



Habitat in flames: How climate change will affect fire risk across koala forests

Farzin Shabani ^{a,*}, Mahyat Shafapourtehrany ^b, Mohsen Ahmadi ^c,
Bahareh Kalantar ^d, Haluk Özener ^b, Kieran Clancy ^e, Atefeh Esmaeili ^f,
Ricardo Siqueira da Silva ^g, Linda J. Beaumont ^h, John Llewelyn ^{i,j}, Simon Jones ^k,
Alessandro Ossola ^{l,m}

^a Department of Biological and Environmental Sciences, College of Arts and Sciences, Qatar University, P.O. Box 2713, Doha, Qatar

^b Kandilli Observatory and Earthquake Research Institute, Department of Geodesy, Bogazici University, 34680, Cengelkoy, Istanbul, Turkey

^c Department of Natural Resources, Isfahan University of Technology, Isfahan, Iran

^d RIKEN Center for Advanced Intelligence Project, Goal-Oriented Technology Research Group, Disaster Resilience Science Team, Tokyo 103-0027, Japan

^e College of Science and Engineering, Flinders University, GPO Box 2100, Adelaide, South Australia 5001, Australia

^f School of Environmental and Rural Science, University of New England, Armidale, NSW 2351, Australia

^g Department of Agronomy, Federal University of Vales do Jequitinhonha e Mucuri, Diamantina, MG, 39100-000, Brazil

^h School of Natural Sciences, Macquarie University, Sydney, New South Wales, Australia

ⁱ Global Ecology / Partuyarta Ngadluku Wardli Kuu, College of Science and Engineering, Flinders University, Adelaide, South Australia, Australia

^j ARC Centre of Excellence for Australian Biodiversity and Heritage, Wollongong, Australia

^k School of Science, RMIT University, Melbourne, VIC, 3000, Australia

^l University of California, Davis, CA, USA

^m School of Agriculture, Food and Ecosystem Sciences (SAFES), The University of Melbourne, VIC, Australia

ARTICLE INFO

Article history:

Received 25 June 2023

Received in revised form 7 August 2023

Accepted 8 August 2023

Available online 14 August 2023

Keywords:

Climate change

60 main tree species browsed by koalas

Decision Tree machine learning algorithm

Fire

ABSTRACT

Aim: Generate fire susceptibility maps for the present and 2070, to identify the threat wildfires pose to koalas now and under future climate change.

Location: Australia.

Time period: Present and 2070.

Major taxa studied: 60 main tree species browsed by koalas.

Method: The Decision Tree machine learning algorithm was applied to generate a fire susceptibility index (a measure of the potential for a given area or region to experience wildfires) using a dataset of conditioning factors, namely: altitude, aspect, rainfall, distance from rivers, distance from roads, forest type, geology, koala presence and future dietary sources, land use-land cover (LULC), normalized difference vegetation index (NDVI), slope, soil, temperature, and wind speed.

Results: We found a general increase in susceptibility of Australian vegetation to bushfires overall. The simulation for current conditions indicated that 39.56% of total koala habitat has a fire susceptibility rating of “very high” or “high”, increasing to 44.61% by 2070.

Main conclusions: Wildfires will increasingly impact koala populations in the future. If this iconic and vulnerable marsupial is to be protected, conservation strategies need to be adapted to deal with this threat. It is crucial to strike a balance between ensuring that

* Corresponding author.

E-mail address: fshabani@qu.edu.qa (F. Shabani).

koala habitats and populations are not completely destroyed by fire while also allowing for forest rejuvenation and regeneration through periodic burns.

© 2023 The Author(s). Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Climate change (IPCC, 2014) and habitat loss (Shabani et al., 2019) are driving global declines in species populations, leading to extinctions (Thomas et al., 2004). If humans fail to slow down anthropogenic climate change, many species will experience range contractions (Chen et al., 2011; Jump and Penuelas, 2005) to the point of extinction (Bellard et al., 2012; Parmesan and Yohe, 2003; Strona and Bradshaw, 2018; Thomas et al., 2004; Urban, 2015). Predictive models of future climates that incorporate current trajectories of greenhouse gas emissions indicate that extreme climatic conditions (floods, droughts, and fires) will increase (Cremen et al., 2021). These extreme events will have detrimental effects on vulnerable species, and international organizations including United Nations (UN), the European Union (EU), and the World Bank have acknowledged the need for climate-related hazard risk reduction through mitigation and adaptation strategies.

Species distribution models (SDMs) integrate empirical data on species occurrences or abundance with environmental factors (Elith and Leathwick, 2009). These models predict the distribution of suitable habitat for species, providing valuable insights into ecological and evolutionary processes (Pollock et al., 2014). SDMs can directly model the distribution habitat for a focal species using environmental variables (Hijmans et al., 2004). Alternatively, they can model the distribution of suitable habitat of other species that the focal species relies on, such as its food sources (Shabani et al., 2019). SDMs are extensively employed in terrestrial, marine, and freshwater contexts, often involving extrapolation across time and space. Indeed, they have been widely used to investigate the impact of future climate change on species distributions (Carlson et al., 2022; Habibullah et al., 2022; Rupasinghe et al., 2022; Varol et al., 2022).

However, suitable habitat alone does not guarantee species survival (Salafsky et al., 2008). Severe climate-related events like wildfires (Tehrany et al., 2019b), cyclones, and floods (Tehrany et al., 2019a) will have adverse effects on species even within their supposedly suitable habitat. In the past, neighbouring populations could recolonize areas after local extinctions caused by such events. However, human-induced habitat loss and fragmentation hampers this recolonization process (Vieira et al., 2022). Moreover, climate change is intensifying the frequency of extreme climate events (Cai et al., 2014). Consequently, safeguarding endangered species requires not only identifying suitable habitat but also understanding the potential impacts of extreme events on those habitats.

Fire is a key force behind carbon cycles and vegetation regeneration (Landry et al., 2015). While wildfires are a natural phenomenon, catastrophic fire events in the 21st century suggest that changing climate is affecting fire regimes (Bowman et al., 2009). High-intensity fires have occurred in regions and seasons where they have not historically occurred (Keeley and Zedler, 2009). The 2019–2020 Black Summer period in Australia resulted in 5.5 million hectares (roughly 7%) of New South Wales being burnt—four times greater than the area of destruction recorded in any previous fire season (Simmons et al., 2021). Over 450 threatened plant species and 293 threatened animal species occur in the footprint of the Black Summer fires (Department of Premier and Cabinet, 2020), and the long-term survival of a significant proportion of these species has been impacted by the fires (Dickman, 2021). Furthermore, 17 of the 22 major vegetation groups found across Australia suffered more extensive fires and higher burning temperatures during the Black Summer fires than ever before (Godfree et al., 2021). Eucalypt tall open forests were one of the most severely affected of these vegetation groups, with a total of 1.14 mega hectares burnt (Godfree et al., 2021).

An important aspect of Australia and its near surrounds is a heritage of unique endemic species, such as the koala (*Phascolarctos cinereus*). The koala is highly specialized with extremely specific habitat and dietary needs (Kjeldsen et al., 2019). Its distribution has contracted since the Last Interglacial period (128–116k years) (Adams-Hosking et al., 2011b), with further rapid contraction and population declines in the 230 years since European colonization. Moreover, it is projected that koala habitat will continue to decline due to climate change (Adams-Hosking et al., 2011a,b; Gordon et al., 1988; Lunney et al., 2012). However, while Shabani et al. (2019) investigated whether past climate conditions could account for observed spatio-temporal range shifts suggested by fossil specimens of koalas, they did not investigate whether other climate-related factors, such as fire, could prevent koalas using otherwise suitable habitat.

In addition to being highly sensitive to changes in climate, habitat reduction and fragmentation arising from land clearing for development has placed more koalas in close proximity to humans. This has escalated mortality rates of koalas due to domestic animal predation and road-kill (Gonzalez-Astudillo et al., 2017; Lunney et al., 2007, 2022b; McAlpine et al., 2015). Barely 230 years after European colonists arrived in Australia, the koala has been classified as “threatened” in over 60% of its current distribution range, with a population decline exceeding 50% (Melzer et al., 2000), although some populations have remained stable (Lunney et al., 2016). The IUCN Red List considers koalas as *Vulnerable* in the Australian states of Queensland and New South Wales, as well as in the Australian Capital Territory. The Australian Environment Protection and Biodiversity Conservation Act of 1999, incorporates the same classification status (Sequeira et al., 2014). A study, using an expert elicitation methodology, estimated the total national koala population to be between 144,000

and 605,000, with a decline of 24% over the past three generations (Adams-Hosking et al., 2016). The main causes of this population decline have been identified as significance of endemic disease (McCallum et al., 2018), threats related to high human population densities (e.g. road kill, attacks by pets; Lunney et al., 2022a) and ongoing pressures from habitat loss and climate change (Shabani et al., 2019).

