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Examining wildfire dynamics using ECOSTRESS data with machine learning approaches: the case of South-Eastern Australia's black summer

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Wildfires are increasing in risk and prevalence. The most destructive wildfires in decades in Australia occurred in 2019–2020. However, there is still a challenge in developing effective models to understand the likelihood of wildfire spread (susceptibility) and pre-fire vegetation conditions. The recent launch of NASA's ECOSTRESS presents an opportunity to monitor fire dynamics with a high resolution of 70 m by measuring ecosystem stress and drought conditions preceding wildfires. We incorporated ECOSTRESS data, vegetation indices, rainfall, and topographic data as independent variables and fire events as dependent variables into machine learning algorithms applied to the historic Australian wildfires of 2019–2020. With these data, we predicted over 90% of all wildfire occurrences 1 week ahead of these wildfire events. Our models identified vegetation conditions with a 3-week time lag before wildfire events in the fourth week and predicted the probability of wildfire occurrences in the subsequent week (fifth week). ECOSTRESS water use efficiency (WUE) consistently emerged as the leading factor in all models predicting wildfires. Results suggest that the pre-fire vegetation was affected by wildfires in areas with WUE above 2 g C kg^{-1} H_2O at 95% probability level. Additionally, the ECOSTRESS evaporative stress index and topographic slope were identified as significant contributors in predicting wildfire susceptibility. These results indicate a significant potential for ECOSTRESS data to predict and analyze wildfires and emphasize the crucial role of drought conditions in wildfire events, as evident from ECOSTRESS data. Our approaches developed in this study and outcome can help policymakers, fire managers, and city planners assess, manage, prepare, and mitigate wildfires in the future.

Introduction

Wildfires have increased in severity and intensity worldwide (Bowman & Sharples, 2023; Lindenmayer & Taylor, 2020). These have sparked significant concern due to their destructive impacts on the environment, climate, communities, human well-being, and economies (Filkov et al., 2020). Among the common sources of wildfires are human activity and natural causes such as lightning strikes, with climate change increasing susceptibility and exacerbating conditions (Lewis et al., 2015). Therefore, reliable wildfire susceptibility models are essential to ensure public safety, natural resource planning, and risk management. Such models could help identify areas with higher fire risk, enabling authorities to prioritize monitoring and resource allocation in those vulnerable regions, even with limited resources (Whitburn et al., 2016).

The robustness and sensitivity of models rely heavily on available data. Before the advent of remote sensing, wildfire occurrences were collected mainly by post-fire field surveys, which were time-consuming and often lacked ignition points (Lim et al., 2019). However, with the introduction of remote sensing methods and satellite monitoring systems, spatially comprehensive datasets are available on demand. This has helped researchers in quantifying climate, topographical, and human factors toward the contribution of wildfires around the world. Fire data products, such as the Moderate Resolution Imaging Spectroradiometer (MODIS), are currently freely available online, enabling access to the timing and spatial distribution of fires and their characteristics worldwide (Wulder et al., 2012).

The variables to predict wildfires can be categorized into topography, vegetation, climate, and human activities (Abram et al., 2021; Fernández-Guisuraga et al., 2023; Ganteaume et al., 2013; Nami et al., 2018; Parisien et al., 2012). Topographic effects on wildfire (e.g., slope, aspect, and elevation) are primarily indirect by influencing the type of vegetation, local climate, and human accessibility (Jaafari et al., 2017; Nami et al., 2018; Parisien et al., 2012). These factors also have direct impacts on wildfire intensity (Cheney & Sullivan, 2008), spread rate (Morandini et al., 2018), and risk of ignition (Calviño-Cancela et al., 2017). Climate variables (rainfall, temperature, humidity, and wind) directly and indirectly influence wildfire events (Jaafari et al., 2017; Nami et al., 2018; Parisien et al., 2012). Recent studies show that heat extremes and drought associated with climate change also make our environment increasingly vulnerable to devastating wildfires (Bowman et al., 2017; Deb et al., 2020; Halofsky et al., 2020; Lim et al., 2019). Several studies over the past century have observed that the fire frequency and area burned correlated with air temperature and precipitation variability, thus increasing the concern over the impact of climate change (Bergeron & Flannigan, 1995; Fried et al., 2004; Zhang et al., 2015). Vegetation (land cover), on the other hand, affects wildfire and fire spread through fuel characteristics such as vegetation type, water availability, evapotranspiration (ET), and evaporative stress index (ESI), affecting the moisture in the plants and fuel load (Archibald et al., 2018; Fisher et al., 2017; Nami et al., 2018). These variables are widely used to analyze and understand burn severity, susceptibility, and occurrences of wildfire (Harrison et al., 2021; Pascolini-Campbell et al., 2022; Pimont et al., 2021).

ECOSTRESS was launched by NASA in June 2018, providing thermal infrared measurements and subsequent science products with approximately 70 m spatial resolution on the ground (Fisher et al., 2020). Data from ECOSTRESS primarily addresses how water availability affects key climate biomes worldwide, drought estimation, and agricultural vulnerability (Anderson et al., 2021; Cooley et al., 2022; Doughty et al., 2023; Fisher et al., 2020; Hamberg et al., 2022). ECOSTRESS also provides these high spatial resolution thermal data at the highest available temporal resolution (1–5 days), allowing researchers and fire management agencies to monitor land surface conditions and respond more effectively to fire risk conditions. ECOSTRESS shows how ecosystems change with climate and creates a crucial link between the water cycle and natural and human-inflicted plant health (Fisher et al., 2017). ET data acquired throughout the day enables the evaluation and measurement of plant stress imposed by seasonal drought and wildfire (Pascolini-Campbell et al., 2022; Poulos et al., 2021). ECOSTRESS offers superior spatiotemporal resolution and the ability to monitor diurnal cycles compared to previous studies (Li et al., 2021; Wen et al., 2022; Xiao et al., 2021). Recent studies have demonstrated that ECOSTRESS-based predictors (ET and ESI) revealed promising relationships between pre-/post-fire vegetation conditions and burn severity, attributing to its ability to monitor and assess the daily patterns of plant stress induced by seasonal drought and wildfires (Hatch et al., 2022; Pascolini-Campbell et al., 2022; Poulos et al., 2021). However, the challenge lies in integrating these variables into predictive models to capture the complex interactions between vegetation stress, environmental conditions, and wildfire dynamics. Further research is needed to understand better how ECOSTRESS data can evaluate pre-fire vegetation conditions and determine wildfire susceptibility.

