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Development of a computationally efficient floodplain ecological response model for large-scale, data-sparse riparian environments

J. Teng[a,*], B. Croke[b,c], D. Tan[d], T. Iwanaga[b,e], A.J. Jakeman[b], C. Pollino[a], D. Stratford[a], J. Vaze[a], W. Dawes[a], P. Bridgeman[f], A. Sengupta[a]

[a] CSIRO Environment, Canberra, ACT, Australia
[b] Institute for Water Futures, Fenner School of Environment and Society, Australian National University, Canberra, ACT, Australia
[c] Institute for Water Futures, Mathematical Sciences Institute, Australian National University, Canberra, ACT, Australia
[d] Australian National University, Canberra, ACT, Australia
[e] Australian Institute of Marine Science, Canberra, ACT, Australia
[f] Department of Climate Change, Energy, the Environment and Water, Canberra, ACT, Australia

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ABSTRACT

Quantitative assessment of floodplain ecological response to flow regimes is challenging but essential for setting targets and estimating impacts for environmental water management. This paper proposes a model that takes long-term (90 years) and large-scale (9 million grid cells) flood maps as input to estimate the response of floodplain vegetation using infinitely differentiable functions. The model, named Floodplain Ecological Response Model (FERM), is calibrated against 1-D temporal Leaf Area Index (LAI) data from the WAVES energy and water balance model at a daily timestep, and validated on the entire floodplain using condition data of the Icon Sites of the Murray River aggregated to a yearly timestep. Results show that FERM can adequately simulate the response of different types of vegetation on the floodplain, while reducing the data requirements and runtime drastically compared to other approaches. The FERM modeling approach is a first step towards a quantitative modeling of floodplain forest ecosystems at large scale with realistic data and computation requirements. It is intended to indicate the potential of such an approach in semi-arid systems where data availability is limited, and to encourage the further research needed to improve our understanding of floodplain forests and our capacity to model the impact of floods on their ecological response.

1. Introduction

The alteration of flows from the natural regime for human use has, in most cases, produced negative ecological responses (Poff and Zimmerman, 2010) and is a consequence of the prioritization of social and economic demands without consideration of ecological needs (Meybeck, 2003). Many countries have now realized the importance of environmental flows. The 2018 Brisbane Declaration and Global Action Agenda on Environmental Flows reaffirmed and expanded on the definition of environmental flows from the 2007 declaration, describing them as ‘the quantity, timing and quality of freshwater flows and levels necessary to sustain aquatic ecosystems which, in turn, support human cultures, economies, sustainable livelihoods, and well-being’ (Arthington et al., 2018). Effective environmental water management requires an understanding of the ecological response to a gradient of flow characteristics in order to evaluate outcomes of proposed management schemes, a prerequisite to the supply of environmental flows (Poff et al., 2010). In short, effective environmental water management requires the ability to map a given set of environmental flows to an ecological response accurately.

1.1. Empirical approaches and the natural flow regime

Quantifying the deviations from the natural flow regime of a river is a reliable approach to modeling the health of reliant ecosystems (Guo et al., 2023). This approach to ecological modeling relies on establishing relationships between flow characteristics or hydrological metrics and biological indicators (Jiang and Chui, 2022). The results from hypothesis testing often inform these relationships as well as specific targets, which management authorities strive to meet in order to maintain

* Corresponding author at: CSIRO Environment, GPO Box 1700, Canberra, ACT 2601, Australia.
E-mail address: Jin.Teng@csiro.au (J. Teng).

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ecological health (Hillebrand et al., 2020; Webb et al., 2013; Yang et al., 2016). Although field studies and hypothesis testing can be executed in a rigorous manner, reservations remain concerning the transferability of relationships to other similar riverine ecosystems with differing topologies (Poff and Zimmerman, 2010). Furthermore, conclusions may only represent relationships from a snapshot in time (Yarnell et al., 2020). Without transferability of conclusions from hypothesis testing, most ecosystems lack data to inform management strategies to protect ecosystems from anthropogenic disturbances. That is, the use of empirically based relationships without considering transferability between ecosystems is often questionable.

Recent methods use a more diverse range of hydrological metrics that rely not purely on magnitude of flow but also timing, frequency, duration, rate of change and deviation from the natural flow regime in order to develop more robust targets as proposed by Yarnell et al. (2020). Methods have been presented to classify targets areas by natural flow regime and ecological characteristics to solve transferability issues (Kennard et al., 2010; Leathwick et al., 2011). However, these methods have data constraints to allow for use in data-sparse environments, which are more common when investigating riparian response (Webb et al., 2013).

1.2. Step-change models

Biologically relevant flow targets have been incorporated in models in the form of step changes whereby meeting or not meeting specific flow targets represents transitions from predefined condition states (e.g., intermediate to good condition) (Overton et al., 2014). Nevertheless, this approach does not consider the continuous nature of the ecological response where targets may be partially met and produce smaller non-negligible responses. Recent approaches using step-change models have sought to overcome underlying issues by using transition probabilities between two states, allowing the calculation of an expected state for a given scenario (Gould et al., 2019). These methods draw inspiration from statistical methods such as Markov chains and stochastic processes. For more complex step-change models, possible states move beyond simple condition health to ecosystem states describing characteristics such as dominant species (Briske et al., 2005). Whilst an improvement, the set of possible states may not be known, thereby imposing more data and knowledge requirements. Unfortunately, data requirements are often not met for regions that are not studied frequently and may result in transition targets and thresholds based on statistically insignificant conclusions (Hillebrand et al., 2020). Notably, step-change models and hydrological targets informed by simple thresholds are commonly found in government policy as they provide a clear definition of acceptable ecological condition.

1.3. Mass and energy balance models

Mass and energy balance models can be used to model vegetation indices (typically Leaf Area Index (LAI)) that are strongly correlated with the health of the vegetation target and derived from modeling carbon fluxes over time (Clark et al., 2011). The approach employing mass and energy balance models is based on modeling physical processes in greater detail rather than drawing statistically significant relationships from observational data. LAI is incorporated in these models as changes in vegetation cover play a fundamental role in modeling mass and energy dynamics. Given the complex interaction between physical systems, these mass and energy balance models have a wide range of applications beyond vegetation dynamics. Often taking a modular structure corresponding to the various physical processes, they produce a detailed representation of the chosen location by modeling key variables over time. However, the highly detailed modeling of physical processes also brings significant data requirements, including detailed meteorological, soil, and vegetation data, as well as substantial computational costs. This can make energy balance models impractical for data-sparse environments (Best et al., 2011; Van Der Tol et al., 2009; Zhang and Dawes, 1998). The 1-D nature of these models also makes it difficult to study the spatial dynamics of the response across large floodplains.