Koalas are dependent on eucalyptus (mainly, *Eucalyptus* spp.) for both shelter and diet. Indeed, koalas are apex herbivores in these systems—they are at the top of the food chain for the plants they consumer (though they are occasionally preyed upon by dingos and large pythons (McAlpine et al., 2006)). Thus, the fundamental requirement for the survival of koala populations is a minimum level of *Eucalyptus* forest cover (Santika et al., 2014) and koala populations are mainly limited by the availability of food and suitable habitat. Species distribution studies considering the impact of climate change on *Eucalyptus* varieties generally project parallel range declines in the varieties for which the koala has adapted to use (Austin and Van Niel, 2011; Booth, 2013, 2017; Booth et al., 2015; Butt et al., 2013; Hughes, 2003; Hughes et al., 1996; Matusick et al., 2013; Mok et al., 2012).

Machine learning and other simulation methods used to construct intelligent models have in recent years been used successfully to produce Forest Fire Susceptibility Mapping for many regions (Dimuccio et al., 2011; Jaafari et al., 2018; Tehrany et al., 2021), enabling the investigation of the magnitude of changes in fire regimes due to climate change. In this study, we use the well-known machine learning method Decision Tree (DT) to generate fire susceptibility maps taking vegetation (and other factors) into account. We aim to (i) generate fire susceptibility maps for the present and 2070 for the entire country, and (ii) identify the proportion of koala habitat that is highly susceptible to fire now and under future climate change. We hypothesize that fire susceptibility will display a notable increase due to Anthropogenic climate change across vegetation types and in koala habitats specifically, possibly leading to a substantial decline in koala populations.

2. Methods

2.1. Koala browse species

There is a wide variety of *Eucalyptus* species that koalas may browse, and their selection depends on factors such as habitat and the availability of food sources. For this study, we compiled a comprehensive list of 60 koala browse species from diverse sources, including a literature review and the research conducted by Shabani et al. (2019).

2.2. Conditioning factors

As shown in Fig. 1 (methodology flowchart), wildfire susceptibility was modelled for current and 2070 for the entire country. All the conditioning factors (altitude, aspect, distance from the river, distance from the road, forest type, geology, LULC, NDVI, slope, soil, and wind speed) between the present and 2070 were consistent over the time except temperature, rainfall and koala food source for which the projections by 2070 were available. We further note that at present, and likely in 2070, there is no koala food source in Northern Territory and koalas are currently only found in Queensland, New South Wales, Victoria, South Australia, and the Australian Capital Territory).

2.3. Data

A wildfire dataset is crucial for assessing model susceptibility. All natural hazard susceptibility analyses (Pradhan, 2010) require two groups of data, namely, inventory factors (independent) and conditioning factors (dependent) (Jebur et al., 2014; Tehrany et al., 2019c). Inventory factors represent the locality of the occurrence; (Tshering et al., 2020; You et al., 2017) conditioning factors represent proxies for the intensity and speed at which the fire spreads (Pourtaghi et al., 2016). In this study, fire inventory maps for each state and the conditioning factors were derived from different sources (Table 1). Further, while koalas are not found throughout Australia, several of the tree species that are edible for koalas can be found in the eastern, northeastern, and southwestern regions of the country. We therefore modelled current and future distributions of koala forests in all Australian states and territories, including those not currently occupied by koala populations, as this allows us to identify opportunities for future ex-situ conservation/translocation projects.

2.4. Inventory data

We used 70% of the total wildfire events for model training and the remaining 30% for testing/validation purposes. Hence, in this study 700 fire events were used to train the model, and the remaining 300 events were chosen for testing. Further, we generated random sample points of non-fire locations and similarly divided them into the training (70%) and testing samples (30%) for further validation purposes.

2.5. Conditioning factors

No standardized framework exists for constructing a dataset of conditioning factors, and in many cases are limited to the data available, which may be sourced from previous studies, and the use of expert knowledge (Eugenio et al.,

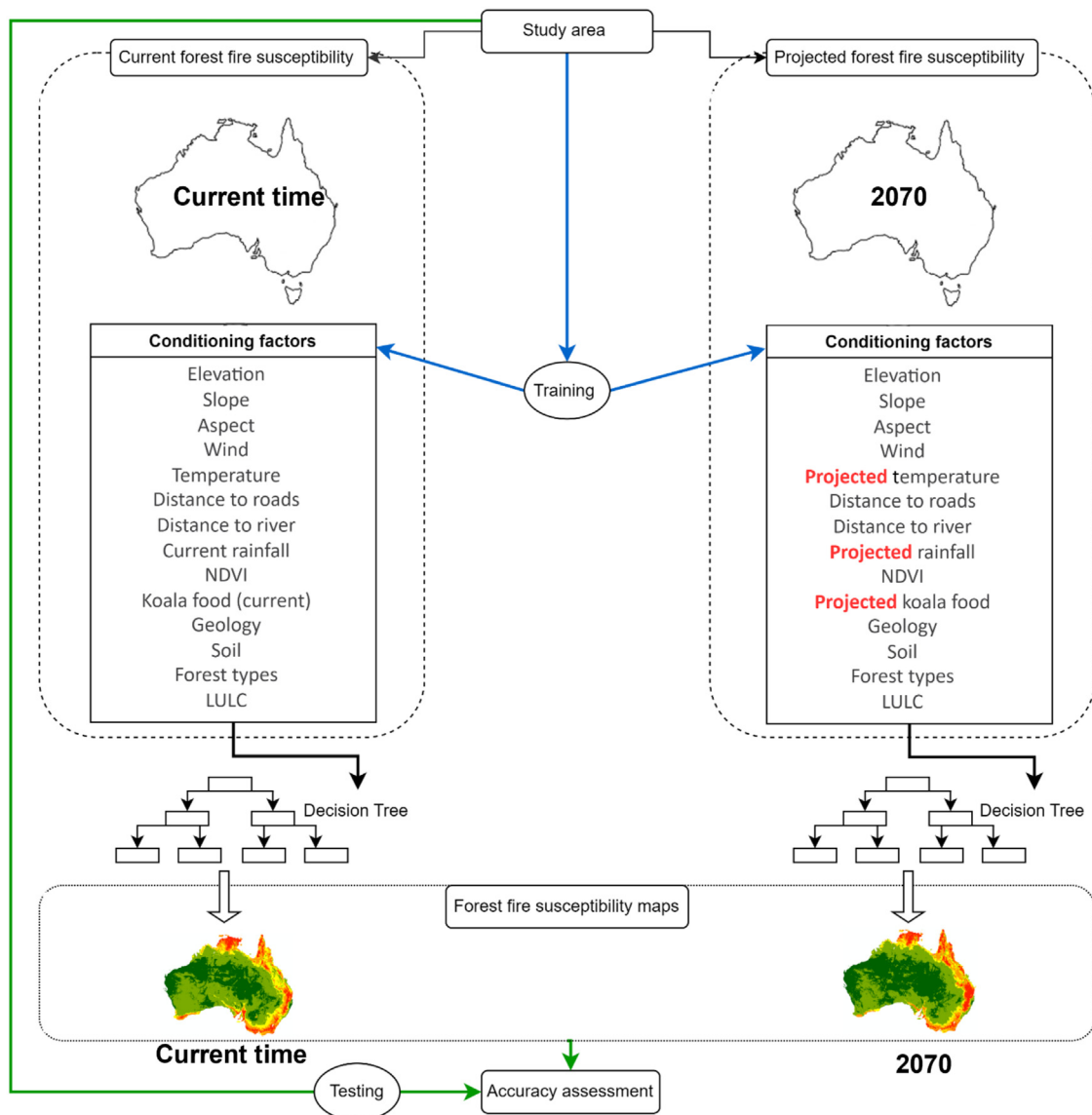


Fig. 1. Methodology flowchart and conditioning factors of this study.

2016; Pourghasemi et al., 2016). We established a dataset of 14 conditioning factors, namely, elevation, slope, aspect, wind speed, temperature, road distance, river distance, rainfall, NDVI, the identity of the 60 koala-browse tree species, geology, soil, forest types, and LULC (Table 1). These factors were used in conjunction with a GIS to produce the maps (see supplementary file).