To predict wildfire events, fire weather indices (FWI) were among the first probability mapping trials. FWI is commonly used to define an area's seasonal and long-time forest fire hazard, produced from environmental factors such as weather data (dry bulb temperature, humidity, wind speed, etc.) to calculate fire danger rating and fuel moisture content (Fosberg, 1978; Srock et al., 2018). This led to the development of spatial models to predict wildfire susceptibility using geographic information systems (GIS) and remote sensing (RS), implemented in different approaches, such as fuzzy logic and the analytical network process (ANP) (Tonini et al., 2020). The conventional parametric statistical modeling techniques, such as fuzzy logic by weighting inputs, may be problematic because of subjective ranking (Satir et al., 2016). An alternative approach is to learn the complex nonlinear relationships associated with fire directly from observational and numerical data modeling using machine learning algorithms (Bui et al., 2018). Recently, machine learning algorithms such as neural networks, support vector machine, random forest (RF), and logistic regression (LR) classifiers have achieved reasonably reliable results in various natural hazard susceptibility mapping studies (Satir et al., 2016). On the other hand, the geographically weighted regression (GWR) algorithm proves to be an effective technique in understanding spatial autocorrelation by connecting multiple local regression models at each data point and weighting all results from the point as a function of distance (Fotheringham et al., 2003; Koutsias et al., 2010; Wang et al., 2005). However, designing wildfire models that effectively incorporate machine learning algorithms to capture pre-fire vegetation conditions remains challenging.

Combining the recent advances in remote measurement (ECOSTRESS) and machine learning for wildfire prediction, this study aims to bridge these capabilities by developing effective wildfire susceptibility models that provide insights into pre-fire vegetation conditions. To this aim, we designed models that incorporate pre-fire vegetation conditions obtained from ECOSTRESS data to predict the probability of future wildfire occurrence. These models make use of various biophysical factors, including MODIS MCD64A1 fire product, digital elevation model (DEM), slope, aspect, ECOSTRESS data (i.e., ET, ESI, land surface temperature—LST, water use efficiency—WUE), NDVI generated from Sentinel-2 data, and rainfall data. The predictability of models and biophysical factors were assessed to understand pre-fire vegetation conditions and wildfire susceptibility (the likelihood or potential of an area experiencing wildfires to indicate the possibility of wildfire occurrence). Finally, we delve into the biophysical factors and their possible applications to enhance operational fire suppression and management.

Materials and Methods

Study area

Our study focuses on the south-eastern region of Australia (Fig. 1). The climate over the region is characterized as temperate, with December and January being the hottest months (Hennessy et al., 2005). In recent years, the south-eastern part has been experiencing increasing frequency of wildfires. However, the 2019–2020 bushfire season was unprecedented in intensity and devastation. It is widely known as 'Black Summer.' Throughout the summer, multiple fires scorched large tracts of land in Victoria and New South Wales of Australia, resulting in 34 fatalities and huge losses of land and wildlife (Bushfires in Victoria—Research Guides, 2020). Fires were ignited in September 2019 and were contained by early March 2020. The state of New South Wales had the highest number of homes lost (2439), followed by Victoria (396). The Black Summer was the worst bushfire season on the state of Victoria's record. New South Wales also experienced the longest continuous burning in the history of Australia's bushfires. It consumed more than 4 million hectares.

The most predominant land cover types in Southeast Australia are hummock grasslands and eucalypt woodlands (Williams et al., 2015). In general, Australia is known to be the lowest-elevation continent in the world, with an elevation averaging 330 m. The highest points on the other continents are all more than twice the height of Australia's highest peak, Mount Kosciuszko, which is 2228 m above sea level.

Data Acquisition and Processing

We chose 2019–2020 data to examine wildfire dynamics, driven by the extreme nature of the fire season, the availability of high-resolution ECOSTRESS data, and the goal of developing robust models capable of depicting severe wildfire events. We used nine variables from four sources as explanatory variables (Table 1). Fire occurrences, referring to actual wildfires, were obtained between September 2019 and March 2020 using the MODIS MCD64A1 (500 m resolution) product (Giglio et al., 2022). These data served as independent variables for building and validating the models and were created to record the presence and absence of fires, classified as 0 and 1, respectively. The centroid pixel points of fire occurrences were then used to align with corresponding values from the ECOSTRESS dataset. Rainfall data were obtained from the Bureau of Meteorology, Australia, for all 7 months, which was then compiled and interpolated using the Inverse Distance Weighting method. DEM derivatives such as slope and aspect were also created. Sentinel-2 L2A data at a resolution of 10 m were used to compute NDVI. This NDVI data was then resampled to match the 70 m resolution of the ECOSTRESS dataset. ECOSTRESS data products, including ET, evaporative stress index (ESI), land surface temperature (LST), and water use efficiency (WUE), acquired from NASA LPDAAC AppEARS, were used to model wildfire dynamics (Fisher et al., 2020; Zhu et al., 2022). A mosaic dataset in a raster format was created for each variable over the 7 months between September 2019 and March 2020. All the selected variables of raster images were resampled to ECOSTRESS datasets to ensure that they were harmonized for subsequent analysis.

Our model aims to understand wildfire susceptibility and pre-fire vegetation conditions. Susceptibility in this study refers to the likelihood or potential of an area experiencing wildfires, indicating the overall possibility of wildfire occurrence. Fire occurrence probability is a numerical value ranging from 0 to 1, quantifying this likelihood. These concepts are closely related to each other. Susceptibility is the broader concept that reflects the potential for wildfire, while fire occurrence probability provides a precise, quantitative measure of that potential. An increase in fire occurrence probability directly correlates with greater susceptibility. Pre-fire vegetation condition is quantified using NDVI, ET, ESI, LST, and WUE for a particular fire season. These variables were calculated during the fire season, aligning with our study's

