Enhancing the Accuracy of Mapping Wildfire Susceptibility through the integration of Remote Sensing Data and Artificial Intelligence (AI)

Discover how a combination of remote sensing and machine learning can accurately predict and dynamically monitor the spread of forest fires. Join me on a journey to explore how remote sensing and machine learning can predict and prevent forest fires.

By Harikesh

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Wildfires

The Costs:	Billions of dollars in property and environmental damage each year
The Causes:	Flammable ecosystems, lightning strikes, human activities, and the effects of climate change
The Impacts:	Economic loss, loss of vegetation and wildlife habitat

Necessity of forest fire prediction tools

Bushfires

Sydney, Brisbane and Perth face 'increased risk of bushfire' this summer

Seasonal bushfire outlook for 2023-24 suggests large areas of eastern Australia could burn but authorities say forecast not as dire as 2019's black summer

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Rafqa Touma
@At_Raf_
Thu 30 Nov 2023 02.31 GMT

Australia on high alert: Upcoming hot and dry summer poses elevated bushfire risk

El Nino will be gracing us for summer and staying. Here is the detail about what to expect in the next couple of months. Picture Shutterstock

El Nino will be gracing us for summer and staying. Here is the detail about what to expect in the next couple of months. Picture Shutterstock

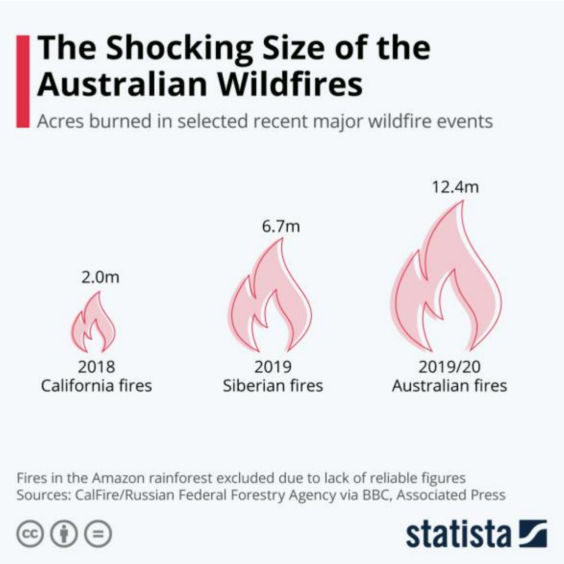
This is branded content.

Well, it's official. It's going to be an El Nino summer.

According to recent forecasts, Australia is set to experience one of its

significantly escalates the nation's vulnerability to

According to ABC 28th September 2023 News, Australia's new fire warnings system needs more improvement to minimise misleading ratings and exaggerated risks.



Queensland bushfires destroy more than 30 homes, multiple watch and act warnings current across the state

By David Chen, Tobi Loftus, Victoria Pengilley, and Jessica van Vonderen

Posted Fri 27 Oct 2023 at 7:07am, updated Fri 27 Oct 2023 at 4:59pm

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Problem Statement

1 Inaccurate predictions

The current prediction models rely on basic mathematical assumptions and average climate models. This results in very inaccurate predictions of fire behaviour, spread, and transition.

2 Delayed and inaccurate data

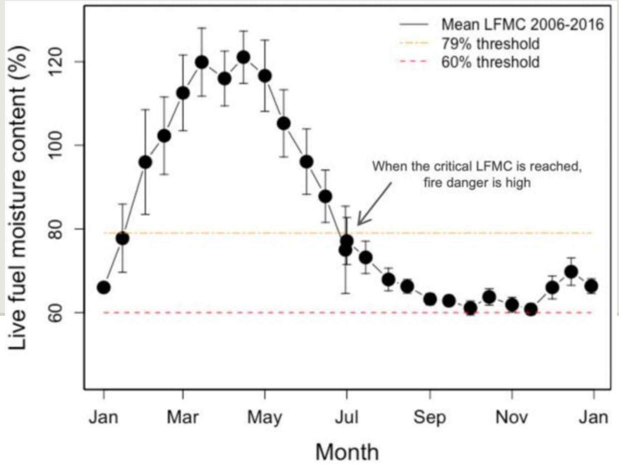
The existing fire-tracking systems are not highly efficient. The fire location may not be reported until it has already grown significantly, making it difficult to manage and control the fire effectively.