1.4. The floodplain ecological response model

The Floodplain Ecological Response Model (FERM), as presented in this paper, utilizes infinitely differentiable functions, built upon well-founded hypotheses and existing knowledge of response to flow conditions (Overton et al., 2014; Roberts and Marston, 2000). These functions are carefully designed to represent the smooth ecological response of targets to wet and dry spells. FERM is a generic conceptual model, which uses physically-based parameters that can be populated from expert knowledge or calibrated to observational data. FERM's output represents the vegetation or guild target's condition or health, with a score ranging from 0 to 1 indicating the worst and best conditions. Taking the duration of wet and dry spells as inputs, FERM models the condition of the target using different calibrated functions for wet and dry periods and whether the target is in a recovering or declining trajectory.

The coupling of FERM and a flood inundation Model allows for a floodplain wide estimate of the ecological response to flows. This method is demonstrated using the flood maps from the Teng-Vaze-Dutta Flood Inundation Model (TVD) (Teng et al., 2015; Teng et al., 2018), which can be used to rapidly evaluate spatial weaknesses of proposed environmental water management plans in a quantitative manner. FERM's modeling of spatio-temporal vegetation condition dynamics allows for the assessment of proposed flow management plans and reveals specific weaknesses that may be present in a considered plan (e.g., insufficient flooding in specific regions of the floodplain).

1.5. Outline of the paper

This paper demonstrates FERM's performance on a section of the Riverland-Chowilla floodplain along the River Murray. The study area is described in Section 2. FERM is calibrated against 1-D temporal LAI data from the WAVES energy and water balance model (Zhang and Dawes, 1998) at a daily timestep and aggregated to a yearly timestep, and validated on the entire floodplain using condition data of the Icon Sites of the Murray River (Cunningham et al., 2009). Sections 3 and 4 detailed the Data, model structure and methods for sensitivity analysis, calibration, and validation. The results are shown in Section 5. The increased speed and accuracy of calibration with deseasonalized input data is presented, a transformation that is highly recommended when calibrating the model with data. FERM's performance on the validation data demonstrates satisfactory accuracy with high spatial and temporal detail whilst providing very reasonable data and computational requirements. In Section 6, we discuss the advantages and limitations of the model and future work. And finally, we summarize the main findings in Section 7.

2. Study area

The FERM is assessed on part of the Riverland-Chowilla floodplain, adjacent to the River Murray (Fig. 1). The study area is upstream of Renmark, covers 355 km^2 and lies close to the border between the states of New South Wales, Victoria, and South Australia. The surrounding area of the floodplain is one of Australia's most developed agriculture regions resulting in extended periods of environmental degradation. Recent droughts have exacerbated this and caused damage to biodiversity hubs including lakes, lagoons, anabranch creeks and wetlands.

The study area is one of the Living Murray icon sites (Murray-Darling Basin Authority, 2011) and is recognized under the Ramsar Convention. Vegetation in this area is predominantly River Red Gums, Black Box Woodlands, lignum shrublands and grasslands. Vegetation cover as classified by a previous study (Murray-Darling Basin Authority, 2011) was used as ecological targets for FERM. Four parameter sets were

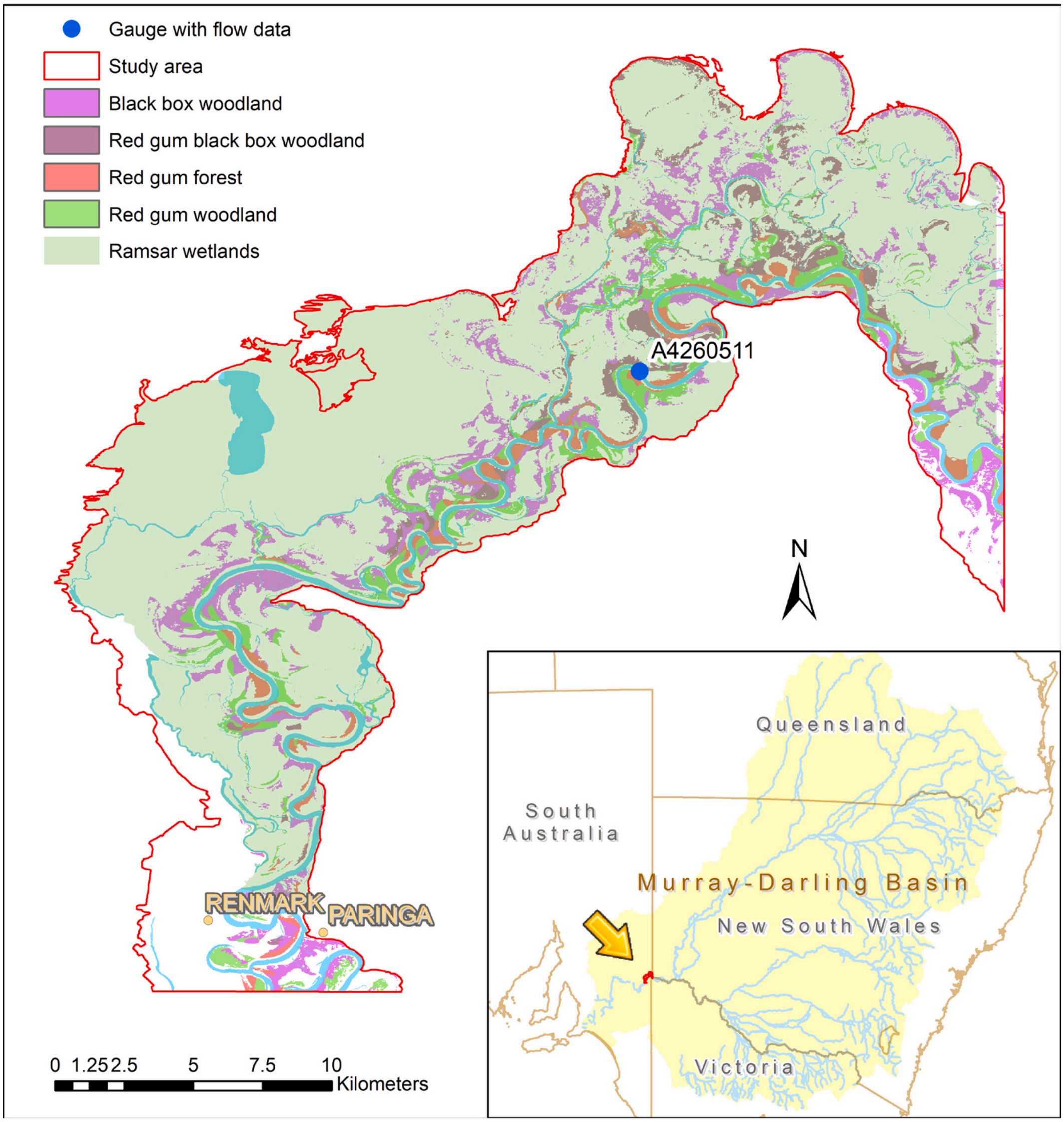

Fig. 1. Riverland-Chowilla floodplain in South Australia. The direction of flow is from northeast to southwest. The distribution of vegetation types is also shown in the map.

calibrated or inferred for each vegetation type: 1. River red gum forest – stands dominated by *E. camaldulensis* with 30–45% projective foliage cover; 2. River red gum woodland – stands dominated by *E. camaldulensis* with 20–25% projective foliage cover; 3. River red gum / black box woodland – mixed stand of *E. camaldulensis* and *E. largiflorens*; 4. Black box woodland – stands dominated by E. largifolrens.