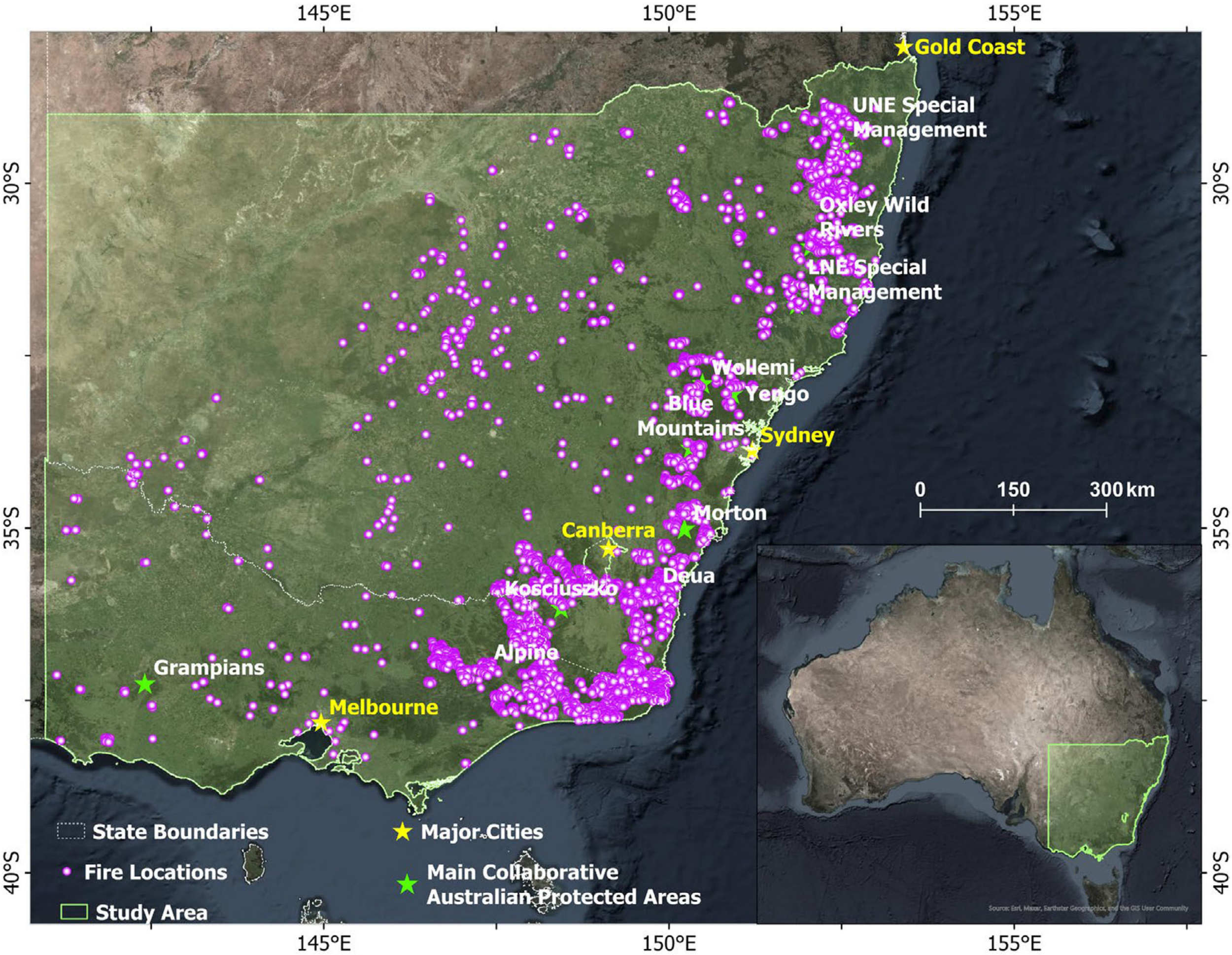

Figure 1. Study area showing ground fire locations in 2019–2020 from MODIS.

focus on the biophysical conditions of vegetation that directly influence fire susceptibility prior to wildfire events. We focused on these explanatory variables contributing to wildfire dynamics rather than specific ignition sources (such as lightning strikes or human activities), which are essential for understanding the initiation of fires. This approach permits us to concentrate on the factors contributing to wildfire susceptibility and pre-fire vegetation conditions, particularly under extreme climate conditions such as those experienced during the 2019–2020 'Black Summer' in South-Eastern Australia.

Design of wildfire models

Two categories of models were developed in this study: general models and monthly models. The general models provide an overarching view of wildfire susceptibility throughout the season, while the monthly models delve into specific time frames. The monthly models build on the insights gained from the general models to provide a finer temporal resolution for understanding and predicting wildfire risk. In essence, the general models set the stage for broader patterns, while the monthly models zoom in on critical periods, offering complementary perspectives on wildfire dynamics.

The general models were explicitly constructed to estimate wildfire susceptibility and quantify the significance of input biophysical factors over the entire wildfire period from September 2019 to March 2020. These models utilized the mean values of explanatory variables at each pixel location within the study area throughout this period as independent input variables, with the samples collected from MODIS ground fire points during 2019–2020 serving as the dependent variable. The study integrated a range of explanatory variables, including ECOSTRESS data, vegetation indices, climatic parameters, and topographical factors to quantitatively assess their respective impacts on wildfire prediction.

Table 1. Explanatory variables used in this research and their data sources.

Category	Explanatory variables	Source
ECOSTRESS	Evapotranspiration (ET) Evaporative stress index (ESI) Land surface temperature (LST) Water use efficiency (WUE)	70 m resolution ECOSTRESS data from LPDAAC AppEARS https://lpdaacsvc.cr.usgs.gov/appeears/
Vegetation Index	Normalized Difference Vegetation Index (NDVI)	SENTINEL-2 Data (10 m resolution, band 4 and 8 is used) https://scihub.copernicus.eu/dhus/#/home
Climate	Rainfall	Bureau of Meteorology, Australia http://www.bom.gov.au/climate/data/
Topography	Elevation	9 arc-second DEM (~250 m resolution) from Geoscience Australia (Hutchinson et al., 2008)
	Slope Aspect	Derived from DEM

To facilitate an efficient allocation of resources, policy implementation, and response to the unique characteristics and demands of specific urban areas, we conducted an evaluation of wildfire susceptibility for cities in South-Eastern Australia. The results of general models were used to assess the extent of fire-affected areas. Meanwhile, we implemented a 5 km radial buffer around the boundaries of each city, following the methodology outlined in Chen et al. (2022). Such analysis considered the extended area of every existing fire object and the temporal spread of fires in proximity, allowing for a more accurate evaluation of each city's susceptibility. Subsequently, we calculated the mean value of the predicted wildfire susceptibility (occurrence probability) within the buffer area to provide a representative measure of the cities' wildfire susceptibility.

The monthly models were designed to capture pre-fire vegetation conditions and predict wildfire spread 1 week ahead. We set up a 3-week time lag for data collection prior to a wildfire event in the fourth week and predict the wildfire susceptibility in the following week (fifth week) using a real-world record of wildfire events. The mean values of the selected data in 3 weeks were computed to minimize or eliminate gaps. The model, for example, to predict wildfire susceptibility in the first week of September (September 1–7), was built using the mean values of explanatory variables during a three-week time from August 1 to August 21. Such a design is to create an effective model to predict wildfire spread and assess the impact of pre-fire plant stress on following wildfire occurrence. The workflow diagram of monthly models is shown in Figure 2. The Australian bushfires started to spread in the first week of September 2019 and faded in early April 2020. The fires ceased at the end of October 2019 in south-eastern Australia and reignited in late November 2019. To understand the impact of change in the climate condition of the country after the first fire and to effectively assess the fire influential factor, we built three monthly models to predict (1) the first week of September (the week when the first wildfire started), (2) the last week of November, and (3) the first week of December (the weeks when the second fire started).

In general, a machine learning approach is based on algorithms that have the capacity to effectively learn from data and make accurate assessments or predictions. This learning process involves modeling the hidden relationships between a set of input variables (explanatory variables) and the occurrences of the phenomenon (the dependent variable) (Tonini et al., 2020). We randomly acquired 2037 wildfire occurrence points within the study area in total. Of these, 70% (1426 wildfire occurrence points) were allocated for training, while the remaining 30% (611 wildfire occurrence points) were reserved for validation. Here, we evaluated LR, GWR, and RF algorithms to create models that fit relationships between wildfire events and the explanatory variables. The fit relationships from these models were then used in the susceptibility mapping and assessment of variable influence. Linear regression (LR), in particular, demands the independence of explanatory variables. To mitigate the impact of the correlation between these variables, we employed a regularization technique using LASSO (L1 regularization). LASSO penalizes the coefficients of correlated variables, prompting the LR model to favor a subset of independent variables and enhance model robustness. Meanwhile, we incorporated the global forest loss due to fire data between 2019 and 2020 (Tyukavina et al., 2022) to validate our results. This dataset maps forest loss due to fire and matches sample-based area estimates ±SE for all continents except Africa.