3 Inadequate data integration

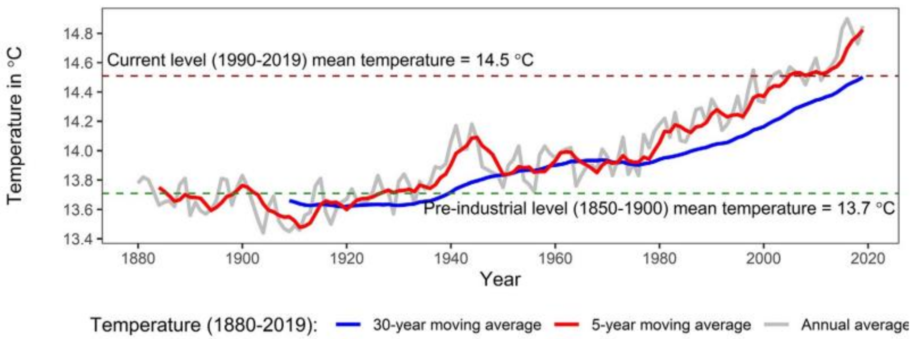
Data on the weather conditions, the topography of the land, and human activity are all critical parameters in predicting forest fires. However, integrating data from multiple sources and in different formats is still a challenge.

Wildfire Prediction: key challenges

Fuel Moisture Content



Climate Change



Terrain Features

Terrain features like topography and slope can influence the direction and intensity of a forest fire, but mapping these features accurately can be difficult.

Human Behaviour

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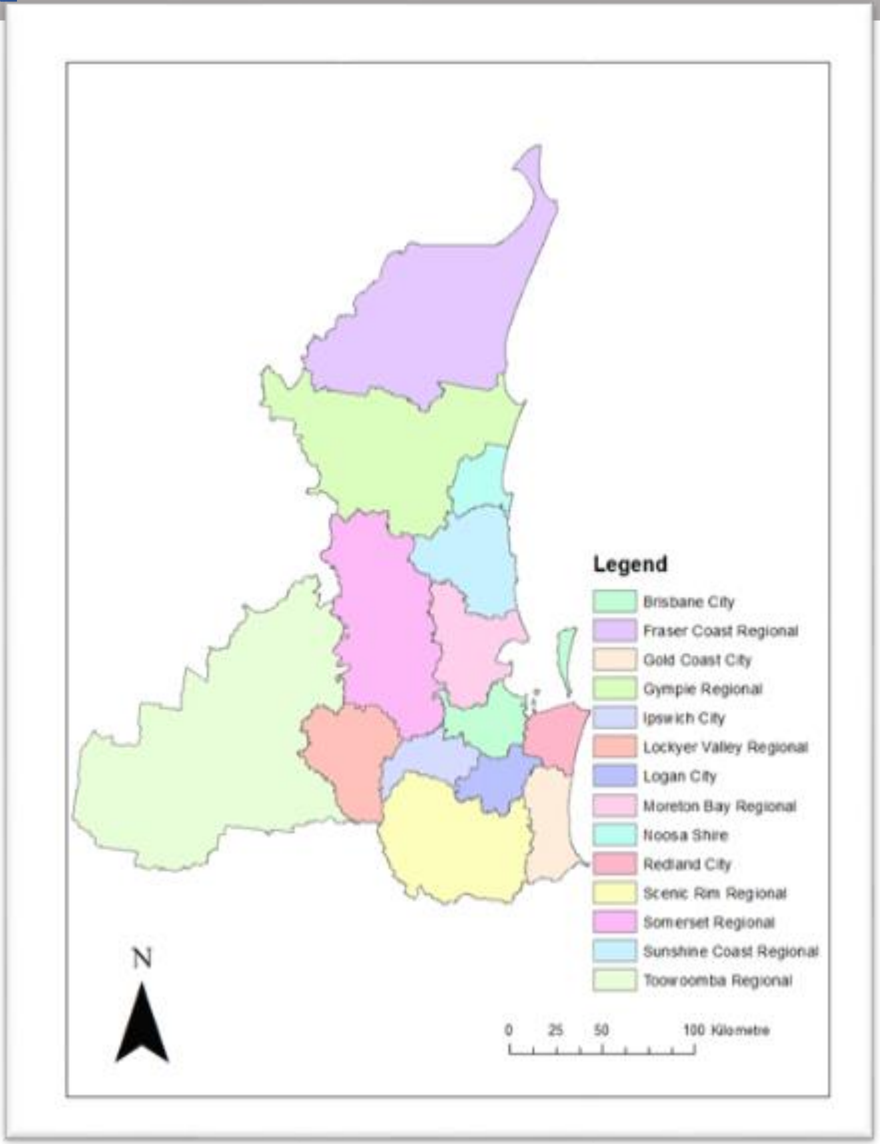
The Study Area

- Specific forest types include remnants of sub-tropical and warm temperate rainforests and moist eucalypt forests that are mainly restricted to the mountain regions.

- Other forest types include tall open forests, open Eucalyptus forests and woodlands, dry eucalypt forests, Melaleuca wetlands, and Banksia low woodlands and heaths.