The government holds recovered environmental water in upstream stores from the study area and uses deliberate releases to maintain ecological health. The targeted release of environmental water aims to maximize the impact of water use on both ecological and societal targets. For example, ensuring surrounding agriculture can continue to function whilst maintaining healthy ecological condition. The study area, like most floodplains, is home to nomadic and migratory birds and is particularly important in drought conditions. The unique interface between the floodplain and the adjacent river provides breeding and growth grounds for native fish, especially in anabranches of the river. The study area is a habitat for the native Murray cod and endangered species such as the Murray hardyhead and southern bell frog (Murray-Darling Basin Authority, 2012).

3. Data

3.1. Flood inundation data from the TVD model

The TVD model (Teng et al., 2015; Teng et al., 2018) is a conceptual flood inundation model that takes gauged flow timeseries as input and simulates flood maps at a daily timestep. It can be run on a fine resolution, in the case study here being at a resolution of 10 × 10 m grid cells. There are 12 river gauges along the reach that supply flow, water level and/or water quality measurements (www.waterconnect.sa.gov.au). The data from gauge A4260511 (downstream of Lock 6, location shown in Fig. 1), constituting the longest and most complete historical record for both water level and flow, were used to model flood inundation. The flow of the river is highly variable seasonally and interannually, with the peak flows occurring from spring (September, October, November) to summer (December, January, February). The river also experiences prolonged droughts, most notably the Millennium Drought, which started in the mid-90s and ended in late 2010.

The TVD model was run from 1928 to 2017 at a daily timestep and the results were aggregated to dry-wet-spell timeseries for each year (An example of the dry-wet-spell code spatial map can be found here: http s://bitbucket.csiro.au/projects/FERM/repos/ferm/browse/sample_data/WetDrySpellCode_1986-07-01-1987-06-30.tif). Firstly, each year of daily spatial data from running TVD were converted to a binary timeseries for each grid cell representing inundation. The binary series was then defragmented, where change intervals lasting less than three days were combined into the previous non-inundated or inundated periods. The resultant timeseries were recorded in an attribute table with a unique identification to each grid cell. The dry-wet-spell information was used in the calibration and validation in this study.

3.2. Point ecological data from the WAVES model for calibration

Point ecological data were obtained from the land surface model WAVES at three different distances from the river. WAVES (Zhang and Dawes, 1998) is a one-dimensional, daily time-step model that simulates the fluxes of mass and energy between the atmosphere, vegetation, and soil systems. It is a process-based model that couples these systems by modeling the interactions and feedbacks between them. The model requires daily meteorological inputs and detailed soil and vegetation parameters that can be obtained through physical measurement, existing literature, or calibration to run daily. Its requirements of daily maximum and minimum temperatures, vapour pressure deficit and total precipitation make WAVES unsuitable for evaluating the efficacy of proposed future flow regimes, but long-term LAI outputs are useful for modeling historic vegetation dynamics. WAVES models carbon fluxes in leaf, stem and root pools and converts the mass of carbon contained in the leaf carbon pool to LAI using specific leaf area (SLA), a measured vegetation parameter. The daily LAI output, standardized to a scale of 0 to 1, from WAVES over 90 years (1928-07-1 to 2018-06-30) is plotted as grey lines in Fig. 4.

3.3. Spatial ecological data for validation

Stand condition scores at a resolution of 25 × 25 m pixels from 2009 to 2015 (excluding 2011 due to missing data) were used to help validate FERM (resampled to 10 × 10 m resolution to be comparable to FERM results). The method for calculating these condition scores were developed to evaluate the condition of the Icon Sites of the Murray River (Cunningham et al., 2009). Stand condition is defined as the average of Plant Area Index (PAI), the latter being percentage of live basal area and crown extent after conversion to scores out of 10 (Cunningham et al., 2009). Stand condition scores were produced for the entire floodplain using a feed-forward neural network taking inputs from Landsat 5/7's reflective bands and the modeled vegetation distribution map. The network was trained on observations at 115 sites and tested on 25 sites. More detail on the neural network applied and how vegetation distributions were modeled can be found in Cunningham et al. (2009). The condition scores were then standardized to a scale of 0 to 1 to make conditional scores comparable to the FERM output. The healthy condition of vegetation near the main channel, as opposed to the poor condition of vegetation farther away, reflects the lack of flooding occurring in 2009 and the preceding decade (during the Millennium Drought).

4. Methods

4.1. Description of the model

FERM models the target response under wet and dry conditions relying on the dependence of floodplain targets on the flood pulse. The model uses existing biological knowledge (Roberts and Marston, 2000) in terms of preference curves (Overton et al., 2014) to model the target condition, where wet and dry conditions have separately parameterized curves. The curves are continuous and infinitely differentiable, representing the ecological targets' smooth condition response. The model's parameters are physically-based, allowing calibration with existing knowledge and use in data-sparse environments; however, calibration can also use observational data. The piecewise nature of FERM allows for the condition output to be produced at a variety of temporal resolutions, avoiding the computation of daily condition scores if not required. Notably, calibration was performed at a daily timestep and validation at a yearly timestep.

FERM produces a smooth curve for each wet and dry spell in a manner that ensures continuity. It calculates the duration of wet spells from the inundation time series. A sigmoidal shaped curve is used to produce condition or health scores over the duration of a given wet or dry spell. The parametrization of the curve depends on the initial condition used (day 0) or final condition of the previous dry or wet spell and the general parameterization of the model. Fig. 2 shows FERM's output on simple data. The response curve during the wet spell in Fig. 2 is given in Eq. (1) below whereas Eq. (9) gives the response curve for dry spells. The physical meaning of the parameters used to define the curves are explained below.

Input

D: duration of a wet or dry spell (days).

${}_IC$: initial condition ∈ [0,1].

Output

C: condition score ∈ [0, 1].