The topographic factors were included on the basis of their influence on climatic factors that impact on fire occurrence (Jaiswal et al., 2002). Increasing landscape elevation from gullies leads to higher temperatures due to greater exposure to sunlight on hill crests, and thus, increased proneness to fire. The greater exposure and reduced physical protection increase wind speeds, thus enhancing the rate of spread. Greater slope increases the fire frontal radiation and convection causing fires to spread more rapidly uphill and move slower downhill. The speed of advance of a fire front doubles per 10-degree slope increase, implying that the advance up a 20-degree slope is four times quicker than over level ground. In general, the forests were mainly located on steep slopes, thus, increasing the risk of fire. Aspect refers to the orientation of the slope face, which impacts soil moisture and temperature levels, as well as exposure to solar radiation. The topographical variables were calculated from LiDAR data obtained from a Digital Elevation Model with 5-metre spatial resolution (Table 1).

The most influential climate variables that impact on fire occurrence are precipitation, temperature, and wind. Higher temperatures reduce the moisture content of the ground level organic matter, particularly dry grasses, decomposing

Table 1
Conditioning & inventory factors and data sources.

Conditioning & inventory factors	Source
Elevation	Light detection and ranging (LiDAR) data from Australia Government/Geoscience Australia: https://ecat.ga.gov.au/geonetwork/srv/eng/catalog.search%23/metadata/89644
Slope	Derived from DEM
Aspect	Derived from DEM
Wind	The Global Wind Atlas https://globalwindatlas.info/
Temperature	(Hijmans et al., 2004)
Distance to roads	Australian government, Geoscience Australia website: http://www.ga.gov.au/data-pubs/maps
Distance to river	Australian government, Geoscience Australia website: https://www.ga.gov.au/scientific-topics/national-location-information/national-surface-water-information
Rainfall	(Hijmans et al., 2004)
NDVI	NDVI factor has been used to measure the vegetation cover. It was prepared using Landsat-8 images according to: where NIR and R values are the infrared and red bands, respectively.
60 species browsed by koala for the present and 2070	Refer to (Shabani et al., 2019): <i>Callitris endlicheri</i> , <i>Casuarina torulosa</i> , <i>Eucalyptus agglomerate</i> , <i>E. albens</i> , <i>E. amplifolia</i> , <i>E. bancroftii</i> , <i>E. baueriana</i> , <i>E. bicostata</i> , <i>E. biturbinata</i> , <i>E. blakelyi</i> , <i>E. bosistoana</i> , <i>E. bridgesiana</i> , <i>E. camphora</i> , <i>E. chloroclada</i> , <i>E. cinerea</i> , <i>E. conica</i> , <i>E. consideniana</i> , <i>E. coolabah</i> , <i>E. crebra</i> , <i>E. cypellocarpa</i> , <i>E. dalrympleana</i> , <i>E. dealbata</i> , <i>E. dwyeri</i> , <i>E. globoidea</i> , <i>E. globulus</i> , <i>E. goniocalyx</i> , <i>E. largiflorens</i> , <i>E. longifolia</i> , <i>E. macrorhyncha</i> , <i>E. maidenii</i> , <i>E. mannifera</i> , <i>E. melliodora</i> , <i>E. macrocarpa</i> , <i>E. microcorys</i> , <i>E. moluccana</i> , <i>E. nicholii</i> , <i>E. nortonii</i> , <i>E. nova-anglica</i> , <i>E. oblonga</i> , <i>E. ovata</i> , <i>E. parramattensis</i> , <i>E. pauciflora</i> , <i>E. pilligaensis</i> , <i>E. polyanthemus</i> , <i>E. populnea</i> , <i>E. prava</i> , <i>E. propinqua</i> , <i>E. pseudoglobulus</i> , <i>E. punctata</i> , <i>E. quadrangulate</i> , <i>E. radiata</i> , <i>E. robusta</i> , <i>E. rossii</i> , <i>E. rubida</i> , <i>E. scias</i> , <i>E. sclerophylla</i> , <i>E. sieberi</i> , <i>E. tereticornis</i> , <i>E. vicina</i> , and <i>E. viminalis</i>
Geology	Australian government, Geoscience Australia website: http://www.ga.gov.au/data-pubs/maps
Soil	Australian Soil Resource Information System Website: https://www.asris.csiro.au/themes/Atlas.html
Forest types	https://www.agriculture.gov.au/abares/forestsaustralia
LULC	Australian government website: https://www.agriculture.gov.au/abares/aclump/land-use/data-download
Wildfires extent (inventory factor)	Australian Government Department of Agriculture, Water, and the Environment Website: https://www.awe.gov.au/abares/forestsaustralia/forest-data-maps-and-tools/spatial-data/forest-fire http://www.environment.gov.au/fed/catalog/main/home.page Australian Government Website: https://data.gov.au/data/dataset/2020-operational-bushfire-boundaries South Australia Government Data Directory: https://data.sa.gov.au/data/dataset/last-fire

leaves and needles, as well as emerging saplings, enhancing susceptibility (Vadrevu et al., 2006). Much of Australia experiences drought conditions, sometimes enduring for years, facilitating the spread of fires. Bureau of Meteorology data indicates that the average warming of the continent has slightly exceeded one degree Celsius since 1910, with the greatest proportion of the increase since 1950. With higher temperatures, fuel loads exist closer to the combustible point and burn faster following ignition.

Wind speeds accelerate the spread of fire by providing more oxygen and pushing the burning front to ignite unburned fuel. Strong winds also contribute to spotting, where burning embers are carried by the wind, causing fires to ignite areas beyond the fire front. These embers can travel up to 30 km downwind. Fires spread slower when wind speeds are below 12–15 km/h. Dry fuels burn faster than damp fuels, so the time since the last rainfall and the amount of rain are crucial factors in assessing susceptibility to fire. Drought or moisture deficit can indicate extreme fire susceptibility. Lower humidity levels increase the likelihood of fire, as vegetation becomes more combustible due to the release of moisture content.

Roads and rivers, and the clearing of firebreaks, can act as physical barriers to fires spreading, areas near close to large bodies of water bodies have a lower susceptibility as surrounding moisture levels will be higher. ArcGIS Pro 3.1. was used

to generate proximity maps of roads and rivers. NDVI values representing vegetation characteristics were downloaded from the website of the Bureau of Meteorology. The monthly NDVI values are derived from the series of cloud-free afternoon observations through the month made by the NOAA satellite.

Presence/absence data for the 60 main tree species browsed by koala (Table S1, also see [McAlpine et al. \(2023\)](#)) were obtained from species distribution modelling results of every single species. The results were modelled using current occurrences and selected climatic and non-climatic variables. Model validation was performed with the current koala-browse species and koala occurrence records ([Shabani et al., 2019](#)). These records were derived from current distribution records and outputs of an ensemble modelling study that incorporated the CCSM4 and MIROC-ESM GCMs and four modelling techniques (generalized linear model, maximum entropy, generalized boosting model, and surface-range envelope) applied to the 60 species for the present day, and 2070 were investigated and results are shown in Fig. S1. [Shabani et al. \(2019\)](#). These results are shown in Fig S1; dark green represents most suitable habitat, light green least suitable, and white unsuitability. Table S1 includes all modelled ([Shabani et al., 2019](#)) 60 species browsed by koala in the present study.

Soil and geology type were also included in the analysis. A soil map (scale 1:250,000) and geology map (scale 1:100,000) were obtained from the national Geoscience Australia website. Trees, shrubs, and flammable forest vegetation types occurring in fire-prone areas enhance the risk associated with ignition ([Sari, 2021](#)). Fuel load quantifies the layers of fallen bark, and other organic litter that characterizes the landscape. The greater and drier the fuel load, the more intense the fire. Loosely compacted fuel layers have greater aeration and, hence, burn faster than more densely compacted and scattered decomposing vegetation. Smaller fuel elements such as twigs ignite more quickly, particularly when dry and less densely layered and in the fire front path. Larger fuels, such as tree trunks, often continue to burn long after the more easily combustible fuels and the passing of the fire front. Eucalypt tree oils promote combustion. LULC constitutes a key factor influencing rate of occurrence of wildfires ([Sari, 2021](#)).

Regarding the data preparation, vector factors such as geology and LULC were converted to raster format. An Euclidean Function was applied to calculate distance factors (road and river). Due to the original spatial resolution of koala food maps (300 × 300 m), other factors were also summarized at the same pixel size. GIS-related analysis was performed in ArcGIS Pro 3.1 (see [Fig. 2](#)).