Vegetation type	Fire intervals in years
Rainforest	Fire exclusion
Wet sclerophyll forest	20–100+
Grassy dry sclerophyll forest and woodlands	3–6
Shrubby dry sclerophyll forest and woodlands	7–25
Coastal heathlands	7–20
Inland (rocky) heathlands	15–50
Paperbark (*Melaleuca quinquenervia*) woodlands	15–30

Suggested fire intervals for vegetation types in Southeast Queensland
(Source: Fisk et al (2003, Table 7.5))



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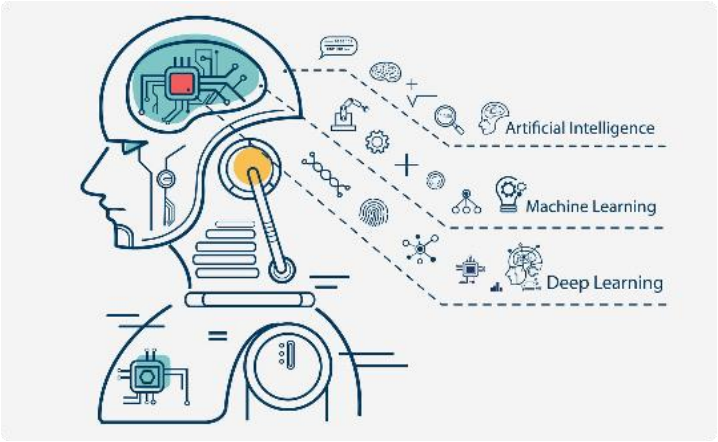
Data Collection and Processing

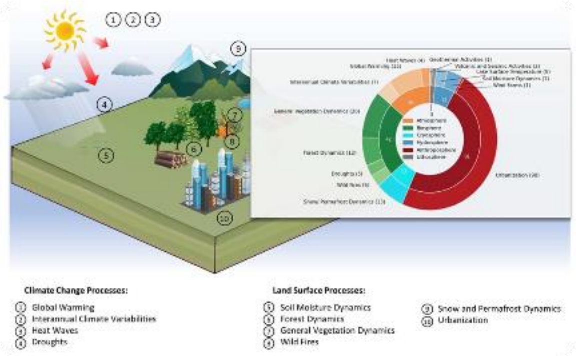
Remote Sensing



Machine Learning

Statistical Analysis

Data Collection



Ground-Based Sensors

Weather Monitoring

Fire Spreading Mechanism and Its Parameters

Factors That Affect Fire Spread	Parameters to Monitor
Fuel Quantity and Quality	Moisture Content in Fuel
Wind Speed and Humidity	Wind Direction and Speed
Surface and Atmospheric Temperature	Temperature Gradient of the Air

Data analysis and results

Parameter	Data description	Expected results
Weather conditions	Humidity, Temperature, Pressure, Wind Speed, Wind Direction	Accurate data on current weather conditions and the predicted conditions for the next few days.
Burned area	Area affected by the forest fire	Accurate estimation of the burned area will help identify the most affected areas and prepare accordingly.
Behaviour and Spread pattern	Burning intensity, direction and acceleration	The predicted behaviour will help define the best management steps, including containment efforts and effective firefighting strategies.