Parameters (see Table 1)

4.1.1. Response under wet spells

The condition score C under wet spells can be calculated as:

$$C = \left[\alpha\left(1 - e^{-(D/d_0)^{n_0}}\right) + {}_IC\right]\left[e^{-(D/(d_1 - D_0))^{n_1}} + C_w\right]^{\lambda}, \tag{1}$$

where n_0 and n_1 are the exponents defining the 'steepness' of the response curve, defined as:.

$$n_0 = 2S_0 + 1, \tag{2}$$

$$n_1 = 2S_1 + 1, \tag{3}$$

Large choices for S_0, S_1 values produce a sharp step-shaped curve, representing an ecological target that is initially unresponsive to flooding before improving. The inflection points of the curve are required to define its shape and are calculated from the parameterization as follows:

$$d_0 = \frac{D_0}{\left(-ln(1 - C_b + \varepsilon)\right)^{1/n_0}}, \tag{4}$$

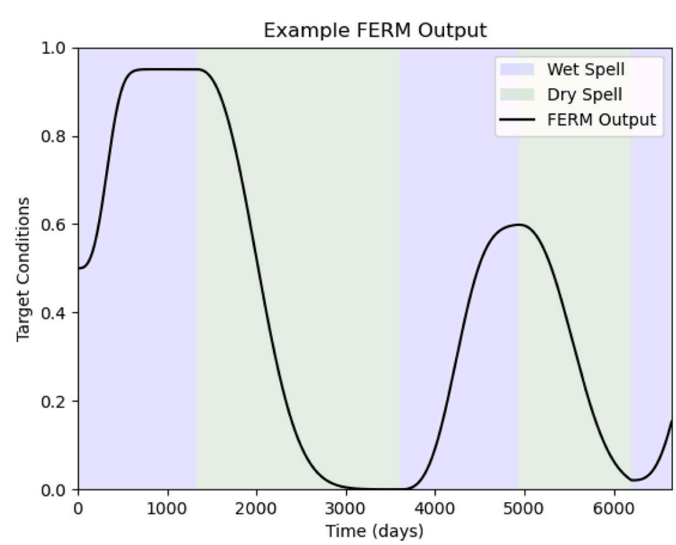

Fig. 2. The plot shows FERM's output with simple artificial data as input. The Inundation binary timeseries data were used as input. Dry-wet spells are also displayed as an intermediate step.

Table 1
FERM parameters and example values for Black Box Woodlands.

Symbol	Description	Data type	Unit	Range ∈	Recommended values for Black Box Woodlands
S_0	Steepness0	integer	–	[0, +∞)	1
S_1	Steepness1	integer	–	[0, +∞)	11
C_w	Worst condition	real	–	[0, 1]	n/a (See distance weighting)
C_b	Best Condition	real	–	[0, 1]	1
$D_{0,min}$	Minimum D_0	real	day	(0, +∞)	3270
$D_{0,max}$	Maximum D_0	real	day	(0, +∞)	30
λ	Drowning switch	integer	–	{0,1}	0
D_1	Drowned threshold	real	day	(0, +∞)	1461 (4 years)
I_C	Critical interval	real	day	(0, +∞)	2367 (3 years)
ε	Constant close to 0	real	–	(0,1)	10^{-9}
${}_I^D C$	Maximum improvement can be achieved under a wet spell in declining trajectory	real	–	[0, 1]	0.38
${}_I^R C$	Maximum improvement can be achieved under a wet spell in recovery trajectory	real	–	[0, 1]	$0.49 \mid {}_I C \in [0, 0.4) \cup (0.6, 1]$ $0.2 \mid {}_I C \in [0.4, 0.6]$
S_2	Steepness2	integer	–	(0, +∞)	0.85
γ, δ	Parameters to define D_2 in relation to initial condition in recovery trajectory	real	–	(−∞, +∞)	15,660, 1.8
ζ, η	Parameters to define D_2 in relation to initial condition in declining trajectory	real	–	(−∞, +∞)	15,660, 0.05
	Additional parameters for distance weighting				
d	Weighting based on average distance to channel	real	–	[0, 1]	0 when distance ≥1 km 1 when distance = 0 km
$C_{w,1}$	Worst condition when d = 1	real	–	[0, 1]	0.8
$C_{w,0}$	Worst condition when d = 0	real	–	[0, 1]	0

$$d_1 = \frac{D_1}{\left(-ln(1 - C_b + \varepsilon)\right)^{1/n_0}}. \tag{5}$$

D_0 is the wet spell duration required in a year for the ecological target to maintain good health, calculated as:

$$D_0 = {}_I C\left(D_{0,max} - D_{0,min}\right) + D_{0,min}. \tag{6}$$

$D_{0,\ min}$ defines the time taken for the ecological target to reach a condition score of $1\text{-}\ \varepsilon$ from a condition score of 0. FERM then assumes that the time taken to reach a condition score of $1\text{-}\ \varepsilon$ is linear within respect to the condition score at the start of the wet spell. Epsilon is used to solve the asymptotic nature of the curve, which allows for physically-based parameterization.

D_1 is the threshold when the wet spell becomes too long that the target declines to the worst possible condition (drowned). As some species thrive with prolonged flooding, this drowning process can be switched off by setting the parameter λ to 0.

The variable α is the maximum increase in condition score that the target can achieve during one continuous wet spell:

$$\alpha = {}_I^D C(1 - T) + {}_I^R CT, \tag{7}$$

where T represents a recovery or declining trajectory. The target is regarded as being in a recovery trajectory when there is at least one wet spell $\geq D_0$ during the critical interval I_C; otherwise, it is treated as in a declining trajectory. Thus

$$T = \begin{cases} 1 & \text{Recovery trajectory} \\ 0 & \text{Declining trajectory.} \end{cases} \tag{8}$$

4.1.2. Response under dry spells

Similarly, the condition score C under a dry spell can be calculated as:

$$C = \left({}_I C - C_w\right)e^{-(D/d_2)^{n_2}} + C_w, \tag{9}$$

where n_2 is the exponent, d_2 (days) is the inflection point used to define the shape of the response curve:

$$n_2 = 2S_2 + 1, \tag{10}$$

$$d_2 = \frac{D_2}{\left(-ln(1 - T + \varepsilon)\right)^{1/n_2}}, \tag{11}$$

where D_2 is the dry spell duration that causes the species to decline to the worst possible condition. It is defined depending on whether the target is on a recovery or declining trajectory.

$$D_2 = D_{2,D}(1 - T) + D_{2,R}T, \tag{12}$$

$$D_{2,R} = \gamma_I C^{\delta}, \tag{13}$$

$$D_{2,D} = \zeta_I C^{\eta}. \tag{14}$$

Eqs. (13) and (14) ensure a physically meaningful D_2 value by asserting that the time taken to decline to the lowest condition is zero if the target is already in a lower condition.

4.1.3. Distance weighting under dry spell

Three parameters are included to bound the target's condition below based on the proximity to any river channel (Table 1). Even though flooding is a significant driver of ecological health in floodplains, ecological targets sufficiently close to the river channel can maintain at least a minimum condition without flooding. The worst condition C_w becomes a variable and is calculated as:

$$C_w = \left(C_{w,1} - C_{w,0}\right)\left(1 - e^{-(d/0.65)^5}\right) + C_{w,0}. \tag{15}$$

The condition score is then calculated using Eq. (9).

4.1.4. Recovering and declining trajectories

Many parameters in FERM come in pairs and, depending on the timing and duration of flooding, the response curve of a given wet or dry spell is parameterized differently. The inclusion of the pairs accounts for lack of flooding. Many ecological targets in a stressed state from long dry spells respond differently when flooding occurs as opposed to the typical response from regular flooding (Overton et al., 2014; Roberts and Marston, 2000). When flooding occurs within the critical interval (Table 1), FERM uses recovering parameters, otherwise declining parameters are used. This can be seen in Eqs. (7) and (12).