In this study, we employed three methods (LR, GWR, and RF) to quantify the importance of input variables in our wildfire susceptibility models. Before applying LR and GWR, we normalized the explanatory variables to a common scale based on their observed maximum and minimum values derived from zonal statistics (Steel et al., 2021; Zhu et al., 2022). This normalization ensures equal levels of contributions from all variables. Such scaling facilitates straightforward comparison and interpretation of variable importance. In the LR model, variable

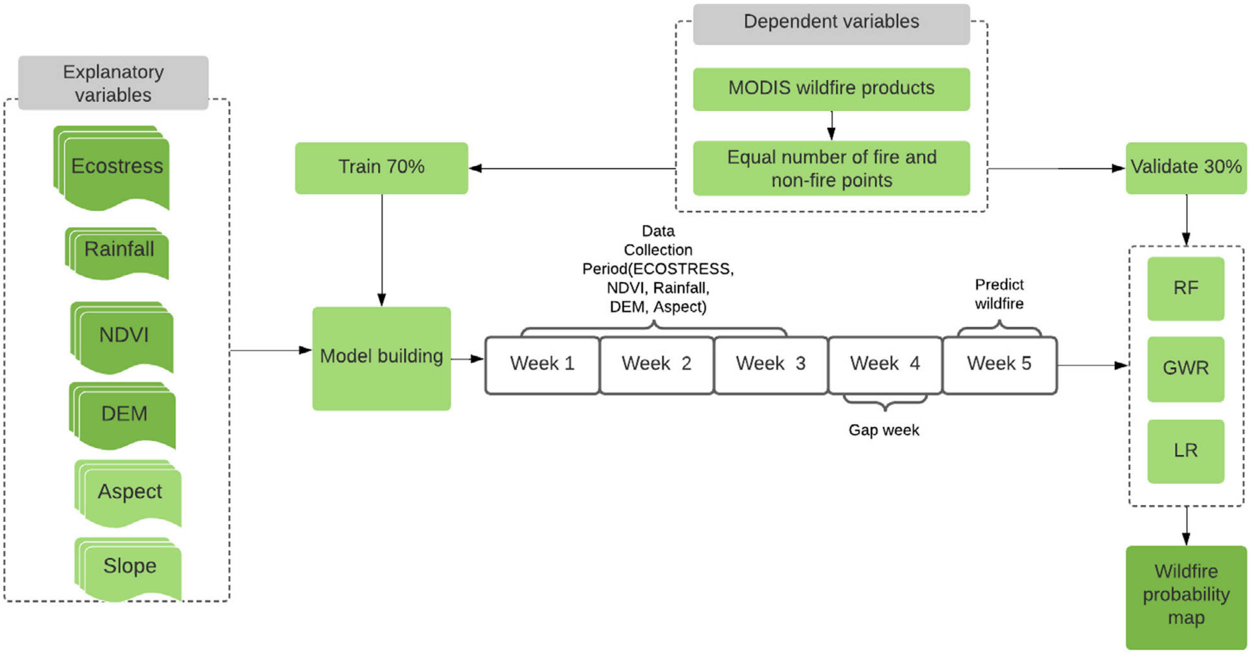

Figure 2. Workflow diagram of the monthly models for the wildfire susceptibility (occurrence probability) map.

importance was quantified using the coefficients derived from the regression, with larger coefficients indicating greater importance in influencing wildfire susceptibility. For GWR, the importance of each variable was determined by calculating the mean of the standardized coefficients from the local models of parameter estimates (Fotheringham et al., 2003). In the RF model, the importance of each input variable was quantified using the mean decrease in accuracy, which assesses the difference in out-of-bag model error between the original dataset and a dataset with the input variable randomly permuted (Liaw & Wiener, 2002).

Our training and validation samples from the MODIS MCD64A1 product record the binary 1 (presence) and 0 (absence) of fires. Therefore, to evaluate the accuracies of wildfire susceptibility modeling, we categorized pixels as either fire or non-fire based on a probability threshold of 0.5. Pixels with a probability greater than 0.5 were identified as fire pixels, while those with a probability of 0.5 or less were identified as non-fire pixels. This binary classification was used to assess the models' performance in predicting fire susceptibility.

Results

The main results of this study are presented as (1) assessing the model performance to evaluate stability and consistency; (2) identifying the cause of fire occurrences by understanding the importance of explanatory variables; and (3) susceptibility mapping, which includes predicting wildfire susceptibility and assessing the cities at risk of wildfire spread.

Model results and accuracy assessment

Given the set of explanatory variables as inputs, we mapped the wildfire susceptibility for each pixel using three models—LR, GWR, and RF. The models were developed to predict wildfire susceptibility for the entire wildfire period (general models), the first week of September, the last week of November, and the first week of December. The performance of these models was assessed through a confusion matrix (Table 2). Overall, the accuracy of all models exceeded 83%, demonstrating the built models' effectiveness by utilizing ECOSTRESS, topography, climate, and vegetation factors. RF produced the highest overall accuracy (91%) for the general model, compared to LR (83%) and GWR (84%). Overall, the general models performed worse than the monthly models except for the RF model for December prediction. LR models showed consistent accuracy (between 83% and 88%) for the general and monthly models. GWR for the general model (84%) has a significantly lower accuracy than monthly models, with more than 92%. RF models present an impressive overall accuracy for the general and monthly models, with more than 90%, except for the model of December (85%).

Table 2. The overall accuracy assessments of wildfire susceptibility models.

Models	Logistic regression	Geographically weighted regression	Random forest
General models	83%	84%	91%
Monthly models			
Sep	83%	95%	92%
Nov	85%	93%	92%
Dec	88%	96%	85%

Importance of explanatory variables

Regression coefficients obtained from LR and GWR models and the relative importance of RF were used to determine the significance of explanatory variables (Table 3). These metrics were used to comprehensively assess the significance of the explanatory variables across different models. General models were created using data from September to March 2020 and monthly models for September, November, and December. Variables from ECOSTRESS, vegetation index, climate, and topography exhibit varying ranks in different models due to their diverse characteristics across models. However, despite these ranking variations, ECOSTRESS WUE consistently emerges as the most significant variable in predicting wildfire susceptibility in the evaluations of both general and monthly models. In the general models, WUE consistently secures the first position in LR and RF and holds the third rank in GWR. Moreover, it consistently ranks in the top four variables in monthly models, except for the September and December models of GWR. The following top-ranking variables are ESI and Slope, significantly contributing to wildfire susceptibility predictions. Other variables, like NDVI and rainfall, also contribute to these predictions. In contrast, aspect, LST, and elevation consistently rank as the least significant variables in these models. Some coefficients are zero in LR with LASSO indicating that the corresponding features are not realistically contributing to the model. This particular procedure essentially excludes these unproductive features from the predictive equation. This is how LASSO penalty effectively performed feature selection.