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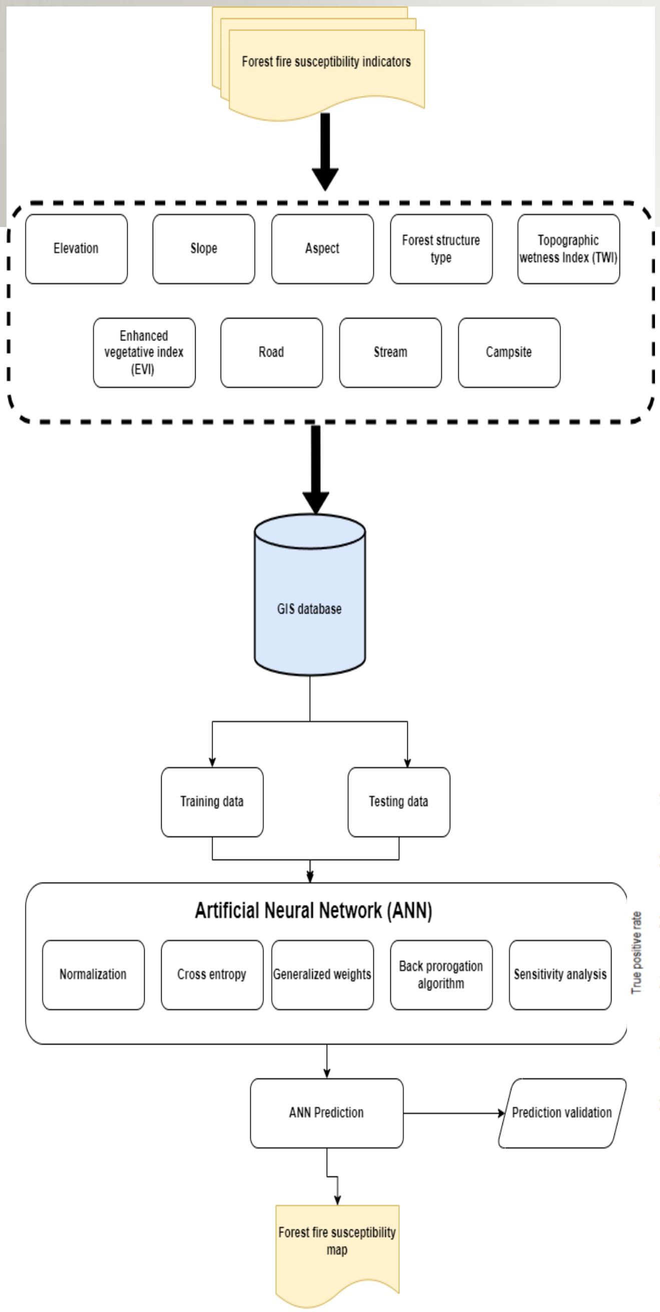
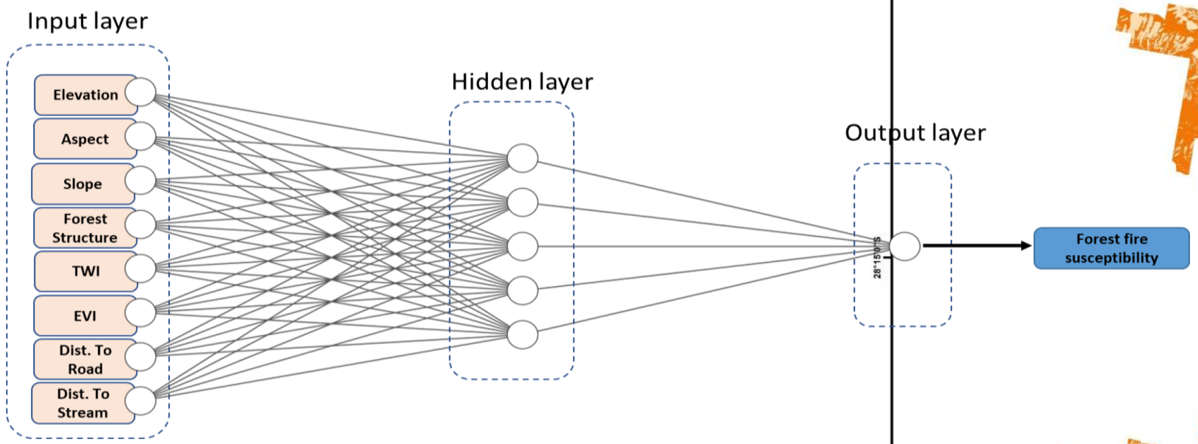
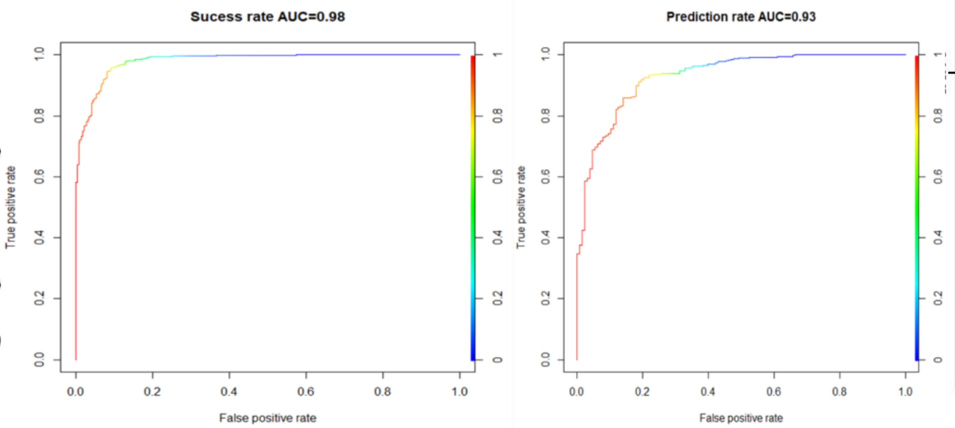
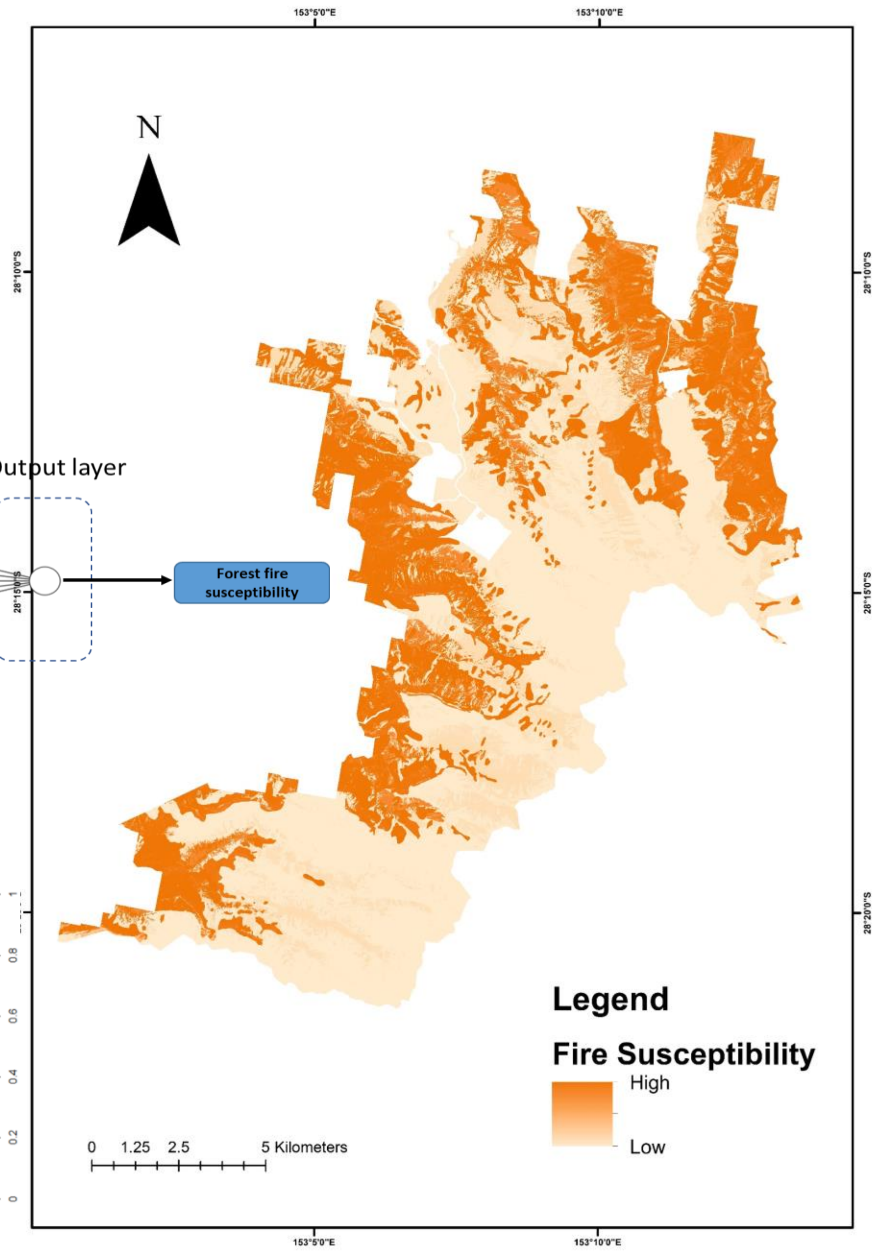
Artificial Neural Network (ANN) Model









