Paper Title : Emulation of wildland fire spread simulation using deep learning
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1. Summary

1.1 Motivation

Faster wildland fire spread models are necessary for prompt reaction and mitigation, as the paper discusses. The goal is to create a more effective strategy because the traditional ones are computationally costly.Inspired by the computational load of simulations, the paper presents an emulator for Deep Neural Networks (DNNs). Retaining accuracy while cutting down on the amount of time needed to estimate wildfire spread is the aim. The project, which focuses on Corsica, intends to develop a tool for prompt and accurate forecasts, supporting choices about the management of wildfires and perhaps saving significant time and money.

1.2 Contribution

In order to facilitate accurate and timely forecasts for wildland fire spread simulations, the research presents a unique Deep Neural Network (DNN) emulator. They compared to traditional approaches that take days, it offers a considerable speed-up, making thousands of simulations viable in seconds.The study's application to Corsica illustrates its applicability and offers advantages for managing wildfire risks in real time.

1.3 Methodology

Rothermel's Rate of Spread (ROS) model is used in ForeFire wildfire spread simulations.Latin Hypercube Sampling was used to create a large dataset (5 million samples) with a variety of environmental characteristics.Using dense blocks for scalar inputs and convolutional blocks for 2D fields, a hybrid DNN architecture was created. Using simulated burnt regions, DNN trained for regression, producing a quick and precise emulator for ForeFire outputs.
The effectiveness of the DNN emulator was shown by its Mean Absolute Percentage Error (MAPE), which was 32.8% and explained 94% of the output variation.

1.4 Conclusion

created a Deep Neural Network (DNN) simulator to forecast wildfire spread quickly and accurately in ForeFire simulations. Thousands of times quicker than ForeFire simulations, DNN calculations offer a useful tool for mapping fire threat and making ensemble forecasts. The DNN technique opens up possibilities for practical usage in forecasting the behaviour of wildfires and is adaptable to different geographies and fire simulators.

2 Limitations

2.1 First Limitation

Extensive resources may be needed to meet the high computational demands of training the DNN, especially in huge areas.

2.2 Second Limitation

The emulator's performance may be affected by adaptation issues when implementing the approach in locations with varying spatial resolutions in data maps.

3 Synthesis

Investigating how well the DNN performs in ensemble predictions using real weather forecasts and comparing it to other approximation methods will direct future work towards practical wildfire risk assessments.