2.6. Decision tree (DT)

DT is a machine learning algorithm ([Bhaduri et al., 2008](#); [Murthy, 1998](#)) regularly used in predictive modelling ([Nefeslioglu et al., 2010](#)) and is considered less complicated than other supervised learning methods such as ANN ([Saito et al., 2009](#)). The DT method has a top-down structure meaning that factors located at the top of a tree will exert a greater impact on wildfire occurrence than those in the lower order. Initially, DT classifies the conditioning factors of the dataset into homogeneous hierarchically-structures trees based on levels of susceptibility ([Witten and Frank, 2002](#)). The predictive efficiency of the output is dependent on the preciseness of the analysis of the set of input variables used in the generation of Decision rules ([Myles et al., 2004](#)). The modelled relationships between variables require no strict assumptions regarding data distribution ([Mingers, 1989](#)) and the format of data format may be nominal or scalar ([Mathuria, 2013](#)).

In simple terms, DT evaluates the comparative importance of the relationship of the dependent variable with each conditioning factor. Trees are constructed downwards from a root node, to a set of internal nodes, and finally to the set of terminal nodes. A binary (yes/no; positive/negative) decision occurs at each node that separates the classes. At each level of the tree, each binary decision produces a further two potential binary options on the following next level. On reaching the terminal node level conditioning factors with a significant impact on fires are reserved for processing, and the remainder rejected.

Numerous processing approach options exist in DT Modelling, including Chi-squared Automatic Interaction Detection (CHAID), Exhaustive CHAID, Classification and Regression Trees (CRT), Quick, Unbiased, and Efficient Statistic Tree (QUEST) ([Kadavi et al., 2019](#)) CHAID was used in this study at each step where the conditioning factor manifesting the most significant relationship with the dependent variable was chosen ([Althuwaynee et al., 2014](#)). Where no class of conditioning factor indicated a significant relationship to the dependent variable, the classes were merged. CHAID has become the method of choice the modelling of natural hazard susceptibility, due to its processing speed and its efficiency in multi-way node splitting ([Dou et al., 2019](#)). The CHAID algorithm was implemented in IBM SPSS Statistics V.27, and the selection of criteria was based on earlier studies. Splitting and merging categories requires values set between 0 and 1. The value of 0.9 was chosen for splitting and 0.001 for merging after a length trial and error process.

2.7. Accuracy assessment

The susceptibility maps were validated calculating the Area Under the Curve (AUC). AUC rates model quality in predicting target occurrences and non-occurrences, hence, susceptible to fire or not, at any point in the modelled area ([Arabameri et al., 2020](#)). AUC validation is frequently chosen for natural hazard models, based on its comprehensiveness and visually interpretable validation method ([Tehrany et al., 2019c](#); [Tshering et al., 2020](#); [Yilmaz, 2009](#)). Commencing by arranging the susceptibility index in descending order, it classifies the index into 100 categories represented on the

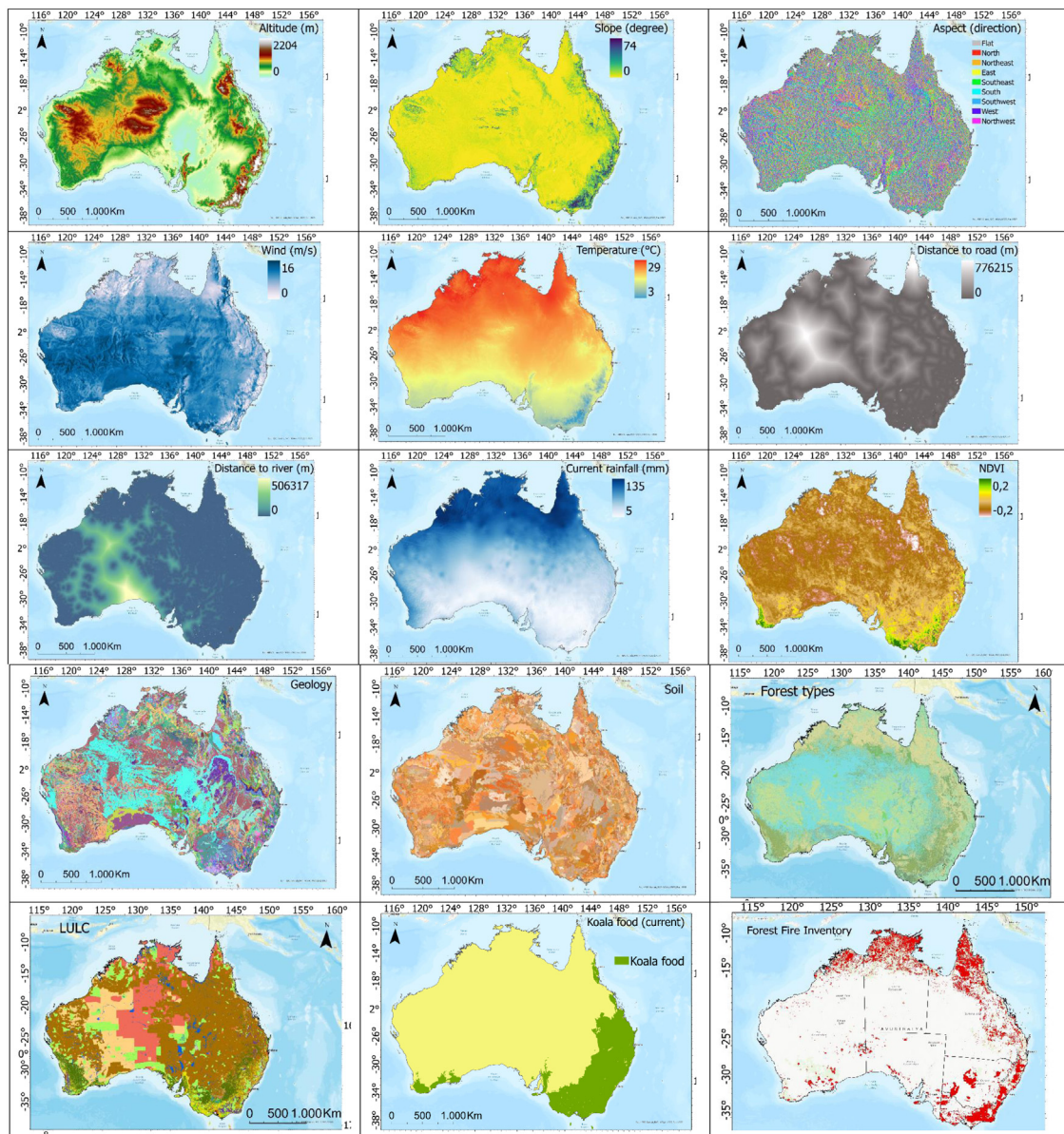


Fig. 2. Conditioning factors dataset at the continental scale. The 14 conditioning factors are elevation, slope, aspect, wind, temperature, road distance, river distance, rainfall, NDVI, 60 koala-browse species, geology, soil, forest types, and LULC. The wildfire inventory factors were obtained from the national Department of Agriculture, Water, and the Environment and other sources. Detailed results and maps of the state-based analysis are reported in the supplementary file.

y-axis, cumulative 1% intervals represented on the x-axis. By overlaying the fire inventory on the susceptibility index, the presence of training and testing fire points in each class can be evaluated, and the rates of prediction and success can be calculated (Tehrany et al., 2021). The closer the values are to 1 on the AUC 0-1 scale, the greater the accuracy of the technique. The fire training and testing datasets showed how method made accurate predictions. In the Australian continent analysis based on 1000 fire points, 700 events were reserved for training and 300 events for testing.