4.2. Sensitivity analysis

In order to assess the sensitivity of the output to parameter choice, Sobol Sensitivity Analysis (Sobol, 1990) was performed on FERM using the data from calibration. Sobol sensitivity analysis is also known as variance-based sensitivity analysis. It is a form of global sensitivity analysis that is commonly used in environmental modeling to test the sensitivity of model parameters to input data. It is used in this study to identify critical variables that significantly affect the model's performance and gain insights into the model's behavior under various conditions. To conduct the sensitivity analysis, we have adopted an open-source libraries, the Sensitivity Analysis Library (SALib) (Herman and Usher, 2017; Iwanaga et al., 2022), which was published in 2013 aimed at simplifying the application of sensitivity analyses.

4.3. Calibration

FERM was calibrated on daily timestep LAI outputs taken from the WAVES water and energy balance model for *Eucalyptus largiflorens* (Black Box) from 1949 to 2018 at three grid cells at different distances from the river. The Shuffle Complex Evolution method was used to fit parameters by maximizing the Nash-Sutcliffe Efficiency (NSE) as the objective function. An NSE of 1 indicates that the model has fit the given data exactly and a value <0 indicates the model performs worse than using the sample mean as a predictor. Minimizing the Root Mean Squared Error (RMSE) as the objective function can be used and will return comparable results to NSE as both are based on the sum of squared residuals. Importantly, when using RMSE as the objective function and as a metric to evaluate model performance, the statistic must be viewed in the context of the magnitude of model outputs. Since FERM returns condition scores between 0 and 1, the RMSE score may be low when a potential calibration of FERM is performing significantly worse than the sample mean. Each calibration run was given a maximum of 150,000 iterations, though all runs terminated early after around 10,000 interactions without further improvement of the objective function.

4.4. Validation

Validation of FERM was performed on the entire floodplain, vegetation grid cells were given a distance weight between 0 and 1 based on their closeness to the main channels, with higher weight corresponding to distance away from the channel. Grid cells with a weight <0.33, 0.33 to 0.66, and >0.66 used parameters calibrated on the near, mid, and far grid cells, respectively. A 'near' grid cell is less than 500m from the main channel. A 'mid' grid cell is 500 m–1000 m from the main channel or less then 500 m to a secondary channel and a far grid cell is more then 1000 m from the main channel or >500 m from a secondary channel.

FERM were run for all the grid cells on the floodplain using flood inundation data taken from the TVD inundation model and the results were compared to condition scores from 2009 to 2015 (excluding 2011) obtained using the same method as Cunningham et al. (2009). The parameterization of each grid cell is determined by the vegetation map obtained from remote sensing data and the cell's proximity to the river as described above. Parameters for Black Box were calibrated using WAVES' output. Parameters for River Red Gum Forest and Woodland were inferred from Black Box parameters in combination with expert knowledge (Roberts and Marston, 2000). FERM was run at a daily timestep, and results aggregated to a yearly timestep across the entire floodplain from 1929 to 2018.The Pearson Correlation Coefficient was used to help assess performance and was calculated from the validation data and FERM output.

4.5. Implementation

FERM was implemented using Python and Cython, the C-extension language. Cython is a superset of Python giving C-like performance whilst maintaining Python-like syntax and allows for easy integration with Python. Cython allows statistically typed Python-like code to be converted to 'C' and compiled providing, on average, 100–1000 times speed up. The speed increase that Cython provides allows FERM to compute 90 years of condition scores on 9 million grid cells for <10 min on a standard laptop. For calibration, 50,000 iterations can be completed in 48 min. The bulk of the computation was implemented in Cython with top level function calls in Python. The calibration of FERM uses the Python package SPOTPY (Ben et al., 2023; Houska et al., 2015), which provides an implementation of the Shuffle Complex Evolution method (commonly referred to as SCE-UA method; Duan et al., 1993).

5. Results

5.1. Sensitivity analysis

The Sobol Sensitivity Analysis results are shown in Fig. 3. The sensitivity of the parameters was analysed with respect to the RMSE between FERM and WAVES' output using SALib (Herman and Usher, 2017; Iwanaga et al., 2022). Besides the abnormal sensitivities discussed below, FERM exhibits relatively uniform sensitivity across parameters. Similar to calibration and validation, this sensitivity analysis would benefit from a wider variety of condition data.

The high sensitivity of ζ stands out. This parameter describes the maximum amount of time it takes for the ecological target to decline to its worst condition from its best possible condition when flooding did not occur in the critical interval. Whilst FERM is most likely sensitive to the choice of ζ, upon further analysis of calibration data, flooding rarely occurred close to the bounds of the critical interval (C.I.). This is reasonable as regular flooding occuring within the bounds of the critical interval would produce consistently high condition scores from WAVES, which is not observed. It follows that the abnormally high sensitivity is most likely a result of the data we have access to and would be lower with a wider variety of input data. Consequently, the model would be more sensitive to corresponding parameters for a recovering trajectory.

On the other hand, the model exhibits low sensitivity towards the two parameters, ${}_{I}^{R}C$ and ${}_{I}^{D}C$, describing the maximum increase in condition during recovering and declining trajectories. It is expected as in the event that the increase in condition exceeds the maximum possible condition, the increase in condition would be capped. For example, if the maximum possible condition is set to 0.5, any choice of parameter greater then 0.5 would give identical results for the duration of a wet spell. The model is therefore insensitive to these two parameters. Although this may indicate over-parametrisation, it could be specifically related to the target species used in this study. Sensitivity analysis performed on a wider variety of target species and locations would be required to confirm this conclusion.

5.2. Calibration

The FERM parameters were calibrated, first using WAVES' raw outputs (the amplitude of the seasonal oscillation parameter contained in FERM was fit at the last step to introduce seasonality), then using seasonality removed data (omit the seasonal oscillation in FERM). As the FERM's target is vegetation condition or health rather than seasonal dynamics, it is more appropriate to derive the FERM parameters by eliminating seasonal oscillation from the WAVES' LAI data. The seasonality of the data was removed using a yearly moving average.

Fig. 4 plots FERM's condition output against the WAVES' LAI (standardized to a scale of 0 to 1) after calibration. The three sets of FERM and WAVES' outputs for grid cells at different proximity to the main river channel (near, mid, far) are displayed in three rows. WAVES' LAI output and FERM's condition output are plotted with seasonality in the left column and without seasonality in the right column. The error statistics RMSE and NSE are presented in the top right corner of each plot.

In all cases, convergence was faster when calibration was performed without seasonality. For the grid cells farther from the river (Mid and Far), the model performed similarly with or without seasonality.

