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Modelling Vegetation Condition using a Water Balance Model and Long Short-Term Memory Networks on a Floodplain Receiving Environmental Water

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Abstract

Environmental water is delivered to floodplains to maintain environmental health in terms of vegetation health and animal populations in arid and semi-arid areas. When and how much environmental water is required to restore or maintain vegetation health requires robust predictions of vegetation response. We used Normalized Differences Vegetation Index (NDVI) derived from 30-year Landsat dataset to represent vegetation condition. A lake water balance model and long short-term memory networks (LSTMs) were coupled to model NDVI. The predictor variables included in the LSTMs are the outputs of the water balance model, climate factors, day of year and previous NDVI values. The model is expected to generate more precise predictions of ecological outcomes under different watering scenarios, and thus has the potential to help environmental water management in the changing climate.

Keywords: environmental water, long short-term memory networks (LSTMs), Normalized Differences Vegetation Index (NDVI), floodplain, Hattah lakes.

1. INTRODUCTION

River floodplains are at risk of degradation because of human activities, river regulation and climate change. To restore and protect floodplain ecosystems, environmental water delivery programs have been implemented around the world. These programs are implemented through engineering-based approaches including inundating floodplains by pumping into canals and then controlling water delivery with regulators to mimic flood events (Wu et al. 2022). The long-term temporal and spatial impact of environmental water for floodplain vegetation has been studied in several semi-arid floodplains in Australia (Wu et al. 2022; Merritt et al. 2010; Thapa et al. 2019). However, previous research has only been done using simple empirical models that do not take hydrological dynamics of floodplain watering sufficiently into account. Using hydrological models would allow us to consider the environmental water volume, flow path and release timing when predicting vegetation condition.

The objective of this study is to construct a model to predict NDVI taking environmental water volume and climate factors into consideration, using Hattah Lakes, north-western Victoria, Australia as a case study. In this research, a lake water balance model is being constructed that considers precipitation, environmental water, lake volume change and evaporation, using a 16-day time step over 30 years. The output of the water balance model combined with precipitation, temperature, evapotranspiration, day of year and previous NDVI, will be used as predictor variables of Long Short-Term Memory networks (LSTMs). LSTMs are deep learning models that have a long-term memory, making them suitable for time series predictions (Reddy and Prasad 2018). The model can be used to verify the effectiveness of environmental water strategies and support environmental water management under the changing climate.

2. LAKE WATER BALANCE MODEL AND LSTMS

2.1 Lake water balance model

Inputs to the water balance model of the floodplain lakes include precipitation, natural floods, and environmental water; the outputs include the change in lake volume and evaporation. The difference between outputs and inputs is considering as a change in soil and groundwater. Because the environmental water is transferred to lakes through a creek and are not able to inundate the vegetation area, it is therefore influencing vegetation through lateral flow of soil water.

The following equations show the lake water balance model under two conditions, environmental water being delivered, or natural floods occurring. In these equations, Δgw represents change in soil and groundwater, P represents precipitation, Ew is environmental water volume staying into the system, Nf is natural floods volume into the system, and ΔVl stands for volume change in Hattah Lakes. The environmental water volume can be extracted from records of the input regulators and output regulators. For the natural floods volume, it is considered as a function of discharge in the River Murray at the Euston regulator upstream of Hattah Lakes and the maximum capacity of Chalka creek – the channel through which environmental water is delivered – (1.04 m^3/s) will be used.

$$\Delta gw = P + Ew - Ev - \Delta Vl \quad \text{when environmental water occurs} \tag{1}$$

$$\Delta gw = P + Nf - Ev - \Delta Vl \quad \text{when natural floods occurs} \tag{2}$$

2.2 LSTMs

LSTM is an artificial recurrent neural network architecture with a long-term memory. In recent years, LSTMs has been successfully applied to many studies involving time series prediction (Li et al. 2017). They have also been used to make NDVI predictions and displayed superior performance to other traditional neural networks (Reddy and Prasad 2018). Therefore, LSTMs are being used in this study to improve NDVI prediction using hydrological and climate factors. Due to the 16-day resolution of Landsat, there are 571 samples, 399 of them will be used as training data, 114 samples will be used as validation data and others will be used for testing. Pixel gaps because of cloud were interpolated from the previous and following images.

2.3 Expected results

The constructed model will provide robust NDVI predictions for different environmental water or natural floods situation under changing climate. Therefore, environmental water can be managed more precisely and effectively to support vegetation growth in floodplain.

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