3. Results

3.1. Fire susceptibility index and DT tree structure

Modelling results at the continental scale under present time indicated that 14.9% of the entire country has a fire susceptibility index of “very high” and “high” (areas shown in red and orange colours in Fig. 3 and S5). Further, the

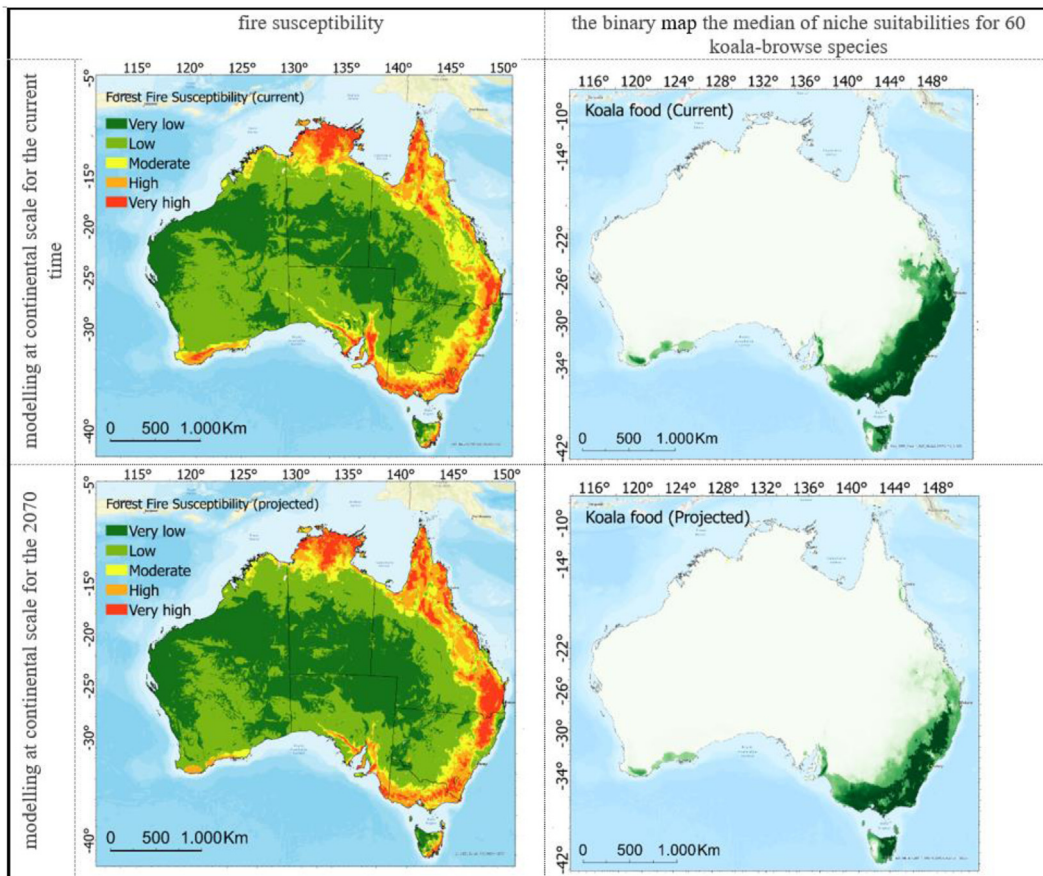


Fig. 3. Wildfire susceptibility index based on modelling at the continental scale and the location of koala-browse species for the present and projected for 2070.

spatial analysis indicated that 39.59% of the area suitable for koala browse species currently have “very high” or “high” fire susceptibility (Fig. 3). Results for 2070 indicated that 15.66% of the entire country would have a fire susceptibility index of “very high” and “high” (Fig. 3 and S5), and that 44.61% of the areas suitable for koala browse species would have “very high” and “high” fire susceptibility (Fig. 3). DT structure for the present at the continental scale identified the presence of koala browse species, altitude, and land use-land cover (LULC) as the most influential factors affecting fire susceptibility, while the most influential factors impacting wildfire distribution for 2070 were forest types, wind, presence of koala browse species, rainfall, and altitude (Refer to SI). In most areas, the DT also identified a northerly aspect as part of the most susceptible branch of DT, implying that the influence of this variable is considerably high (Refer to SI).

In each state and territory where koalas naturally inhabit, there has been an expansion in the extent of their habitat categorized as possessing a “high” or “very high” susceptibility to fire (refer to SI for state-specific outcomes). The findings reveal that within Queensland (QLD) and South Australia (SA), 65.24% and 89.11% of the entire koala habitat, respectively, are projected to exhibit a “very high” or “high” rating of fire susceptibility.

4. Discussion

The primary aim of our study was to assess fire susceptibility in koala habitat now and in the future. Using the dynamic Decision Tree machine learning algorithm, a series of fire susceptibility maps were generated (refer to SI). Modelling results at the continental scale showed a general increase of fire susceptibility, with the proportion of Australia experiencing “high” or “very high” fire susceptibility increasing from 14.9% now to 15.66% by 2070. Remarkably, 39.56% of the total habitat of koalas are in areas identified as having fire susceptibility index of “very high” and “high” now, and this percentage would likely increase to 44.61% by 2070. While a larger portion of the koala’s range is becoming highly susceptible to fire, it does not automatically imply habitat loss for them. Koalas may still be able to survive in these areas if: (1) their food sources can also withstand the fire-prone conditions, and (2) koalas can re-populate previously burnt-out areas from neighbouring habitat – a task that is becoming more difficult due to habitat fragmentation and the

increasingly large areas being burnt (Lunney et al., 2007, 2004, 2017; Matthews et al., 2007). However, koalas will walk many kilometres to relocate after fire (Matthews et al., 2016).

The state-based modelling results (Refer to SI) showed that fire susceptibility of koala habitat increased more in QLD and SA than in other states. By 2070, 65.24% and 89.11% of the total koala habitat (the main 60 koala-browse, eucalypt forests and woodlands) in QLD and SA are located in areas projected to have high or very high fire susceptibility (Fig. 3, also see SI). While many of the affected browse species have an inherent resilience to fire, the massive biogeographic and demographic impact of widespread wildfires may leave ecosystems declining on a landscape-scale, increasing their susceptibility to regeneration failure (Stevens-Rumann et al., 2018).

As yet, there is insufficient knowledge regarding the direct responses of forest species to megafires, with post-fire assessments tending to rely on expert opinion (Legge et al., 2022) or extrapolating the extent of fire coverage regardless of its severity/heat intensity (Ward et al., 2020). A forum of the Royal Zoological Society of NSW covered this theme with original contributions (Dickman et al., 2022; Ensbey et al., 2023). Continued research on the impact of megafire and the longer-term post-fire recovery is essential, given that cool, patchy burning may offer a tool for management in reducing severity in certain forests (Hislop et al., 2020; Lydersen et al., 2017).

The predicted increase in susceptibility to fire in koala habitat, together with the declining area of koala-suitable habitat (Shabani et al., 2019), will have a compounding impact on the historical trend that has led to their Red List status and national classification as *Vulnerable* (Law et al., 2017). Fires of greater severity will likely reduce the quality of koala habitats, increase fragmentation of habitats, and directly kill more koalas, invoking the genetic factors that end in the extinctions of isolated groups of a species via the loss of diversity (i.e., the extinction vortex). Research indicates that koala browsing of epicormic growth supports the recolonization of burned-out eucalypt forest and woodland around 18 months after the occurrence of a fire, (Matthews et al., 2016) but demographic data on koala population responses, particularly in the longer-term, is lacking. Indeed, populations can still be depressed by 63% a decade after a fire event (Legge et al., 2022).

We emphasize the importance of incorporating field validation as an integral component of habitat management. Mitchell et al. (2021) suggested that utilizing layered datasets, each with specific attributes, rather than mapping approaches that combine multiple habitat attributes into a single map, would offer greater flexibility and usefulness to stakeholders. This approach would enable stakeholders to utilize individual layers or combine them as needed for their specific requirements. Further, there are assumptions and limitations inherent in presence-only data, as well as in modelled projections based on climatic factors and envelopes. These include mismatches of scale and resolution (Wiens et al., 2009), dispersal barriers, novel biotic interactions, and limited documentation on projected natural disturbances (Elith et al., 2011). Nonetheless, koala-browse species projections over multiple time periods on the continental-scale offers a useful baseline for biogeographical interpretations and conservation application. According to our maps, Tasmania shows a significant amount of suitable habitat, which is less prone to wildfires compared to the mainland. While this opens up the possibility of translocating animals to the region, koalas have had a devastating impact in some areas they have been introduced to (Kangaroo Island (Masters et al., 2004) and the species has been identified as a potential threat to Tasmanian biodiversity (Department of Primary Industries Parks Water and Environment Tasmania Australia, 2011)). Indeed, our findings demonstrating the suitability of Tasmania for koalas emphasize the potential risk posed by their introduction to the region.

5. Conclusion

We investigated changes in the susceptibility of Australia's vegetation to wildfire between the present and 2070. Our results indicated a general increase in fire susceptibility across the country. Future fuel loads will reflect the impacts of changing climate, biomass growth, fuel decay, and fire consumption of fuel. Projecting the dynamics of future fire is linked to research on these factors. Through our study, we aimed to raise awareness among landscape managers regarding the limitations of habitat maps and the risks associated with fire susceptibility. Our goal is for this increased awareness to advance decision-making and habitat conservation of one of Australia's most iconic and vulnerable species.

CRedit authorship contribution statement

Farzin Shabani: Conceived and designed the experiments, Performed the experiments, Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Mahyat Shafapourtehrany:** Conceived and designed the experiments, Performed the experiments, Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Mohsen Ahmadi:** Conceived and designed the experiments, Performed the experiments, Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Bahareh Kalantar:** Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Haluk Özener:** Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Kieran Clancy:** Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Atefeh Esmaeili:** Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Ricardo Siqueira da Silva:** Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Linda J. Beaumont:** Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **John Llewelyn:** Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Simon Jones:** Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft. **Alessandro Ossola:** Analyzed the data, Contributed reagents/materials/analysis tools, Writing – original draft.