When comparing the variations among different models, it becomes evident that the variable rankings in general models across various algorithms exhibit better consistency and stability than the monthly model rankings. Specifically, the general models, such as LR and RF, demonstrate similar variable rankings, while GWR shows slight variations from them. The monthly models also yield results similar to the general models, albeit with slightly higher variations in variable rankings. Overall, LR general and monthly models in variable rankings are more stable than RF and GWR.

Based on the analyses above, it is noteworthy that ECOSTRESS WUE consistently ranks as the top-ranking variable. Statistical analysis of fire occurrence was conducted concerning the data ranges of these main predictor variables to delve deeper into their impact based on the general model of LR. This can examine pre-fire

Table 3. Regression coefficients of explanatory variables in LR and GWR models and variable importance in RF models for general and monthly models.

	ECOSTRESS				Vegetation Index	Climate	Topography		
Explanatory variables	ESI	WUE	ET	LST	NDVI	Rainfall	Slope	Elevation	Aspect
Logistic regression									
General	3.02	22.79	0	0	0.46	−1.68	5.28	2.91	−0.28
Sep	0	5.72	−1.47	−0.73	3.07	−8.38	3.29	1.13	−0.91
Nov	0.01	4.97	0	−1.11	6.76	0	3.14	0.30	−0.85
Dec	0.04	0	0	0	7.32	0	3.93	0.86	−0.01
Geographically weighted regression									
General	0.08	0.11	−0.06	−0.08	−0.02	−0.12	−0.28	−0.04	0.00
Sep	0.10	−0.02	−0.14	−0.13	−0.02	−3.29	−0.14	−0.01	0.00
Nov	−0.72	0.72	0.70	−0.18	0.11	0.18	0.02	−0.08	0.00
Dec	−0.66	0.10	1.04	0.10	−0.01	0.17	0.22	−0.13	0.00
Random forest									
General	0.07	0.24	0.09	0.07	0.06	0.08	0.21	0.14	0.03
Sep	0.07	0.29	0.05	0.06	0.08	0.22	0.1	0.09	0.03
Nov	0.07	0.24	0.05	0.05	0.27	0.06	0.13	0.09	0.04
Dec	0.1	0.11	0.25	0.03	0.27	0.06	0.12	0.05	0.02

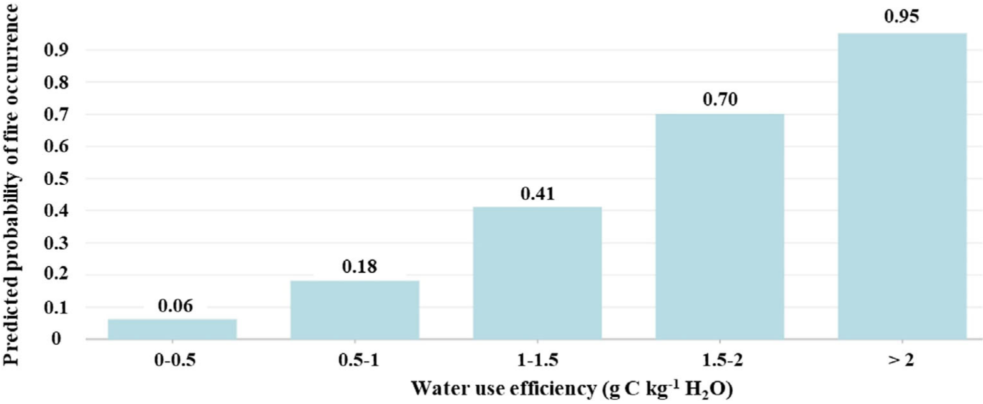

Figure 3. The influence of the main predictor variable ECOSTRESS WUE for fire occurrence is based on the general model of logistic regression.

vegetation conditions and their correlation with different wildfire probabilities during the fire season. As depicted in Figure 3, the probability of fire occurrence increases as ECOSTRESS WUE values rise, highlighting the significant relationship between fire occurrence and these variables. In the general model of LR (Fig. 4a), WUE had an average of 1.88 g C kg^{-1} H_2O across the study area during the fire season and exhibited a significant correlation with wildfire, with an LR coefficient of 16.17. Significantly, 95% of the vegetation burned during wildfires has WUE values greater than 2 g C kg^{-1} H_2O.

Spatial distribution of wildfire susceptibility

The susceptibility maps of South-Eastern Australia were predicted based on general models of LR, GWR, and RF to provide an overview of the probability of wildfire occurrence. All three models produced the maps with a resolution of 70 m in line with the spatial resolution of ECOSTRESS datasets. According to Figure 4, the susceptibility maps consistently indicate that the likelihood of wildfire occurrence is highest along the coastal areas, consistent with observations made during the 2019–2020 wildfire event and forest loss due to fire (Tyukavina et al., 2022).

The wildfire probability maps from the three models reveal the hotspot areas of wildfire occurrence. These areas are predominantly concentrated in the protected areas, particularly within national parks characterized by vegetated regions, including Alpine, Kosciuszko, Deua, Wollemi, Morton, Blue Mountain, LNE Special Management, and UME Special Management. As an example, we provide a close-up view of the wildfire-prone areas within the Alpine National Park region, projected by the LR general model in Figure 4b. These areas are vulnerable to wildfire from the prediction maps of the three models. Consistent with the variable importance results, the susceptibility maps generated by the LR (Fig. 4a) and RF (Fig. 4d) general models exhibit a higher degree of similarity than those produced by GWR (Fig. 4c).

Figure 5 illustrates the cities prone to wildfires based on the susceptibility results of RF general model. According to the predictions, the Macedon Ranges and Murrindindi in Victoria State, the mid-north coast, and Coffs Harbor regions (between Blue Mountain and Clarence Valley) in New South Wales show high susceptibility to wildfires, followed by the greater Sydney and Melbourne areas. This information is vital for policymakers, fire managers, forest rangers, and urban planners in evaluating, managing, preparing for, and mitigating wildfire risks in proximity to cities around wildland biomes.