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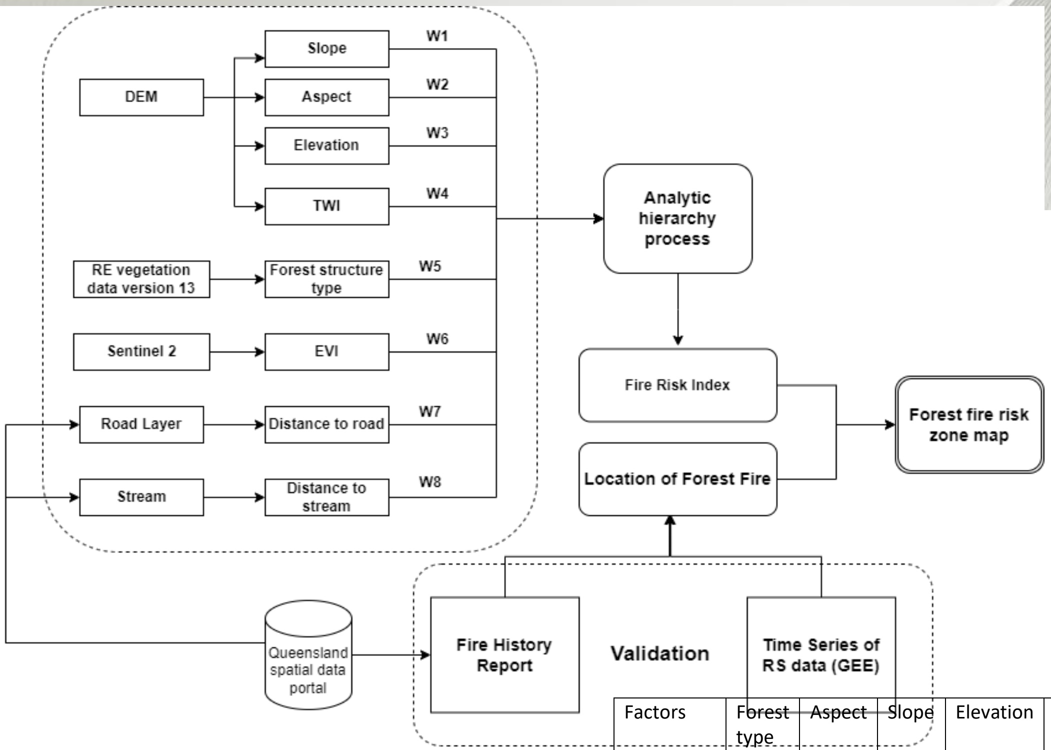
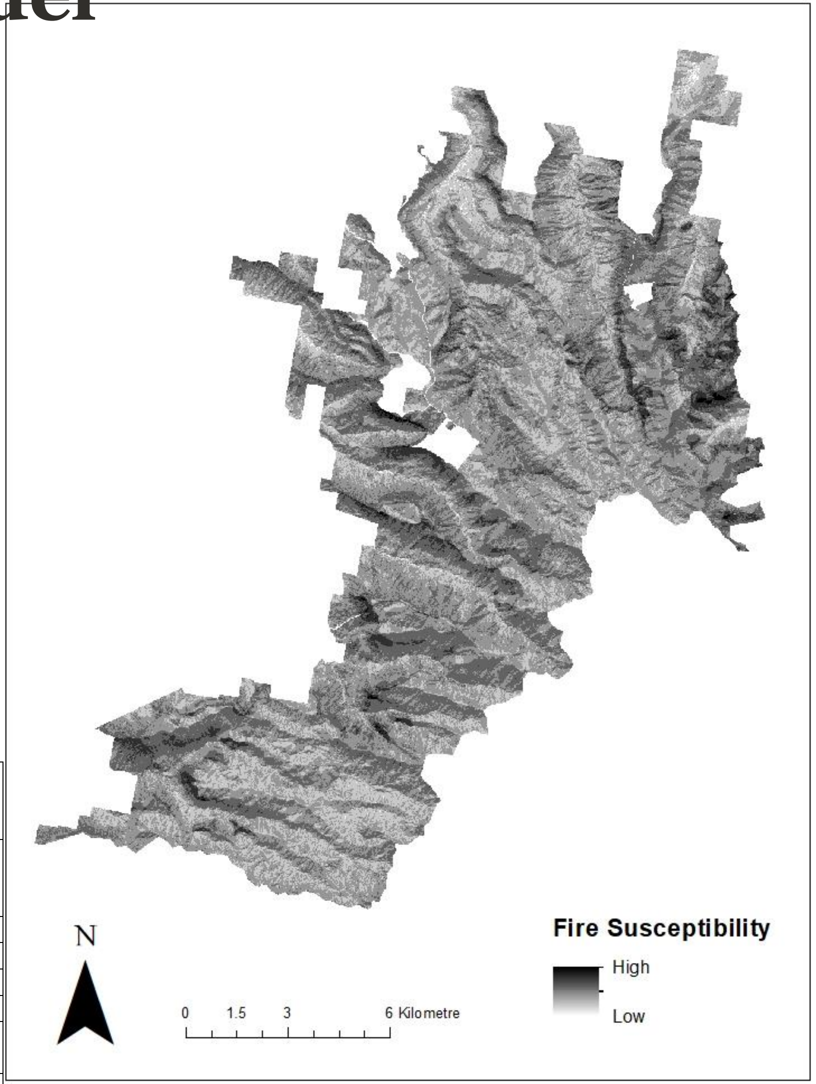
Analytical Hierarchical Process (AHP) Model