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.

Data availability

Data will be made available on request.

Acknowledgment

Open Access funding provided by the Qatar National Library.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.eti.2023.103331>.

References

- Adams-Hosking, C., Grantham, H., Rhodes, J., McAlpine, C., Moss, P., 2011a. Modelling climate-change-induced shifts in the distribution of the koala. *Wildl. Res.* 38 (2), 122–130.
- Adams-Hosking, C., McBride, M.F., Baxter, G., Burgman, M., De Villiers, D., Kavanagh, R., Lawler, I., Lunney, D., Melzer, A., Menkhorst, P., 2016. Use of expert knowledge to elicit population trends for the koala (*Phascolarctos cinereus*). *Divers. Distrib.* 22 (3), 249–262.
- Adams-Hosking, C., Moss, P., Rhodes, J., Grantham, H., McAlpine, C., 2011b. Modelling the potential range of the koala at the Last Glacial Maximum: future conservation implications. *Aust. Zool.* 35 (4), 983–990.
- Althuwaynee, O.F., Pradhan, B., Park, H.-J., Lee, J.H., 2014. A novel ensemble decision tree-based Chi-squared automatic interaction detection (CHAID) and multivariate logistic regression models in landslide susceptibility mapping. *Landslides* 11 (6), 1063–1078.
- Arabameri, A., Karimi-Sangchini, E., Pal, S.C., Saha, A., Chowdhuri, I., Lee, S., Tien Bui, D., 2020. Novel credal decision tree-based ensemble approaches for predicting the landslide susceptibility. *Remote Sens.* 12 (20), 3389.
- Austin, M., Van Niel, K., 2011. Impact of landscape predictors on climate change modelling of species distributions: a case study with *Eucalyptus fastigata* in southern New South Wales, Australia. *J. Biogeogr.* 38 (1), 9–19.
- Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W., Courchamp, F., 2012. Impacts of climate change on the future of biodiversity. *Ecol. Lett.* 15 (4), 365–377.
- Bhaduri, K., Wolff, R., Giannella, C., Kargupta, H., 2008. Distributed decision-tree induction in peer-to-peer systems. *Stat. Anal. Data Min. ASA Data Sci. J.* 1 (2), 85–103.
- Booth, T., 2013. Eucalypt plantations and climate change. *Forest Ecol. Manag.* 301, 28–34.
- Booth, T., 2017. Impacts of climate change on eucalypt distributions in Australia: an examination of a recent study. *Aust. For.* 80 (4), 208–215.
- Booth, T., Broadhurst, L., Pinkard, E., Prober, S., Dillon, S., Bush, D., Pinyopusarerk, K., Doran, J., Ivkovich, M., Young, A., 2015. Native forests and climate change: lessons from eucalypts. *Forest Ecol. Manag.* 347, 18–29.
- Bowman, D.M., Balch, J.K., Artaxo, P., Bond, W.J., Carlson, J.M., Cochrane, M.A., D'Antonio, C.M., DeFries, R.S., Doyle, J.C., Harrison, S.P., 2009. Fire in the earth system. *Science* 324 (5926), 481–484.
- Butt, N., Pollock, L., McAlpine, C., 2013. *Eucalypts* face increasing climate stress. *Ecol. Evol.* 3 (15), 5011–5022.
- Cai, W., Borlace, S., Lengaigne, M., Van Rensch, P., Collins, M., Vecchi, G., Jin, F.F., et al., 2014. Increasing frequency of extreme El Niño events due to greenhouse warming. *Nat. Clim. Chang.* 4 (2), 111–116.
- Carlson, C.J., Albery, G.F., Merow, C., Trisos, C.H., Zipfel, C.M., Eskew, E.A., Olival, K.J., Ross, N., Bansal, S., 2022. Climate change increases cross-species viral transmission risk. *Nature* 607 (7919), 555–562.
- Chen, I., Hill, J., Ohlemüller, R., Roy, D., Thomas, C., 2011. Rapid range shifts of species associated with high levels of climate warming. *Science* 333 (6045), 1024–1026.
- Cremen, G., Galasso, C., McCloskey, J., 2021. Modelling and quantifying tomorrow's risks from natural hazards. *Sci. Total Environ.* 152552.
- Department of Premier and Cabinet, (2020). Final Report of the NSW Bushfire Inquiry available at <https://www.dpc.nsw.gov.au/publications/categories/nsw-bushfire-inquiry/>.
- Department of Primary Industries Parks Water and Environment Tasmania Australia, 2011. Pest risk assessment; Koala (*Phascolarctos cinereus*). available at <https://nre.tas.gov.au/Documents/Koala-Pest-Risk-Assessment-.pdf>.
- Dickman, C.R., 2021. Ecological consequences of Australia's Black Summer bushfires: Managing for recovery. *Integr. Environ. Assess. Manag.* 17 (6), 1162–1167.
- Dickman, C.R., Hutchings, P., Law, B., Lunney, D., 2022. Raking over the ashes: assessing the impact of fire on native fauna in the aftermath of Australia's 2019–2020 fires. *Aust. Zool.* 42 (2), 643–653.
- Dimuccio, L.A., Ferreira, R., Cunha, L., de Almeida, A.C., 2011. Regional forest-fire susceptibility analysis in central Portugal using a probabilistic ratings procedure and artificial neural network weights assignment. *Int. J. Wildland Fire* 20 (6), 776–791.
- Dou, J., Yunus, A.P., Bui, D.T., Merghadi, A., Sahana, M., Zhu, Z., Chen, C.-W., Khosravi, K., Yang, Y., Pham, B.T., 2019. Assessment of advanced random forest and decision tree algorithms for modeling rainfall-induced landslide susceptibility in the Izu-Oshima Volcanic Island, Japan. *Sci. Total Environ.* 662, 332–346.
- Elith, J., Leathwick, J.R., 2009. Species distribution models: ecological explanation and prediction across space and time. *Annu. Rev. Ecol. Evol. Syst.* 40, 677–697.
- Elith, J., Phillips, S., Hastie, T., Dudík, M., Chee, Y., Yates, C., 2011. A statistical explanation of MaxEnt for ecologists. *Divers. Distrib.* 17 (1), 43–57.
- Ensby, M., Legge, S., Jolly, C.J., Garnett, S.T., Gallagher, R.V., Lintermans, M., Nimmo, D.G., Rumpff, L., Scheele, B.C., Whiterod, N.S., 2023. Animal population decline and recovery after severe fire: Relating ecological and life history traits with expert estimates of population impacts from the Australian 2019–20 megafires. *Biol. Cons.* 283, 110021.
- Eugenio, F.C., dos Santos, A.R., Fiedler, N.C., Ribeiro, G.A., da Silva, A.G., dos Santos, Á.B., Paneto, G.G., Schettino, V.R., 2016. Applying GIS to develop a model for forest fire risk: A case study in Espírito Santo, Brazil. *J. Environ. Manag.* 173, 65–71.