Discussion

Model performance and application scenarios

This research presents an in-depth analysis of wildfire dynamics in South-Eastern Australia and examines various biophysical factors, including slope, elevation, aspect, rainfall, NDVI, and ECOSTRESS data as independent variables to establish the cause-and-effect relationship with fire points as the dependent variable. It should be noted that our study is the largest wildfire ECOSTRESS analysis to date (Bonney et al., 2020; Pascolini-Campbell et al., 2022; Poulos et al., 2021). It focuses on quantifying the impact of drought on wildfire using NASA's ECOSTRESS, which assesses the effects of water availability on climate biomes worldwide (Fisher et al., 2020). Creating high-resolution (70-meter) wildfire susceptibility images using these models proves valuable for visualizing fire during wildfire seasons. Tyukavina et al. (2022) identified forest loss due to wildfires across temperate regions of Australia (Fig. 4). Our wildfire susceptibility maps align

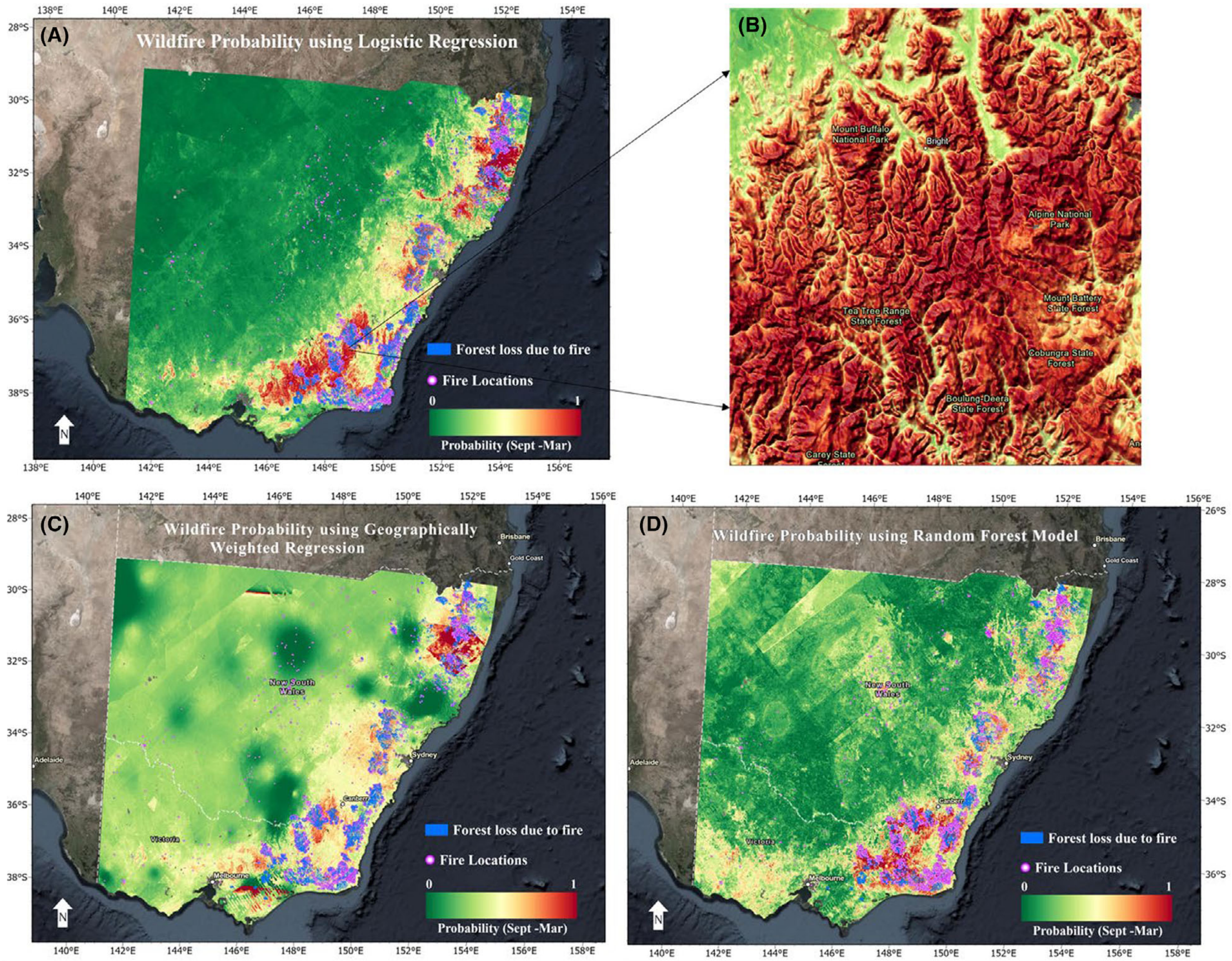

Figure 4. Wildfire susceptibility (occurrence probability) maps overlaid with fire locations and forest loss due to fire: (a) logistic regression, (b) a zoomed-in version of highly susceptible fire areas within the Alpine National Park region produced by logistic regression, (c) geographically weighted regression, and (d) random forest. The maps use a probability scale ranging from 0 to 1. Areas with a probability value of 0 are considered not vulnerable to fire, while areas with a probability value of 1 are the most susceptible.

with their findings. While our study focuses on wildfires from September 2019 to March 2020, the forest loss dataset spans the entire years of 2019 and 2020. Despite not being perfectly aligned in dates, we qualitatively observed that the regions identified as highly susceptible in our models closely correspond with areas of forest loss due to wildfires. This comparison validates our model's reliability and demonstrates its effectiveness in identifying the areas with different levels of wildfire susceptibility.

Although MODIS fire detection operates at a 500-meter resolution, we used the central point of the MODIS 500-meter grid cells to represent wildfire occurrences. In contrast, high-resolution datasets, such as Sentinel-2 and ECOSTRESS-derived variables, were used as independent variables. We built machine-learning models using these variables to predict wildfire susceptibility. While MODIS may miss smaller fires due to its resolution limitations, the detailed high-resolution predictor variables provide critical insights into local conditions. This approach enhances our ability to predict potential fire-prone areas. By integrating MODIS fire data with high-resolution independent variables, we can generate detailed 70-meter wildfire susceptibility maps, effectively capturing fine-scale variations in wildfire risk.

We constructed general and monthly wildfire susceptibility prediction models utilizing machine learning and biophysical factors. The general models provide an overall insight into the critical biophysical factors contributing to wildfire occurrence. Therefore, this model can be valuable in pinpointing areas (such as the mid-north coast and Coffs Harbor regions in New South Wales, as shown in Fig. 5) that demand intensive monitoring. The monthly