Factors	Forest type	Aspect	Slope	Elevation	TWI	Distance to road	Distance to stream	EVI	Camping Site	Criteria Weights	Criteria weight (%)
Forest structure type	0.397	0.700	0.370	0.292	0.245	0.176	0.144	0.153	0.121	0.289	28.875
Aspect	0.050	0.087	0.476	0.146	0.123	0.396	0.096	0.026	0.242	0.182	18.239
Slope	0.057	0.010	0.053	0.389	0.368	0.264	0.096	0.026	0.152	0.157	15.702
Elevation	0.066	0.029	0.007	0.049	0.061	0.044	0.216	0.204	0.091	0.085	8.526
TWI	0.099	0.044	0.009	0.049	0.061	0.044	0.216	0.128	0.030	0.076	7.556
Distance to road	0.099	0.010	0.009	0.049	0.061	0.044	0.192	0.230	0.061	0.084	8.383
Distance to stream	0.066	0.022	0.013	0.005	0.007	0.005	0.024	0.204	0.061	0.045	4.533
EVI	0.066	0.087	0.053	0.006	0.012	0.005	0.003	0.026	0.212	0.052	5.227
Camping Site	0.099	0.011	0.011	0.016	0.061	0.022	0.012	0.004	0.030	0.030	2.959



$$\boldsymbol{FRI} = \sum_{\boldsymbol{i}=1}^{\boldsymbol{n}} \boldsymbol{W_i} * \boldsymbol{p}$$

$$= (\boldsymbol{FS} * \boldsymbol{W}1) + (\boldsymbol{A} * \boldsymbol{W}2) + (\boldsymbol{S} * \boldsymbol{W}3) + (\boldsymbol{E} * \boldsymbol{W}4) + (\boldsymbol{TWI} * \boldsymbol{W}5) + (\boldsymbol{DR} * \boldsymbol{W}6) + (\boldsymbol{DS} * \boldsymbol{W}7) + (\boldsymbol{EVI} * \boldsymbol{W}8) + (\boldsymbol{CS} * \boldsymbol{W}9)$$