- Godfree, R.C., Knerr, N., Encinas-Viso, F., Albrecht, D., Bush, D., Christine Cargill, D., Clements, M., Gueidan, C., Guja, L.K., Harwood, T., 2021. Implications of the 2019–2020 megafires for the biogeography and conservation of Australian vegetation. *Nature Commun.* 12 (1), 1023.
- Gonzalez-Astudillo, V., Allavena, R., McKinnon, A., Larkin, R., Henning, J., 2017. Decline causes of Koalas in South East Queensland, Australia: a 17-year retrospective study of mortality and morbidity. *Sci. Rep.* 7 (1), 1–11.
- Gordon, G., Brown, A., Pulsford, T., 1988. A koala (*Phascolarctos cinereus* Goldfuss) population crash during drought and heatwave conditions in south-western Queensland. *Aust. J. Ecol.* 13 (4), 451–461.
- Habibullah, M.S., Din, B.H., Tan, S.-H., Zahid, H., 2022. Impact of climate change on biodiversity loss: global evidence. *Environ. Sci. Pollut. Res.* 29 (1), 1073–1086.
- Hijmans, R., Cameron, S., Parra, J., Jones, P., Jarvis, A., 2004. The WorldClim interpolated global terrestrial climate surfaces.
- Hislop, S., Stone, C., Haywood, A., Skidmore, A., 2020. The effectiveness of fuel reduction burning for wildfire mitigation in sclerophyll forests. *Aust. For.* 83 (4), 255–264.
- Hughes, L., 2003. Climate change and Australia: trends, projections and impacts. *Austral Ecol.* 28 (4), 423–443.
- Hughes, L., Cawsey, E., Westoby, M., 1996. Climatic range sizes of *Eucalyptus* species in relation to future climate change. *Global Ecol. Biogeography Lett.* 2, 3–29.
- IPCC, 2014. Mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change 1454. p. 147.
- Jaafari, A., Zenner, E.K., Pham, B.T., 2018. Wildfire spatial pattern analysis in the Zagros Mountains, Iran: A comparative study of decision tree based classifiers. *Ecol. Inform.* 43, 200–211.
- Jaiswal, R.K., Mukherjee, S., Raju, K.D., Saxena, R., 2002. Forest fire risk zone mapping from satellite imagery and GIS. *Int. J. Appl. Earth Obs. Geoinf.* 4 (1), 1–10.
- Jebur, M.N., Pradhan, B., Tehrany, M.S., 2014. Optimization of landslide conditioning factors using very high-resolution airborne laser scanning (LiDAR) data at catchment scale. *Remote Sens. Environ.* 152, 150–165.
- Jump, A., Penuelas, J., 2005. Running to stand still: adaptation and the response of plants to rapid climate change. *Ecol. Lett.* 8 (9), 1010–1020.
- Kadavi, P.R., Lee, C.-W., Lee, S., 2019. Landslide-susceptibility mapping in Gangwon-do, South Korea, using logistic regression and decision tree models. *Environ. Earth Sci.* 78 (4), 116.
- Keeley, J.E., Zedler, P.H., 2009. Large, high-intensity fire events in southern California shrublands: debunking the fine-grain age patch model. *Ecol. Appl.* 19 (1), 69–94.
- Kjeldsen, S.R., Raadsma, H.W., Leigh, K.A., Tobey, J.R., Phalen, D., Krockenberger, A., Zenger, K.R., et al., 2019. Genomic comparisons reveal biogeographic and anthropogenic impacts in the koala (*Phascolarctos cinereus*): a dietary-specialist species distributed across heterogeneous environments. *Heredity* 122 (5), 525–544.
- Landry, J.-S., Matthews, H.D., Ramankutty, N., 2015. A global assessment of the carbon cycle and temperature responses to major changes in future fire regime. *Clim. Change* 133, 179–192.
- Law, B., Caccamo, G., Roe, P., Trusking, A., Brassil, T., Gonsalves, L., McConville, A., Stanton, M., 2017. Development and field validation of a regional, management-scale habitat model: A koala *Phascolarctos cinereus* case study. *Ecol. Evol.* 7 (18), 7475–7489.
- Legge, S., Rumpff, L., Woinarski, J.C., Whiterod, N.S., Ward, M., Southwell, D.G., Scheele, B.C., Nimmo, D.G., Lintermans, M., Geyle, H.M., 2022. The conservation impacts of ecological disturbance: Time-bound estimates of population loss and recovery for fauna affected by the 2019–2020 Australian megafires. *Global Ecol. Biogeogr.*
- Lunney, D., Crowther, M., Wallis, I., Foley, W., Lemon, J., Wheeler, R., Madani, G., Orscheg, C., Griffith, J., Krockenberger, M., 2012. Koalas and climate change: a case study on the Liverpool Plains, north-west New South Wales. In: Lunney, D., Hutchings, P. (Eds.), *Wildlife and Climate Change: Towards Robust Conservation Strategies for Australian Fauna*. Royal Zoological Society of NSW, Mosman, NSW, Australia, pp. 150–168.
- Lunney, D., Gresser, S.M., Mahon, P.S., Matthews, A., 2004. Post-fire survival and reproduction of rehabilitated and unburnt koalas. *Biol. Cons.* 120 (4), 567–575.
- Lunney, D., Gresser, S., O'Neill, L.E., Matthews, A., Rhodes, J., 2007. The impact of fire and dogs on koalas at Port Stephens, New South Wales, using population viability analysis. *Pac. Conserv. Biol.* 13 (3), 189–201.
- Lunney, D., Moon, C., Sonawane, I., Predavec, M., Rhodes, J.R., 2022a. A 6-year study of mitigating koala roadkill during an upgrade of the Pacific Highway at Lindsay's cutting, Coffs Harbour New South Wales. *Aust. Mammal.* 44 (3), 305–318.
- Lunney, D., Predavec, M., Miller, I., Shannon, I., Fisher, M., Moon, C., Matthews, A., Turbill, J., Rhodes, J., 2016. Interpreting patterns of population change in koalas from long-term datasets in Coffs Harbour on the north coast of New South Wales. *Aust. Mammal.* 38 (1), 29–43.
- Lunney, D., Predavec, M., Sonawane, I., Kavanagh, R., Barrott-Brown, G., Phillips, S., Callaghan, J., Mitchell, D., Parnaby, H., Paull, D.C., 2017. The remaining koalas (*Phascolarctos cinereus*) of the Pilliga forests, north-west New South Wales: refugial persistence or a population on the road to extinction? *Pac. Conserv. Biol.* 23 (3), 277–294.
- Lunney, D., Predavec, M., Sonawane, I., Moon, C., Rhodes, J.R., 2022b. Factors that drive koala roadkill: an analysis across multiple scales in New South Wales, Australia. *Aust. Mammal.* 44 (3), 328–337.
- Lydersen, J.M., Collins, B.M., Brooks, M.L., Matchett, J.R., Shive, K.L., Povak, N.A., Kane, V.R., Smith, D.F., 2017. Evidence of fuels management and fire weather influencing fire severity in an extreme fire event. *Ecol. Appl.* 27 (7), 2013–2030.
- Masters, P., Duka, T., Berris, S., Moss, G., 2004. Koalas on Kangaroo Island: from introduction to pest status in less than a century. *Wildl. Res.* 31 (3), 267–272.
- Mathuria, M., 2013. Decision tree analysis on j48 algorithm for data mining. *Int. J. Adv. Res. Comput. Sci. Softw. Eng.* 3 (6).
- Matthews, A., Lunney, D., Gresser, S., Maitz, W., 2007. Tree use by koalas (*Phascolarctos cinereus*) after fire in remnant coastal forest. *Wildl. Res.* 34 (2), 84–93.
- Matthews, A., Lunney, D., Gresser, S., Maitz, W., 2016. Movement patterns of koalas in remnant forest after fire. *Aust. Mammal.* 38 (1), 91–104.
- Matusick, G., Ruthrof, K., Brouwers, N., Dell, B., Hardy, G., 2013. Sudden forest canopy collapse corresponding with extreme drought and heat in a mediterranean-type eucalypt forest in southwestern Australia. *Eur. J. For. Res.* 132 (3), 497–510.
- McAlpine, C.A., Callaghan, J., Lunney, D., Rhodes, J.R., Goldingay, R., Goulding, W., Adams-Hosking, C., Fielding, K., Hetherington, S.B., Brace, A., 2023. Influences on koala habitat selection across four local government areas on the far north coast of NSW. *Aust. Ecol.*
- McAlpine, C., Lunney, D., Melzer, A., Menkhorst, P., Phillips, S., Phalen, D., Ellis, W., Foley, W., Baxter, G., de Villiers, D., 2015. Conserving koalas: a review of the contrasting regional trends, outlooks and policy challenges. *Biol. Cons.* 192, 226–236.
- McAlpine, C., Rhodes, J., Callaghan, J., Bowen, M., Lunney, D., Mitchell, D., Pullar, D., Possingham, H., 2006. The importance of forest area and configuration relative to local habitat factors for conserving forest mammals: a case study of koalas in Queensland, Australia. *Biol. Cons.* 132 (2), 153–165.
- McCallum, H., Kerlin, D.H., Ellis, W., Carrick, F., 2018. Assessing the significance of endemic disease in conservation—koalas, chlamydia, and koala retrovirus as a case study. *Conserv. Lett.* 11 (4), e12425.
- Melzer, A., Carrick, F., Menkhorst, P., Lunney, D., John, B., 2000. Overview, critical assessment, and conservation implications of koala distribution and abundance. *Conserv. Biol.* 14 (3), 619–628.
- Mingers, J., 1989. An empirical comparison of selection measures for decision-tree induction. *Mach. Learn.* 3 (4), 319–342.