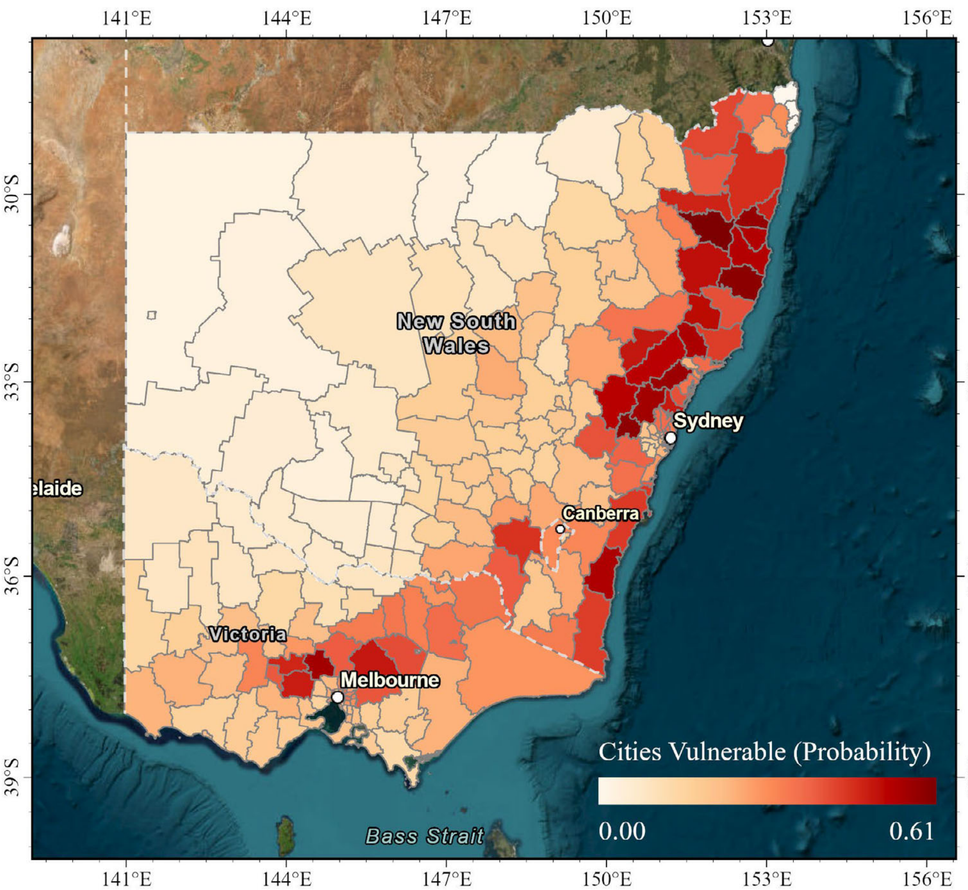

Figure 5. Map showing the ranking of wildfire probability in different districts of the study area. Maroon represents regions more vulnerable to wildfire, while areas with light yellow show less susceptibility.

models can predict the likelihood of wildfire spreading in the near future (1 week ahead) and identify the key controlling factors of the pre-fire during that period. These results can guide firefighters and forest managers in planning and implementing fire-fighting measures in advance.

Previous studies consider pre-fire vegetation conditions over months or years, which can provide valuable insights into longer-term ecological trends (Forkel et al., 2019; Kuhn-Régnier et al., 2021). However, our study aims explicitly to predict wildfire susceptibility based on the vegetation conditions within the current fire season, emphasizing real-time wildfire prediction. By concentrating on the 3 weeks preceding the wildfire, we developed monthly models to capture the most relevant data for predicting wildfire susceptibility, demonstrating that the vegetation's response to environmental stressors directly indicates wildfire risk during the current season (Coop et al., 2016). This focus provides the most practical and relevant information for timely predicting and managing imminent wildfire threats using recent biophysical conditions from readily available and easily manageable satellite data over a short period of time.

Model testing is crucial in choosing the most appropriate model, enhancing reliability, and minimizing uncertainty. Overall, the RF model exhibited the highest accuracy, followed by the GWR and LR mode (Table 2). Therefore, the RF general and monthly models are suitable for precise prediction scenarios, particularly in applications related to wildfire prevention and management departments (Collins et al., 2018; Gibson et al., 2020; Mohajane et al., 2021). However, they are often not easily explainable due to their complex machine-learning nature. GWR generates a local regression model at each point (pixel) based on locally associated similar or more homogeneous pixels. Consequently, these local models are generally higher than those of a single regression model for the entire image (Fotheringham et al., 2003; Oliveira et al., 2014). The LR models can offer advantages in representing the relationship between dependent and explanatory variables on a global scale (Iban &

Sekertekin, 2022; Lee, 2005). Furthermore, they provide consistent results across both general and monthly models.

Influential factors and their implications

This study explored the influencing factors, including ECOSTRESS (ESI, WUE, ET, and LST), vegetation index (NDVI), climate (rainfall), and topography, that contribute to wildfire susceptibility and effectively demonstrated their significance. The study identified WUE from NASA's ECOSTRESS as the most critical factor. WUE, the ratio of carbon uptake to water use, averages 1.88 g C kg^{-1} H_2O over the study area during the fire season. As demonstrated in Figure 3, areas with WUE exceeding 2 g C kg^{-1} H_2O have a 95% probability of experiencing vegetation burning during wildfire events. Previous studies have demonstrated that the increase in WUE can be attributed to droughts and rising temperatures (Hatfield & Dold, 2019; Pascolini-Campbell et al., 2022; Peters et al., 2018). Plants respond to droughts by partially closing their stomata to limit their evaporative water loss, even though this comes at the expense of carbon uptake through photosynthesis. This trade-off strategy maximizes their WUE, as observed in numerous individual plants in laboratory and field settings (Peters et al., 2018; Tyukavina et al., 2022). Plant types exhibited convergence in WUE irrespective of climate (Cooley et al., 2022). This indicates that South-Eastern Australia likely experienced drought conditions during the wildfire season, a conclusion supported by previous studies (Bowman, Williamson, Price, et al., 2021; Bowman, Williamson, Gibson, et al., 2021; Byrne et al., 2021; Deb et al., 2020; Kumar et al., 2021; Rao et al., 2022; Squire et al., 2021).

Another evidence linking the Black Summer in South-Eastern Australia to drought is the ESI, which has been shown to contribute to wildfire predictions (Richardson et al., 2022). ESI has also been demonstrated to be effective at capturing early signs of "flash droughts," occurring during extended periods of hot, dry, and windy conditions leading to rapid depletion of moisture (Deng et al., 2022; Edris et al., 2023). Various studies have shown that the propagation of wildfires is significantly impacted by vegetation conditions, which is an essential factor in determining fuel characteristics such as vegetation type, water availability, drought, and ET (Taufik et al., 2017). These factors, in turn, affect the moisture levels in the plants and fuel load, ultimately influencing the spread and intensity of the fire (Nurdiati et al., 2022). Our results emphasize that ECOSTRESS WUE and ESI effectively detected and revealed the drought conditions associated with South-Eastern Australia's Black Summer.

Although the positive coefficient for ESI in Table 3 might initially seem counterintuitive—suggesting a higher likelihood of fire in wetter conditions—this can be explained by vegetational seasonal dynamics and ecological characteristics. ESI typically reflects water availability, with higher ESI values indicating lower water stress and relatively wetter conditions. Our study focused on periods of seasonal vegetation growth, specifically during the spring and summer. During these times, higher ESI values often correspond to increased vegetation growth. This lush growth results in greater biomass that becomes highly combustible, thereby elevating the risk of wildfires as the season progresses (Byrne et al., 2021; Collins et al., 2023). This aligns with ecological patterns observed in many regions where rapid vegetation growth during wetter periods can increase fuel availability, leading to higher fire risk once the vegetation becomes dry (Ellis et al., 2022; Sullivan et al., 2012). Therefore, the temporal lag effect should happen between the high ESI (wetter conditions) and the subsequent drying out of vegetation. As the vegetation dries, it can contribute to increased fuel loads, elevating the risk of fire outbreaks.