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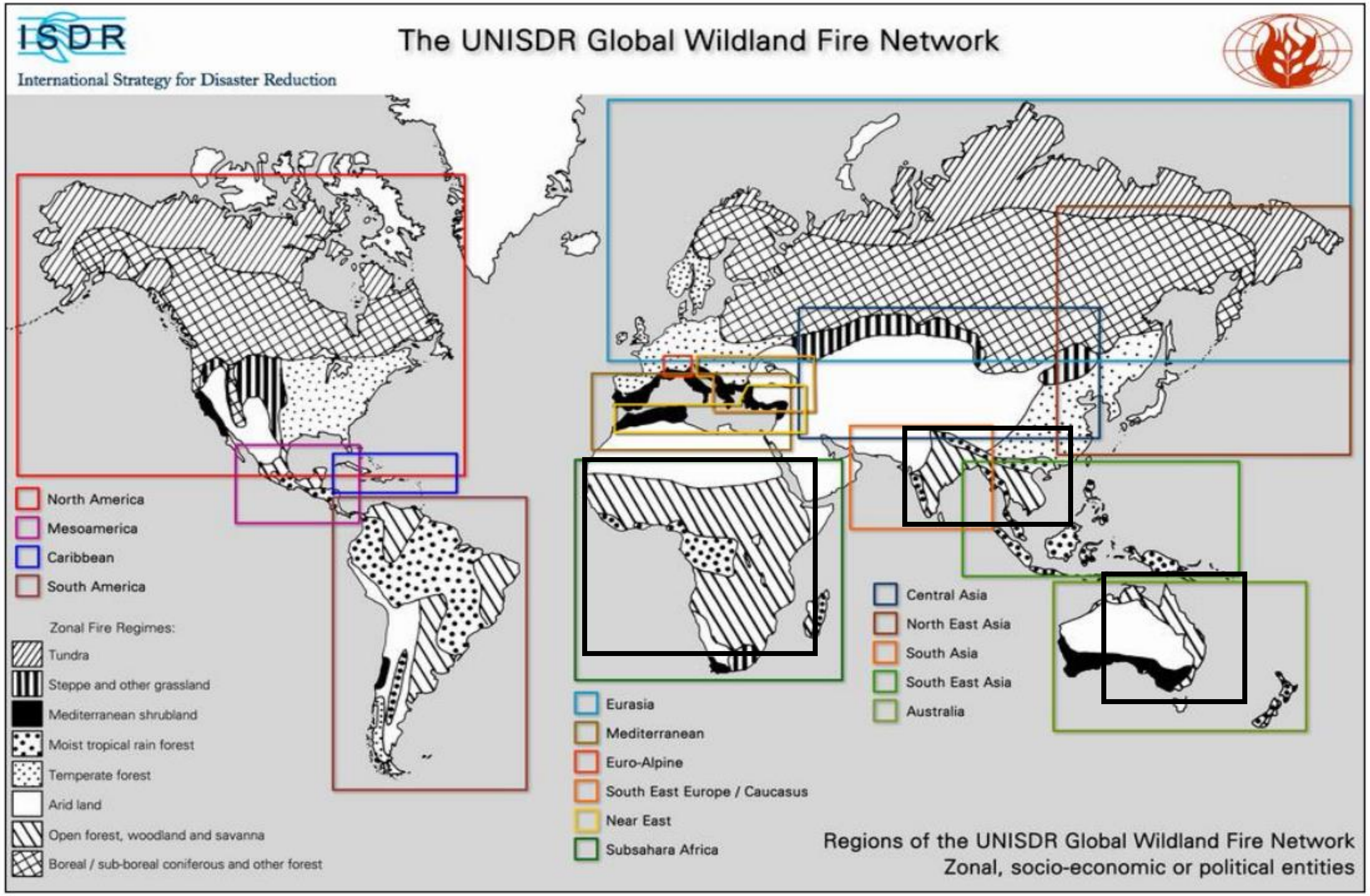
Future implications