- Mitchell, D.L., Soto-Berelov, M., Langford, W.T., Jones, S.D., 2021. Factors confounding koala habitat mapping at multiple decision-making scales. *Ecol. Manag. Restor.* 22 (2), 171–182.
- Mok, H., Arndt, S., Nitschke, C., 2012. Modelling the potential impact of climate variability and change on species regeneration potential in the temperate forests of South-Eastern Australia. *Global Change Biol.* 18 (3), 1053–1072.
- Murthy, S.K., 1998. Automatic construction of decision trees from data: A multi-disciplinary survey. *Data Min. Knowl. Discov.* 2 (4), 345–389.
- Myles, A.J., Feudale, R.N., Liu, Y., Woody, N.A., Brown, S.D., 2004. An introduction to decision tree modeling. *J. Chemom. J. Chemom. Soc.* 18 (6), 275–285.
- Nefeslioglu, H., Sezer, E., Gokceoglu, C., Bozkir, A., Duman, T., 2010. Assessment of landslide susceptibility by decision trees in the metropolitan area of Istanbul, Turkey. *Math. Probl. Eng.* 2010.
- Parmesan, C., Yohe, G., 2003. A globally coherent fingerprint of climate change impacts across natural systems. *Nature* 421 (6918), 37–42.
- Pollock, L.J., Tingley, R., Morris, W.K., Golding, N., O'Hara, R.B., Parris, K.M., Vesik, P.A., McCarthy, M.A., 2014. Understanding co-occurrence by modelling species simultaneously with a Joint Species Distribution Model (JSDM). *Methods Ecol. Evol.* 5 (5), 397–406.
- Pourghasemi, H.R., Beheshtirad, M., Pradhan, B., 2016. A comparative assessment of prediction capabilities of modified analytical hierarchy process (M-AHP) and mamdani fuzzy logic models using Netcad-GIS for forest fire susceptibility mapping. *Geomat. Nat. Hazards Risk* 7 (2), 861–885.
- Pourtaghi, Z.S., Pourghasemi, H.R., Aretano, R., Semeraro, T., 2016. Investigation of general indicators influencing on forest fire and its susceptibility modeling using different data mining techniques. *Ecol. Indic.* 64, 72–84.
- Pradhan, B., 2010. Application of an advanced fuzzy logic model for landslide susceptibility analysis. *Int. J. Comput. Intell. Syst.* 3 (3), 370–381.
- Rupasinghe, R., Chomel, B.B., Martínez-López, B., 2022. Climate change and zoonoses: A review of the current status, knowledge gaps, and future trends. *Acta Trop.* 226, 106225.
- Saito, H., Nakayama, D., Matsuyama, H., 2009. Comparison of landslide susceptibility based on a decision-tree model and actual landslide occurrence: the Akaishi Mountains, Japan. *Geomorphology* 109 (3–4), 108–121.
- Salafsky, N., Salzer, D., Stattersfield, A.J., Hilton-Taylor, C., Neugarten, R., Butchart, S.H., Collen, B., Cox, N., Master, L.L., O'Connor, S., 2008. A standard lexicon for biodiversity conservation: unified classifications of threats and actions. *Conserv. Biol.* 22 (4), 897–911.
- Santika, T., McAlpine, C., Lunney, D., Wilson, K., Rhodes, J., 2014. Modelling species distributional shifts across broad spatial extents by linking dynamic occupancy models with public-based surveys. *Divers. Distrib.* 20 (7), 786–796.
- Sari, F., 2021. Forest fire susceptibility mapping via multi-criteria decision analysis techniques for Mugla, Turkey: A comparative analysis of VIKOR and TOPSIS. *Forest Ecol. Manag.* 480, 118644.
- Sequeira, A., Roetman, P., Daniels, C., Baker, A., Bradshaw, C., 2014. Distribution models for koalas in South Australia using citizen science-collected data. *Ecol. Evol.* 4 (11), 2103–2114.
- Shabani, F., Ahmadi, M., Peters, K., Haberle, S., Champreux, A., Saltré, F., Bradshaw, C., 2019. Climate-driven shifts in the distribution of koala browse species from the last interglacial to the near future. *Ecography* 42 (9), 1587–1599.
- Simmons, J.B., Paton-Walsh, C., Mouat, A.P., Kaiser, J., Humphries, R.S., Keywood, M., Sutresna, A., Griffith, D.W., Naylor, T., Ramirez-Gamboa, J., 2021. The gas and aerosol phase composition of smoke plumes from the 2019–2020 black summer bushfires and potential implications for human health.
- Stevens-Rumann, C.S., Kemp, K.B., Higuera, P.E., Harvey, B.J., Rother, M.T., Donato, D.C., Morgan, P., Veblen, T.T., 2018. Evidence for declining forest resilience to wildfires under climate change. *Ecol. Lett.* 21 (2), 243–252.
- Strona, G., Bradshaw, C., 2018. Co-extinctions annihilate planetary life during extreme environmental change. *Sci. Rep.* 8 (1), 16724.
- Tehrany, M.S., Jones, S., Shabani, F., 2019a. Identifying the essential flood conditioning factors for flood prone area mapping using machine learning techniques. *Catena* 175, 174–192.
- Tehrany, M.S., Jones, S., Shabani, F., Martínez-Álvarez, F., Tien Bui, D., 2019b. A novel ensemble modeling approach for the spatial prediction of tropical forest fire susceptibility using LogitBoost machine learning classifier and multi-source geospatial data. *Theor. Appl. Climatol.* 137 (1), 637–653.
- Tehrany, M.S., Kumar, L., Shabani, F., 2019c. A novel GIS-based ensemble technique for flood susceptibility mapping using evidential belief function and support vector machine: Brisbane, Australia. *PeerJ* 7, e7653.
- Tehrany, M.S., Özener, H., Kalantar, B., Ueda, N., Habibi, M.R., Shabani, F., Saeidi, V., Shabani, F., 2021. Application of an ensemble statistical approach in spatial predictions of bushfire probability and risk mapping. *J. Sens.* 2021.
- Thomas, C., Cameron, A., Green, R., Bakkenes, M., Beaumont, L., Collingham, Y., Erasmus, B., De Siqueira, M., Grainger, A., Hannah, L., 2004. Extinction risk from climate change. *Nature* 427 (6970), 145–148.
- Tshering, K., Thinley, P., Shafapour Tehrany, M., Thinley, U., Shabani, F., 2020. A comparison of the qualitative analytic hierarchy process and the quantitative frequency ratio techniques in predicting forest fire-prone areas in Bhutan using GIS. *Forecasting* 2 (2), 36–58.
- Urban, M., 2015. Accelerating extinction risk from climate change. *Science* 348 (6234), 571–573.
- Vadrevu, K.P., Eaturu, A., Badarinath, K., 2006. Spatial distribution of forest fires and controlling factors in andhra pradesh, India using spot satellite datasets. *Environ. Monit. Assess.* 123 (1), 75–96.
- Varol, T., Canturk, U., Cetin, M., Ozel, H.B., Sevik, H., Zeren Cetin, I., 2022. Identifying the suitable habitats for Anatolian boxwood (*Buxus sempervirens* L.) for the future regarding the climate change. *Theor. Appl. Climatol.* 150 (1–2), 637–647.
- Vieira, L., Sobral-Souza, T., Spector, S., Vaz-de Mello, F.Z., Costa, C.M., Louzada, J., 2022. Synergistic effects of climate and human-induced landscape changes on the spatial distribution of an endangered dung beetle. *J. Insect Conserv.* 26 (2), 315–326.
- Ward, M., Tulloch, A.I., Radford, J.Q., Williams, B.A., Reside, A.E., Macdonald, S.L., Mayfield, H.J., Maron, M., Possingham, H.P., Vine, S.J., 2020. Impact of 2019–2020 mega-fires on Australian fauna habitat. *Nat. Ecol. Evol.* 4 (10), 1321–1326.
- Wiens, J., Stralberg, D., Jongsomjit, D., Howell, C., Snyder, M., 2009. Niches, models, and climate change: assessing the assumptions and uncertainties. *Proc. Natl. Acad. Sci.* 106 (Supplement 2), 19729–19736.
- Witten, I.H., Frank, E., 2002. Data mining: practical machine learning tools and techniques with java implementations. *ACM Sigmod Rec.* 31 (1), 76–77.
- Yilmaz, I., 2009. Landslide susceptibility mapping using frequency ratio, logistic regression, artificial neural networks and their comparison: a case study from Kat landslides (Tokat–Turkey). *Comput. Geosci.* 35 (6), 1125–1138.
- You, W., Lin, L., Wu, L., Ji, Z., Zhu, J., Fan, Y., He, D., 2017. Geographical information system-based forest fire risk assessment integrating national forest inventory data and analysis of its spatiotemporal variability. *Ecol. Indic.* 77, 176–184.