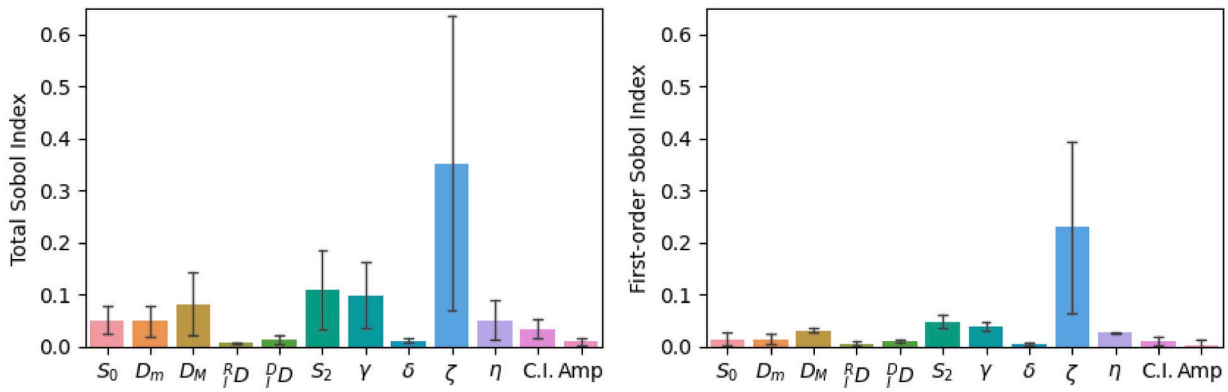

Fig. 3. First-order and total Sobol Indices of Sobol Sensitivity Analysis on FERM. C.I. is the critical interval, D_m and D_M are $D_{0,\ min}$ and $D_{0,\ Max}$ from Table 1. Amp is the Amplitude of seasonal oscillations.

However, calibration with seasonality exhibited significantly slower convergence and had to be run with approximately 50% more iterations for the Shuffled Complex Evolution method. For the grid cell closest to the river, the final parameters obtained from raw data performed significantly worse than parameters obtained from calibration without seasonality with an NSE of 0.38 compared to 0.53 (RMSE of 0.19 compared to 0.16).

The FERM condition output can capture the general trend of LAI produced by the WAVES model, though underestimates peak target conditions and does not fit small changes. This performance is expected given the simplicity of FERM's inputs. The RMSE and NSE generally reflect this with all model performances (NSE of approximately 0.5). The results indicate that FERM is comparable with WAVES whilst using significantly less data and computational resources (as detailed in Section 4.5).

5.3. Validation

The parameters used for validation were obtained through calibration with the removal of seasonality from the WAVES' LAI data. The FERM output and validation data for 2009 are presented in Fig. 5 and the Pearson Correlation Coefficient (r) in Table 2. The years 2009 and 2010 are at the end of the Millennium drought and when flood dependent vegetation will be in or close to their most stressed conditions. Model performance in these years is a good indicator of the performance of the worst possible condition constraints within the model. The Pearson correlation coefficient, in ranging from 0.61 to 0.85, suggests reliable performance of the minimum condition constraints. This is observed qualitatively in Fig. 5 by the healthy vegetation distributed about the main channel and poor condition farther from the main channel in both the validation map and the condition outputs from FERM. The excellent performance of FERM on Black Box is a result of the distribution of Black Box much farther from the channel where performance is better.

By itself, the Pearson correlation coefficient is a poor measure of model performance. It is important to look at the parameters of a linear regression (slope and intercept) between the reference and model values. The slope should be near one and the intercept near zero. Figs. 6 and 7 show these as well as the RMSE and NSE values. Fig. 6 displays the performance metrics when the minimum condition of the model is constrained to the minimum value in the 2009 time series. Fig. 7 shows the unconstrained results. Constraining the minimum condition greatly improves the model performance for all metrics. In both figures, the model performs much better for land uses that include Black Box Woodlands. The performance for River Red Gum Woodlands is particularly poor. This is expected as the model is mostly calibrated to Black Box Forest response, due to limited information available for River Red Gum Forest and Woodland.

6. Discussion

The model developed here is capable of long-term (century-scale) simulation of large-scale floodplains. Taking outputs from a flood inundation model, such as the TVD model used in the case study, FERM can rapidly simulate vegetation conditions on the floodplain. This paper presents the model on a study area of 355 km^2 with a resolution of 10 $\times$ 10 m. Using the timeseries of inundation maps, the model can reproduce the overall spatial pattern of stand condition, which was generated using a neural network model combining ground-based observations and satellite imagery (Cunningham et al., 2009). This allows longer-term simulation of historical floodplain condition and of the impact of future inflow scenarios. FERM also fits temporal trends particularly with respect to Black Box Woodlands and notably lower performance on River Red Gum. As observed in calibration, FERM captures the response to flood pulses well whilst underestimating peak target conditions.

The calibration and validation of FERM does not present an improvement in accuracy compared to current methods but rather an ability to produce comparable results. The goal of FERM is to model vegetation health at high spatial and temporal detail with minimal data and computational requirements whilst maintaining satisfactory accuracy. FERM does not seek to produce more accurate results than existing methodology, but rather to provide an accessible model for environmental water management. Many management and conservation organizations lack data or computation resources to perform adequate quantitative analysis for decision making. On the other hand, research on floodplain species and their water requirements is more readily available. FERM allows users to leverage expert knowledge on ecological targets to perform quantitative analysis of the ecological response to flooding. Given the global demand for effective floodplain management, FERM's minimal requirements make it highly suitable for widespread adoption in this field.

Understanding the uncertainty present in FERM's outputs is important. The sensitivity analysis performed in this paper highlighted FERM's high sensitivity to the parameter governing the duration of decline, ζ, and insensitivity to parameter's describing the maximum possible increase in condition during a wet spell, ${}^R_I C$ and ${}^P_I C$. Ultimately, a wider variety of data would be needed to rigorously assess sensitivities within the model as multiple hypotheses about the cause of high or low parameter sensitivities remain. Furthermore, the impact of uncertainty within the flood inundation modeling should be quantified to better inform results. Like many ecological studies, a rigorous assessment of sensitivity and uncertainty is currently limited by data availability. Data on a wider of ecological species and study areas would help.

