred ICE plot of precipitation 3 months prior: (a) Lake Lockie (the first connected lake); (b) Lake Hattah; (c) Lake Bulla; (d) Lake Arawak; (e) Lake Yerang; (f) Lake Mournpall; (g) Lake Konardin; (h) Lake Yelwell; and (i) Lake Bitterang. The orange dotted line represents the average PDP line, while the blue lines depict the individual ICE lines for each instance.

4.1 | NDVI response to environmental water volume and its spatial pattern

Our finding of the importance of environmental water 3 months prior aligns with previous findings, suggesting its greater significance compared with water from 1 or 2 months prior to data collection (Wu et al., 2022). Also, as noted above, environmental water has a greater impact on vegetation health than natural floods, a finding of major significance.

The PDP plots showed increases in NDVI with environmental water volume 3 months prior, but this relation has an upper limit above which NDVI remains stable. This breakpoint can serve as a useful guideline for floodplain managers when determining the appropriate volume of environmental water, thereby enhancing water use efficiency. However, the partial dependence estimates are less reliable at these greater volumes because of the smaller number of data points (Molnar, 2019). Further monitoring that takes in periods with larger volumes of environmental water would provide more data points and increase the reliability of the model at these higher levels.

The variable results among lakes demonstrate spatial heterogeneity in terms of model performance, feature importance, and partial dependence degree. We discovered that lakes with higher percentages of boundary pixels exhibit poorer model performance. The boundary pixels commonly include mixed land uses, thereby causing the NDVI to not solely represent the condition of trees. Therefore, in future study, selection of pixels for fringing area by clustering methods (Wang et al., 2022) to classify the mixed-vegetation pixels, or to simply exclude boundary pixels, could be used to improve the model performance.

The feature importance and partial dependences plots highlight substantial differences between the four southern lakes and the five northern lakes. In the southern lake, the feature *environmental water 3 months prior* is more important and partial dependence degree of that feature is greater. One of the key factors explaining these findings is the variation in hydrological conditions. Lake Lockie, being the first lake in the filling sequence in the southern area (Figure 2), receives environmental water earlier (McCarthy et al., 2009). Moreover, Lake Hattah and Lake Arawak experienced inundation by environmental water prior to 2010 for longer periods compared with northern lakes (Palmer et al., 2021). These conditions make environmental water more impactful on the fringing trees of the southern lakes. The size of the lake may also be an explanation for these discrepancies. For instance, Lake Mournpall, located in the northern region, is six times larger than lakes Bulla and Arawak in the south (Table 1). This means that it requires much more water to be delivered through Chalka Creek to reach the fringing trees. Conversely, Lake Bulla in southern area is the smallest among the lakes, and therefore, with same volume of environmental water flowing through Chalka Creek, the fringing trees can benefit more because of the lake's proximity to the adjacent lakes.

4.2 | Environmental water strategies and management implications

Bearing in mind the spatial distribution of the results, we suggest that floodplain managers could consider different strategies for the improvement of different regions in Hattah Lakes. It should be remembered that both temperature and rainfall have greater effects on NDVI than environmental water. However, these are not under the control of managers, who must work with the 'levers' available to them.

The health of vegetation in the fringing areas of lakes can be enhanced by maintaining current environmental water strategies and utilizing existing or newly constructed infrastructure. The modelled results show that the current environmental water strategy helps to improve tree health in the fringing areas of Hattah Lakes, especially after 2013 when the Chalka Creek pumping station (MDBA, 2018) was built to increase the capacity to deliver larger amounts of environmental water into the Hattah Lakes system. This is consistent with in situ monitoring of Hattah Lakes, which showed tree canopy cover of river red gum increasing after watering from 2014 to 2020 (Moxham et al., 2020). In other systems, using existing irrigation supply infrastructure has proven to be an effective and water-saving option for watering floodplain to help improve vegetation condition, requiring considerably less water than what is needed to induce an overbank flood (Stewardson & Guarino, 2018).

This research has the potential to inform decision-making for environmental water use to enhance the fringing trees of floodplain lakes. Findings that NDVI increases with environmental water volume, but not beyond a threshold of total delivery volume, can inform improved environmental water management across diverse environmental water scenarios. In years with abundant water, fringing trees will not exhibit increased greenness beyond this threshold volume. Conversely, during periods of reduced water availability, we recommend that managers deliver as much water as possible to the floodplain lakes to maintain the condition of fringing trees. Future studies on the optimal frequency of environmental watering are still needed to support the design of efficient and effective environmental water management strategies. It is crucial to prioritize the maintenance of flow variability rather than stable flows for regulated ecosystems, as the rivers and adjacent floodplains rely on annual and interannual fluctuations (Naiman et al., 2008). Previous investigations have determined that a flooding frequency of every 3 years optimally supports the life cycles of river red gums, which comprise most of the fringing trees (Catelotti et al., 2015). Increasing flows in early August to ensure water availability for the trees in late September will take advantage of the amplified evaporative demand (through increasing temperatures) and solar radiation characteristic of the spring season (Doody et al., 2014). Therefore, based on current knowledge, we suggest that environmental water management should aim to inundate lake fringing areas every 3 years from August to September by allocating environmental water at the modelled volume threshold identified in this research to maintain fringing tree health. More studies on environmental water frequency would be useful to help improve outcomes through adaptive management.

4.3 | Recommendations for future research

The long-term Landsat dataset provides continuous monitoring of floodplain vegetation condition, overcoming the limitation of the irregular and point-based field data. This enables us to model long-term vegetation condition using daily hydrological and climate records, which is not achievable using field-based monitoring. In the future, remote sensing datasets can be updated to higher resolution satellite imagery, such as Sentinel-2 imagery with a 10-m resolution, to capture more detailed vegetation conditions. By employing per-pixel modelling (training models for each pixel), we can explore potential spatial differences in the floodplain, gaining deeper insights into the distribution and variation of vegetation responses across the area.

In this work, random forest regression, in combination with 'Black Box' explanation methods, has been demonstrated to effectively extract the quantitative relationship between NDVI and hydrological and climate factors. This type of relationship has proved difficult to describe using classical statistical regression methods, such as generalized additive mixed modelling (GAMM) (Wu et al., 2022).

We found that climate factors play an important role in vegetation growth. Hotter and drier climates in the future will have a negative impact on floodplain vegetation. Modelling vegetation condition under various climate predictions and environmental water scenarios would be a good approach to developing management plans for effective vegetation protection under climate change. However, it is important to acknowledge that random forest regression has its limitations; for instance, it is not suitable for data extrapolation (Breiman, 2001). Thus, it becomes necessary to consider alternative modelling methods, such as neural networks (Wang et al., 2022), to achieve accurate modelling results for future NDVI predictions.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in USGS Landsat (https://developers.google.com/earth-engine/datasets/catalog). These data were derived from the following resources available in the public domain: Google Earth engine (https://developers.google.com/earth-engine/datasets/catalog).

ORCID

Chunying Wu https://orcid.org/0000-0002-4957-3331

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SUPPORTING INFORMATION

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