Remote Sensing Applications: Society and Environment 1 (2015) 85–97

Contents lists available at ScienceDirect

Remote Sensing Applications: Society and Environment

journal homepage: www.elsevier.com/locate/rsase

MODIS NDVI based metrics improve habitat suitability modelling in fragmented patchy floodplains

Li Wen[a,*], Neil Saintilan[b], Xihua Yang[c], Simon Hunter[a], Dan Mawer[a]

[a] Waters, Wetlands and Coasts Science, Office of Environment and Heritage, 59 Goulburn Street, Sydney, NSW 2000, Australia
[b] Department of Environmental Sciences, Macquarie University, Sydney, NSW 2109, Australia
[c] Ecosystem Management Science, Office of Environment and Heritage, 10 Valentine Ave, Parramatta, NSW 2150, Australia

ARTICLE INFO

Article history:
Received 8 April 2015
Received in revised form
3 August 2015
Accepted 6 August 2015
Available online 31 August 2015

Keywords:
Species distribution model
Maxent
MODIS NDVI
Niche overlap
Murray Darling Basin
Turtle

ABSTRACT

Most early studies applying species distribution models (SDM) at large spatial scales (e.g. global, continental or regional scale) use climatic/topographic predictors only. Remotely sensed datasets are increasingly being used in local scale SDM for identifying, characterizing and predicting animal habitats at the finer scales that are more relevant for on ground biodiversity management. However, the SDMs based on remotely sensed data are rarely assessed in highly fragmented landscapes, such as floodplains. In this study, we explore the efficiency of using variables derived from time series of MODIS NDVI in models predicting three turtle distributions in the highly fragmented Murray Darling Basin (MDB), Australia. For each of the three broadly distributed turtles, namely, *Macrochelodina expansa*, *Chelodina longicollis* and *Emydura macquarii*, we built five sets of Maxent (maximum entropy modelling) SDMs, using a combination of the three classes of predictors (climatic, topographic, and remotely sensed). We assessed the predictive power of these models using the area under the receiver operating characteristic (AUC). In addition, we compared the models in terms of niche overlap and the landscape metrics computed from the predicted distribution maps. Our results demonstrated that the full models, which integrated all three classes of predictors, were superior to other models with significantly higher AUC values ($p < 0.001$), and was consistent for all three turtle species. For the best performing models, the NDVI-based predictors had a larger contribution. Comparing with models with bioclimatic/topographic variables, the models with topographic and NDVI-derived predictors had much higher niche similarity with the best model (Schoener's *D* was 0.95, 0.95 and 0.94 for *C. longicollis*, *E. macquarii* and *M. expansa*, respectively). Furthermore, models including topographic and NDVI-derived variables predicted a more irregular and patchier configuration of suitable habitats reflecting the highly heterogeneous nature of the MDB floodplains. Our results demonstrated that NDVI based metrics have great potential in modelling species distribution in fragmented patchy floodplains.

1. Introduction

Floodplains are among the most diverse, dynamic, productive and populated (Naiman et al., 1993) but also the most threatened (Tockner and Stanford, 2002) ecosystems on Earth. Threats are mainly related to human activities such river regulation and land clearing that cause habitat loss and fragmentation (Krause et al., 2011). For example, in

* Corresponding author. Tel.: +61 2 99955054; fax: +61 2 99955924.
E-mail address: li.wen@environment.nsw.gov.au (L. Wen).

http://dx.doi.org/10.1016/j.rsase.2015.08.001

Murray–Darling Basin (MDB), the largest and most commercially important river system in Australia, extensive agricultural and water resource developments have caused widespread degradation of both riverine and floodplain biota with over 80% of the sub-basins in poor or very poor condition (Davies et al., 2010). Currently, management interventions, such as green infrastructure (European Commission, 2011) and environmental water application, i.e. allocating water to sustain the ecological integrity of aquatic system (Mac Nally et al., 2014), are been increasingly implemented to maintain and restore the degraded ecosystems for biodiversity conservation. Because of the multifunctional nature of floodplains, identifying and preserving the distinct populations and their suitable habitats in these highly fragmented landscape are the key to the sustainability of any management programme.

Species distribution models (SDMs) aim to predict the distribution of a species in geographic space based on its known distribution in ecological/environmental space. Through numerically relating the known species' occurrence records with a suite of environmental variables of those locations, the environmental conditions that are suitable for a species can be defined (Elith and Leathwick, 2009). In the past three decades, SDMs are increasingly being used in many biological fields including biodiversity research (e.g. Thuiller et al., 2004), conservation biology (e.g. Guisan and Thuiller, 2005) and invasion biology (e.g. Palaoro et al., 2013). The central premise of this approach is that the environmental conditions at the occurrence locations can reasonably explain species' physiology and probability of persistence (Franklin, 2013). Among the diverse applications, SDMs have been established as important management tools for predicting species distribution and identifying suitable habitat to inform conservation decisions and priorities (Scott et al., 2002; Austin, 2007; Carvalho et al., 2010).