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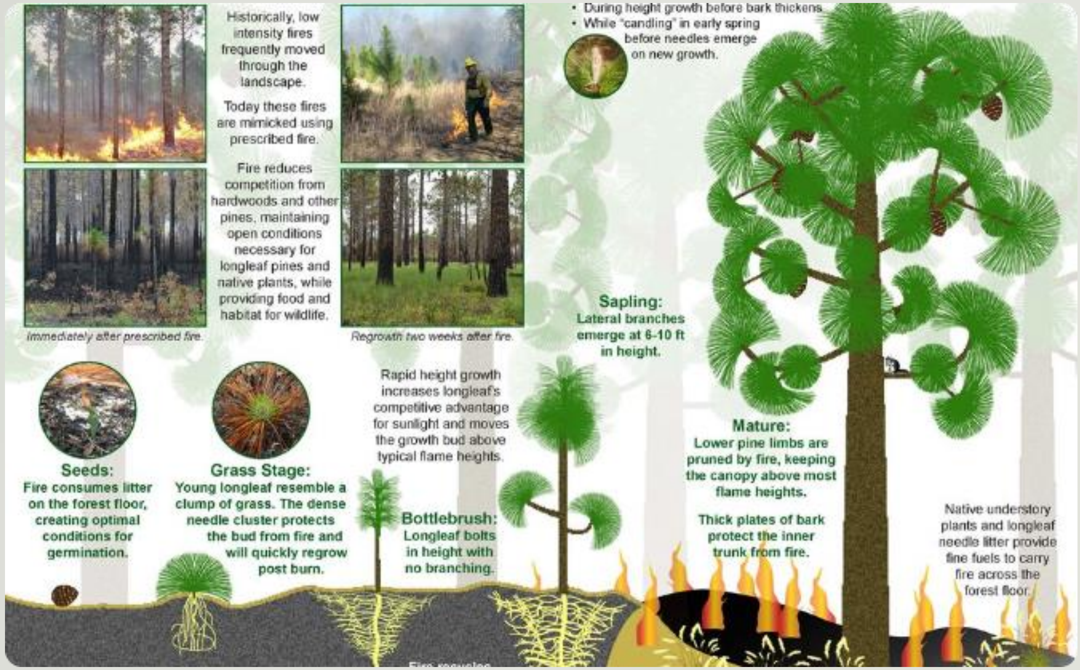

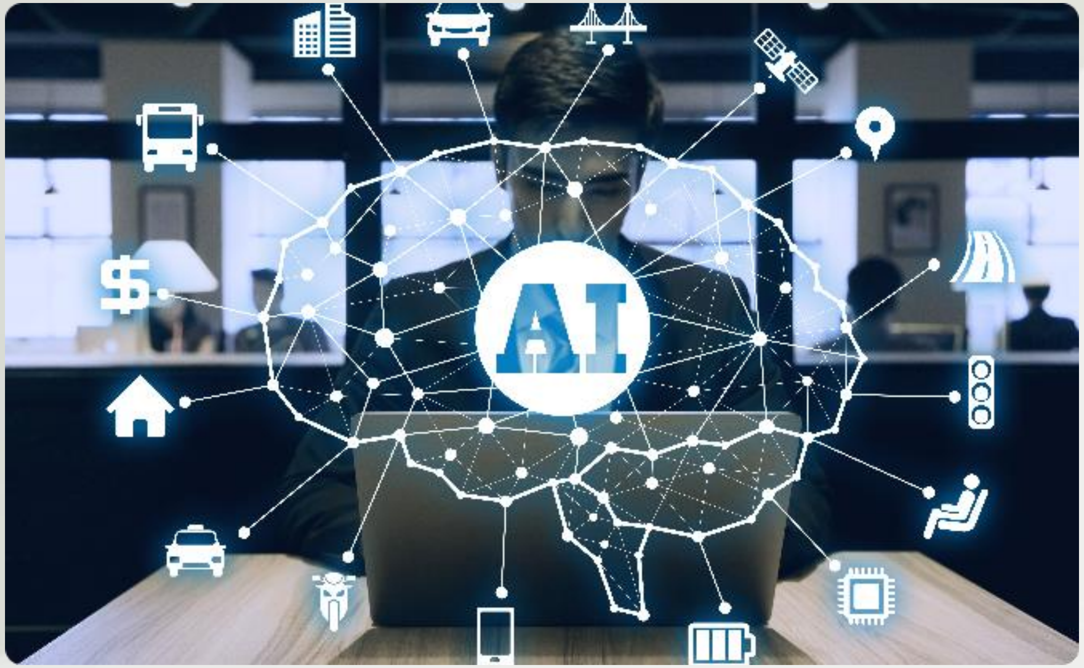

Conclusion

The devastating impact of forest fires on the environment, property and wildlife cannot be ignored. The proposed solution uses advanced technology and techniques to predict forest fires' behaviour and spread accurately. Using remote sensing and machine learning algorithms for forest fire prediction enables more proactive decision-making that can significantly reduce the damage caused by these disasters.

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Thank You for Listening

I appreciate your attention to this important research work. I am excited to contribute to the growing field of remote sensing and machine learning, and hope that work will have a positive impact on fire management and environmental preservation.

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Thanks!

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