NDVI has been identified as one of the top explanatory variables for fire occurrences, which aligns with the findings of previous research conducted by Zhang et al. (2013) and Murphy et al. (2019). NDVI is a measure used to assess the level of greenery in a region. According to previous studies, NDVI serves as a "switch" to indicate whether a region is vegetated rather than directly predicting specific outcomes (Murphy et al., 2019; Zhang et al., 2013). Meanwhile, NDVI is indirectly linked to water content in leaves, which acts as a proxy for fuel moisture content (Tavakkoli Piralilou et al., 2022; Zacharakis & Tsihrintzis, 2023). Fuel moisture content is a primary factor in fire behavior and spread by directly affecting the flammability of vegetation (Yebra et al., 2018). Our study aligns with these findings, further confirming that NDVI is a critical factor in predicting wildfire susceptibility.

While our results indicate rainfall as a significant factor (Chéret & Denux, 2007), it may not have been the primary contributor to the wildfires. For instance, in November and December, some areas exhibited a high predicted probability of wildfires despite receiving relatively high levels of rainfall. On the contrary, some areas received substantial rainfall in September, which marked the beginning of the wildfire season. However, these areas did not experience any wildfires. Consequently, it is reasonable to conclude that the absence of rainfall alone may not be the sole reason behind the wildfire spread. Other factors and conditions likely played significant roles (Harrison et al., 2021; Pascolini-Campbell et al., 2022; Pimont et al., 2021).

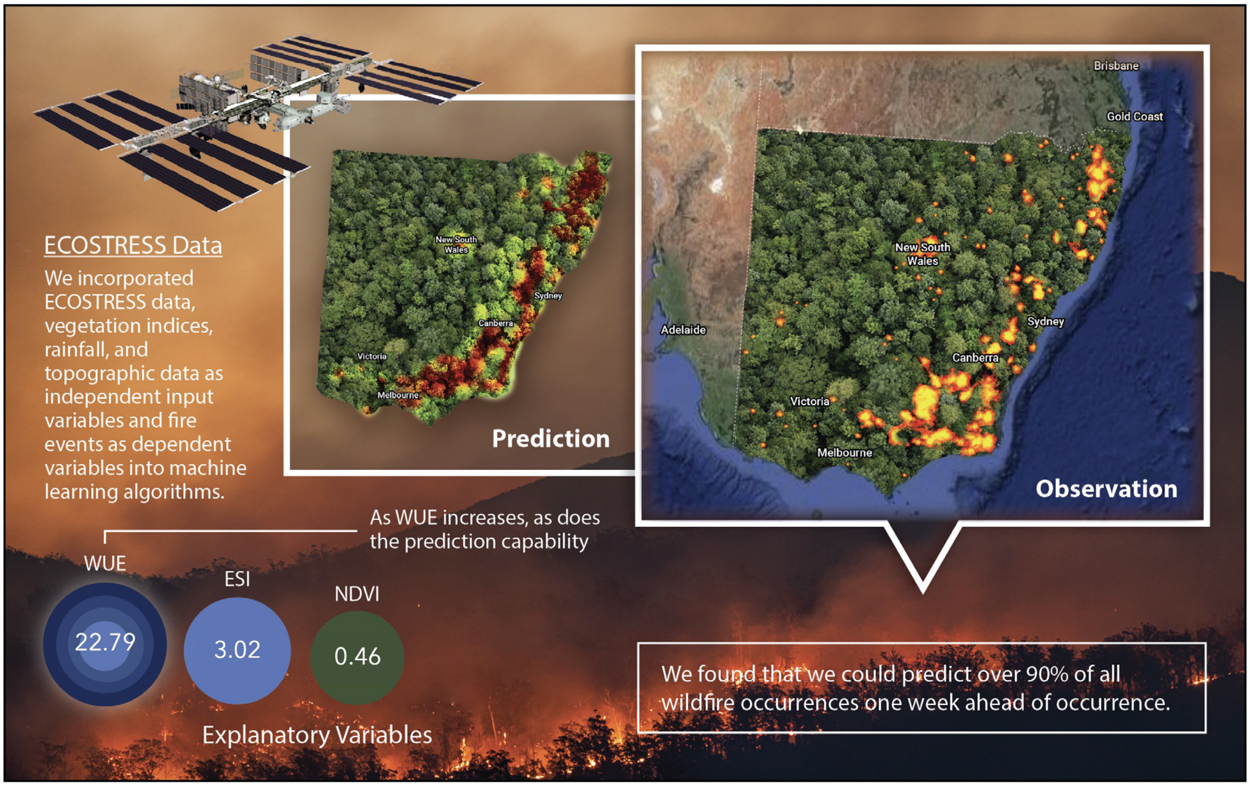

Figure 6. Using NASA ECOSTRESS and other data in conjunction with machine learning, we were able to predict >90% of wildfire occurrences 1 week ahead of time for Australia's 2019–2020 fire season. WUE and evaporative stress index (ESI) were major predictor variables based on the general logistic regression model coefficients (Table 3).

Few studies show that the change in LST is likely to cause wildfire spread (Halofsky et al., 2020; Lim et al., 2019). However, our data revealed that the LST of South-Eastern Australia during the wildfire season did not exhibit an effective increase compared to the pre-fire season. Our findings further indicate that LST was the least influential factor in predicting wildfire susceptibility, as observed in both general and monthly models. The South-Eastern Australia wildfires occurred from September 2019 to March 2020, with an initial cessation in late October 2019 in South-Eastern Australia followed by a reignition in late November 2019. The most severe fires occurred from December 2019 to January 2020, during the wintertime (Abram et al., 2021). Notably, LST during that period did not reach levels comparable to the initial stage of the wildfires between September and October, contributing to its reduced significance as a predictive factor.

In summary, our findings indicate that drought is a significant contributing factor to wildfire events, which is in line with the results reported by Clarke et al. (2022) and Lim et al. (2019). Prolonged droughts have increased the likelihood of wildfires and made them more challenging to control (Bowman et al., 2009; Canadell et al., 2021). Meanwhile, our study highlights the significance of using NASA's ECOSTRESS data to assess the impact of water availability on key climate biomes worldwide (Fisher et al., 2020; Zhu et al., 2023). We quantified the influence of drought on wildfires based on ECOSTRESS WUE and ESI data. This underscores the value of ECOSTRESS data in current and future wildfire prediction analyses.

Conclusions

Our research has developed general and monthly models to predict wildfire occurrences by combining machine learning algorithms with various biophysical factors (Fig. 6). These models effectively serve different application scenarios—general models provide a comprehensive perspective on wildfire susceptibility for wildfire prevention and monitoring. In contrast, monthly models can understand pre-fire vegetation conditions and predict the likelihood of wildfire spread in the near future (1 week ahead), aiding in proactive fire-fighting measures. Notably, both models consistently identified ECOSTRESS

WUE as the most influential factor, with 95% of wildfire-affected vegetation displaying WUE values exceeding 2 g C kg^{-1} H_2O. Furthermore, ECOSTRESS ESI was identified as a significant contributor to wildfire predictions. These influencing factors indicated the pivotal role of drought conditions in wildfire occurrences, as observed from ECOSTRESS data. The findings provide insight into developing effective strategies for managing, preventing, mitigating, monitoring, and predicting wildfires.

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Conflict of Interest

The authors declare no conflict of interest, financial or otherwise.

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