SDMs are now widely used across terrestrial, freshwater, and marine realms for both animals and plants (Elith and Leathwick, 2009). Nonetheless, there were few applications of SDMs in the highly fragmented patchy floodplains (but see Shirley et al., 2013). In such environments, small habitat patches are surrounded by a matrix of converted area, and are often hydraulically disconnected by a network of canals, levee banks and roads (Wen et al., 2013). The "patchy distribution" may pose a challenge for SDMs because coarse resolution (e.g. >1 km) climatic and topographic predictors are often used as environmental predictors of a species' distribution. Even though these parameters broadly determine the species' fundamental niche (Woodwards, 1987), the static and relatively uniform topographic and climatic variables may lack discriminating power for floodplain habitats. Thus, finer scale habitat quality variables are needed to produce accurate predictions (Wilson et al., 2013). Although habitat data acquired through ground surveys allow the development of SDMs based on variables that are more causally related to species occurrence, resource constraints typically prevent detailed habitat assessments that involve extensive surveys, especially for river basin level or regional studies.

The accelerating availability of diverse, remotely sensed products opens up the possibility to investigate the causal or driving forces for species' distribution beyond topographic and climatic conditions (Bradley and Fleishman, 2008; Spanhove et al., 2012) by adding measured land surface characteristics, such as land cover change, vegetation phenology and structure (Cord et al., 2014). In many cases, the inclusion of predictor variables derived from remotely sensed data improves the accuracy of the model (Pettorelli et al., 2011). In particular, these models tend to refine the maps of species distribution and habitat, compared with models limited to climatic and topographical variables (Morán-Ordóñez et al., 2012). Remotely sensed data provide measurements and surrogates directly related to vegetation type and structure, biomass, and other ecosystem variables that collectively improve our understanding of habitat characteristics (Pettorelli et al., 2005, 2011; Bradley et al., 2012; Wen et al., 2012). Of the many high resolution remote sensing products, the multi-temporal MODIS NDVI retains information along environmental gradients (Bradley and Fleishman, 2008; McGarigal et al., 2009; Pettorelli et al., 2011) as well as accounting for intra- and inter-annual changes in the environment (Cord and Rödder, 2011). Therefore, using time series of MODIS NDVI can reduce classification and interpretation errors common in categorical predictor variables such as land use and vegetation type (McGarigal et al., 2009). This is particularly beneficial when modelling animal distributions at ecological transitional zones or in highly patchy and dynamic environments such as floodplains.

In this study, we are interested in modelling the current distribution of three freshwater turtles in the MDB within New South Wales. There are four species of freshwater turtle inhabiting the MDB, of which three, the broad-shelled turtle (*Macrochelodina expansa*), the eastern snake-necked (or long-necked) turtle (*Chelodina longicollis*) and the Murray (or Macquarie) turtle (*Emydura macquarii*) are widely distributed (Georges and Thomson, 2010). The three species co-exist, and share elements of a common habitat, such as slow flowing streams and rivers, but each species has its own particular habitat requirements. *M. expansa* is a selective and specialised predator. Its preferred habitats are permanent waters such as rivers or deep-water lakes with an abundance of snags. *C. longicollis* is an omnivorous scavenger. It prefers shallow lakes, the highly productive floodplain swamps, and ephemeral water bodies with abundant invertebrates. *E. macquarii*, like *M. expansa*, is dependent on permanent and stable water bodies. *E. macquarii* feeds on vertebrate carrion and aquatic plants. It is able to scrape periphyton from submerged logs. We exclude from the modelling the western saw-shelled turtle (*Myuchelys bellii*), which is confined to a few headwater streams (Fielder et al., 2012). Globally, freshwater turtles are one of the most threatened animal groups, with many species already listed as critically endangered (Buhlmann et al., 2009). Although only *M. expansa* is listed as threatened in Victoria and South Australia, there is evidence that the population of all three turtles in the MDB are declining (Chessman, 2011), primarily in response to habitat loss, fragmentation and degradation. Sufficient knowledge of the current distribution is required to mitigate these threats for the restoration and conservation of the turtle populations. Thus, understanding whether fine-scale predictor-based remote sensing data are needed to accurately predict turtle occurrence has direct management implications.