FERM's minimal data requirements offer a significant advantage

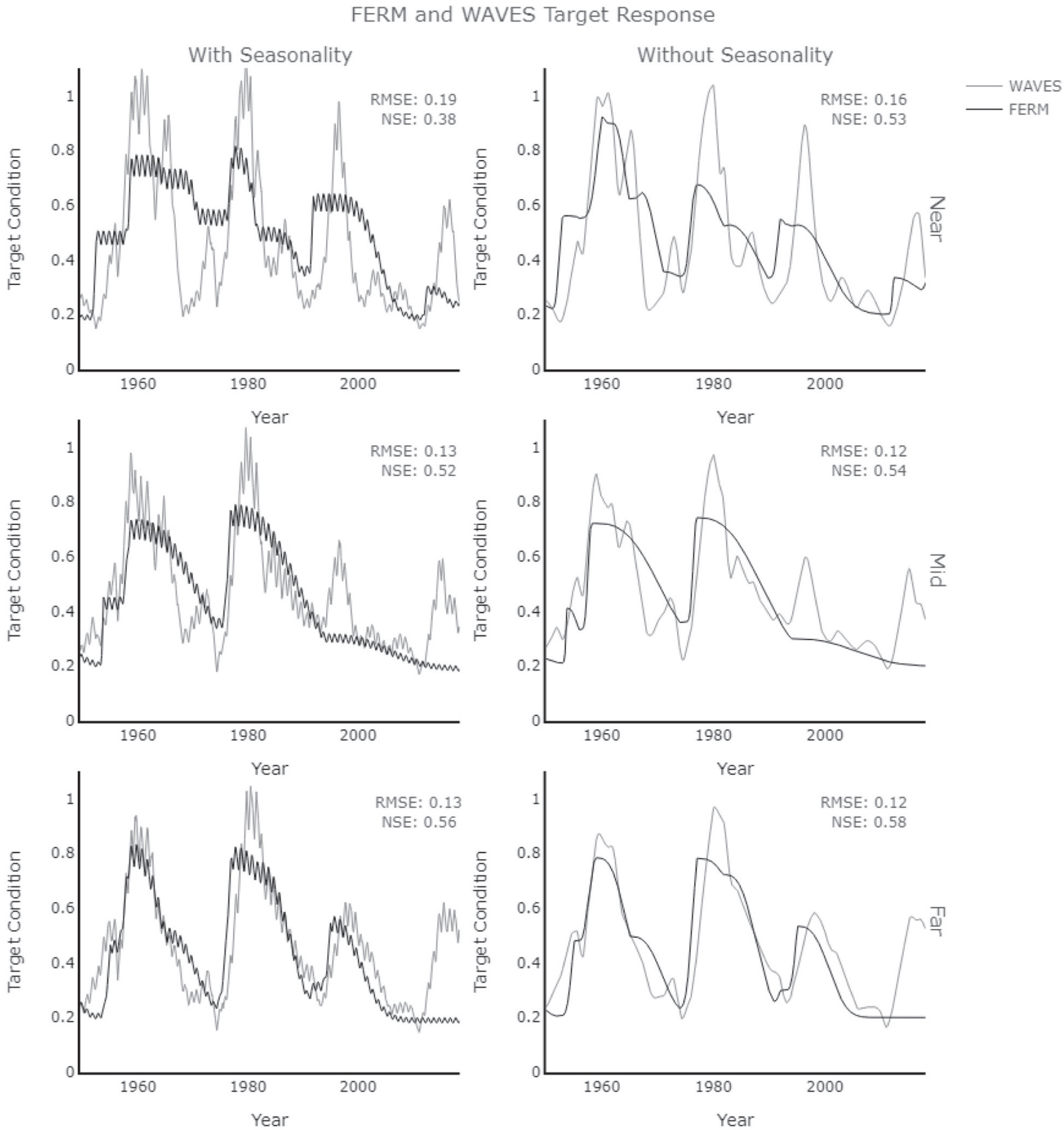

Fig. 4. Calibration (left) of FERM using WAVES' data with seasonality (raw output) and calibration (right) of FERM using WAVES' data without seasonality (365 day moving average) at three different proximities (0-500 m, 500 m-1 km, above 1 km) to the main river channel.

over land surface models, which require substantial meteorological and soil data. Describing the natural flow regime for a given study area to assess the impact of alterations more data intensive than FERM (Brouziyne et al., 2021). The use of continuous, infinitely differentiable preference curves captures the smooth nature of the ecological response and is an improvement on step-based models where hydrological conditions surrounding thresholds produce a wide variety of modeled responses. The continuous response is often more desirable than presence-only distribution models or habitat simulation models for long-lived vegetation species (Tripathi et al., 2022) as satisfactory vegetation health is often the primary objective for conservation bodies.

FERM maintains the computational feasibility of the step-change models allowing for floodplain wide modeling at high spatial temporal resolution whilst performing well on validation data. Physically-based parameterization allows for parameter selection without target condition data, a situation that is common in areas not frequently studied. The models can assimilate data or expert knowledge on the minimum condition of the target to produce more accurate results, as demonstrated in Fig. 6 where data from the Millenium Drought was incorporated. Even though mass and energy balance models or land surface models may capture continuous ecological response, their significant data and computational requirements make them completely infeasible for floodplain-wide modeling (Wood et al., 2011).

Due to a lack of the necessary observational data, common in semi-arid systems, the modeling approach has been calibrated to output from the WAVES mass and energy balance model. As a result, the current model's ability to represent actual systems is limited by WAVES' capacity to capture the behavior of these systems in the application to the

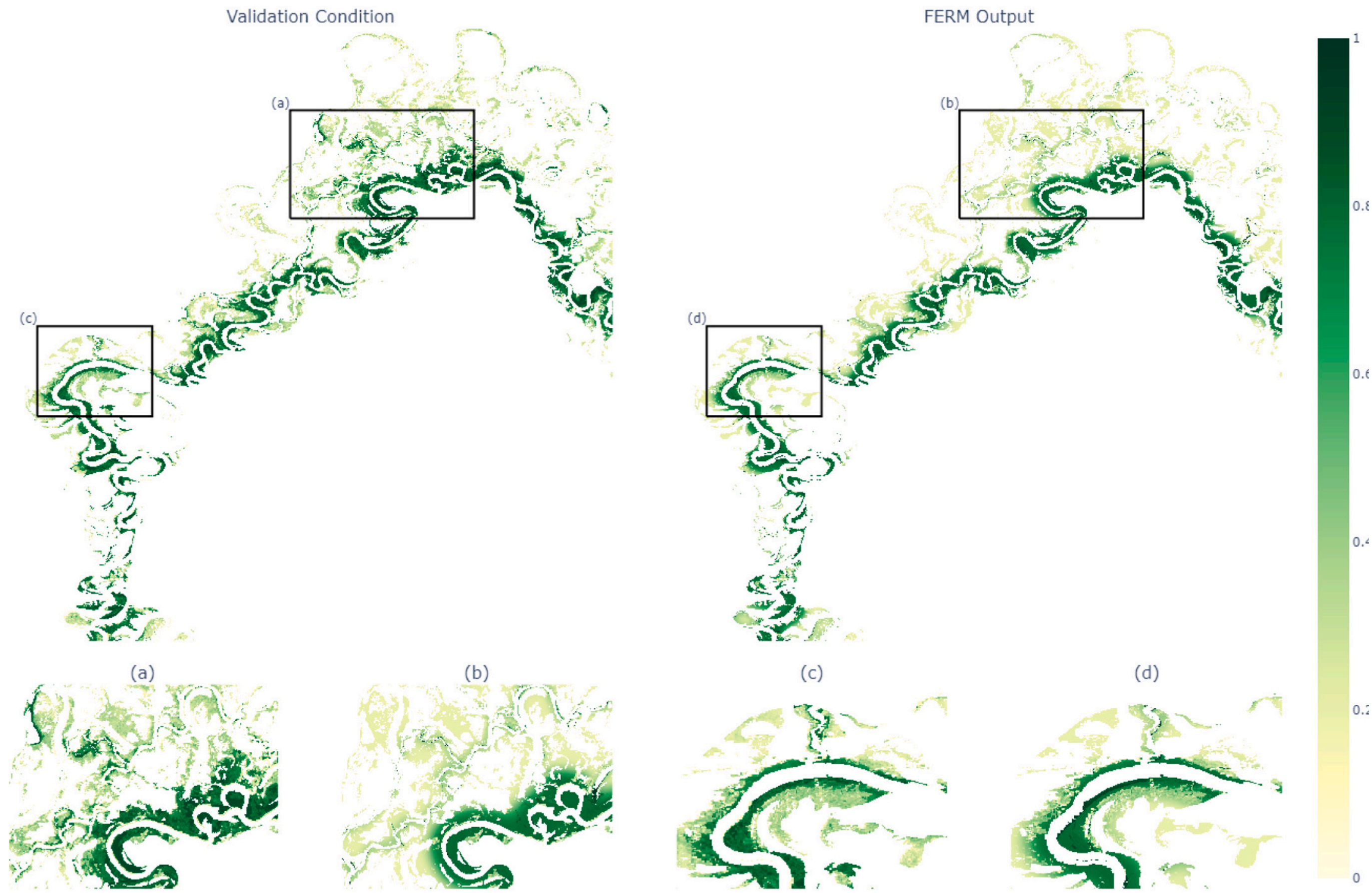

Fig. 5. Spatial maps show comparison of condition scores from Cunningham et al. (2009) for 2009 (left, and zoomed in panels a and c) and FERM (right, and zoomed in panels b and d).

Table 2
Pearson correlation coefficient by vegetation type and validation years.

Target / Correlation	River Red Gum Forest	River Red Gum Woodland	Black Box and Red Gum Woodland	Black Box Woodland
2009	*0.62*	*0.67*	*0.75*	*0.85*
2010	*0.61*	*0.67*	*0.74*	*0.84*
2012	*0.61*	*0.65*	*0.72*	*0.83*
2013	*0.60*	*0.65*	*0.72*	*0.84*
2014	*0.61*	*0.65*	*0.73*	*0.84*
2015	*0.60*	*0.65*	*0.73*	*0.84*

case study site considered here. The model performance is anticipated to improve as better data becomes available on the response of floodplain vegetation to floods and dry periods.

FERM makes a number of assumptions about floodplain forest response to flooding events. The underlying philosophy used in formulating the model is to avoid having thresholds as this leads to issues with model behavior in that discontinuity occurs at the boundaries (Kavetski et al., 2006a, 2006b; Kavetski and Kuczera, 2007). Instead, the model has been formulated using smooth (infinitely differentiable) functions. Though the model has a reasonable agreement with the Cunningham et al. (2009) study, there is still room for improvement in the model formulation. Addressing non-essential assumptions such as stationary vegetation distributions, and thorough sensitivity analysis with a wider variety of data are currently the largest areas of possible improvement.

7. Conclusions

The main contribution of this work is the development of a methodology to quantify the ecological response on floodplains to changes in flow at the most relevant spatial and temporal scales. FERM is able to capture general spatial and temporal trends, demonstrated by its performance in comparison to the remote sensing derived condition scores. The model can be used with a conceptual flood inundation model to rapidly evaluate spatial weaknesses of proposed environmental water management plans in a quantitative manner. The low computational cost makes it possible to model ecological response for multiple scenarios, over longer time periods, and across large floodplains hosting significant ecosystems, which to date have not been possible to model at this level of detail. The modest data requirements enable applications in areas with high data sparsity, which is common in many riverine ecosystems. The continuous, smooth response curves simulated by FERM that avoid the impact of thresholds also represent an improvement compared to other step-change approaches. It aims to support robust decision making at varying temporal scales by setting tangible metrics to evaluate the outcomes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

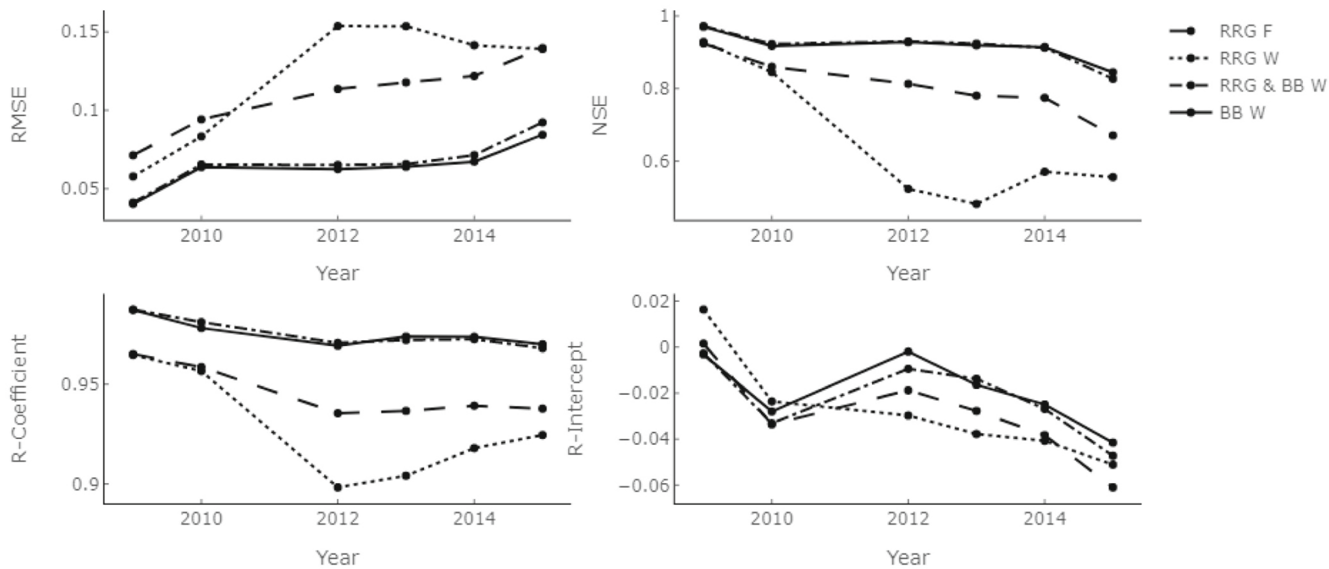

Fig. 6. Performance statistics comparing the FERM model and Cunningham et al. (2009) when the minimum condition of the FERM model is constrained by the minimum condition in 2009. 'RRG F' in the legend represents River Red Gum Forest, 'RRG W' – River Red Gum Woodland, 'RRG & BB W' – River Red Gum and Black Box Woodland, 'BB W' – Black Box Woodland. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 7. Validation performance statistics comparing the FERM model and Cunningham et al. (2009) when the minimum condition is calculated wtih Eq. (15).

Data availability

The FERM model is an open-source software. The source code and sample data can be found here: https://bitbucket.csiro.au/projects/FERM. Version 1 of the model code is also available on Zenodo at https://doi.org/10.5281/zenodo.8088534.

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