FireCast: A Hybrid Physics-Informed Diffusion Model for Nowcasting Wildfire Spread from Geostationary Satellite Data

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INTRODUCTION

Wildfires evolve rapidly under changing wind, humidity, and terrain conditions, posing severe threats to ecosystems and human communities. Accurate short term nowcasting of fire spread is essential for emergency response and evacuation planning. Traditional physics based propagation models rely on simplified assumptions and often produce overly smooth, low resolution forecasts.

Purely data driven deep learning models can capture complex spatial patterns from satellite imagery but may ignore physical constraints governing fire dynamics. Such approaches risk generating unrealistic or physically inconsistent predictions, limiting reliability in operational wildfire management scenarios.

METHODOLOGY

FireCast employs a hybrid deterministic stochastic framework that integrates physics informed cellular automaton modeling with diffusion based generative refinement. Meteorological inputs from ERA5 and terrain elevation data from a digital elevation model drive the cellular automaton to produce a coarse wildfire perimeter forecast that respects wind direction, humidity, and topographic constraints.

The deterministic forecast is then used as a strong condition for a diffusion model built on the CasFormer architecture. The stochastic refinement module learns high frequency spatial structures from historical Himawari 8 and 9 satellite imagery, enhancing boundary realism while preserving physically consistent spread dynamics.

The architecture combines rule based propagation modeling with conditional generative learning to balance stability and expressiveness. The diffusion network iteratively denoises the conditioned perimeter representation to recover fine scale geometric details and complex fire front morphology.

The model was trained and validated on 50 major wildfire events comprising approximately 4000 spatiotemporal sequences from the Asia Pacific region. Quantitative evaluation using Dice Similarity Coefficient and Hausdorff Distance demonstrates improved accuracy and boundary precision compared to deterministic cellular automata and purely data driven U Net baselines.

FireCast Hybrid Deterministic Stochastic Forecasting Framework

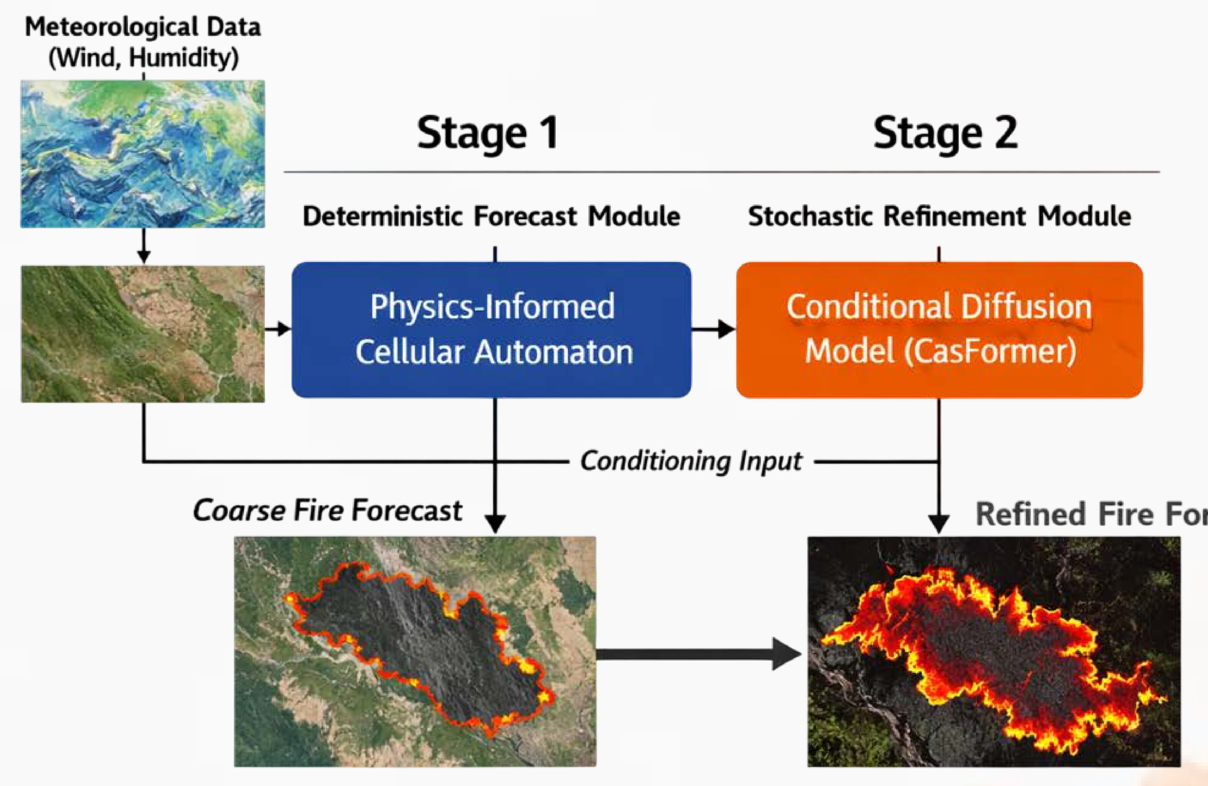

Figure 1. Two stage FireCast architecture integrating a physics informed cellular automaton with a conditional diffusion model for high fidelity wildfire nowcasting.

DATASET AND EXPERIMENTAL SETUP

FireCast was trained and validated on a curated dataset of 50 major wildfire events from the Asia Pacific region. The dataset comprises approximately 4000 spatiotemporal satellite sequences acquired from Himawari 8 and 9 geostationary platforms.

Meteorological variables including wind and humidity were obtained from the ERA5 reanalysis dataset, while terrain elevation data were extracted from a digital elevation model. The model was evaluated for 120 minute nowcasting performance using Dice Similarity Coefficient and Hausdorff Distance to assess spatial overlap accuracy and boundary precision.

RESULTS AND DISCUSSION

The experimental evaluation demonstrates that FireCast achieves superior wildfire nowcasting performance for 120 minute forecasts. The model attains a Dice Similarity Coefficient of 0.84 and a Hausdorff Distance of 3.21 pixels, significantly outperforming both the deterministic cellular automaton baseline and the purely data driven U Net under identical evaluation conditions.

The integration of physics informed cellular automaton modeling with conditional diffusion refinement enables effective capture of both large scale spread dynamics and fine scale perimeter irregularities. The diffusion based stochastic module enhances geometric realism by reconstructing high frequency boundary structures while preserving consistency with meteorological and topographic constraints.

Comparative analysis shows clear improvements over the standalone deterministic CA, which produces overly smooth boundaries, and the U Net model, which may violate physical spread behavior. FireCast maintains stable performance across diverse wildfire events and varying atmospheric conditions within the Asia Pacific region.

The hybrid deterministic stochastic formulation ensures both quantitative accuracy and qualitative realism in predicted fire perimeters. These results validate the effectiveness of combining physics based modeling with generative diffusion learning for trustworthy and high fidelity environmental nowcasting.

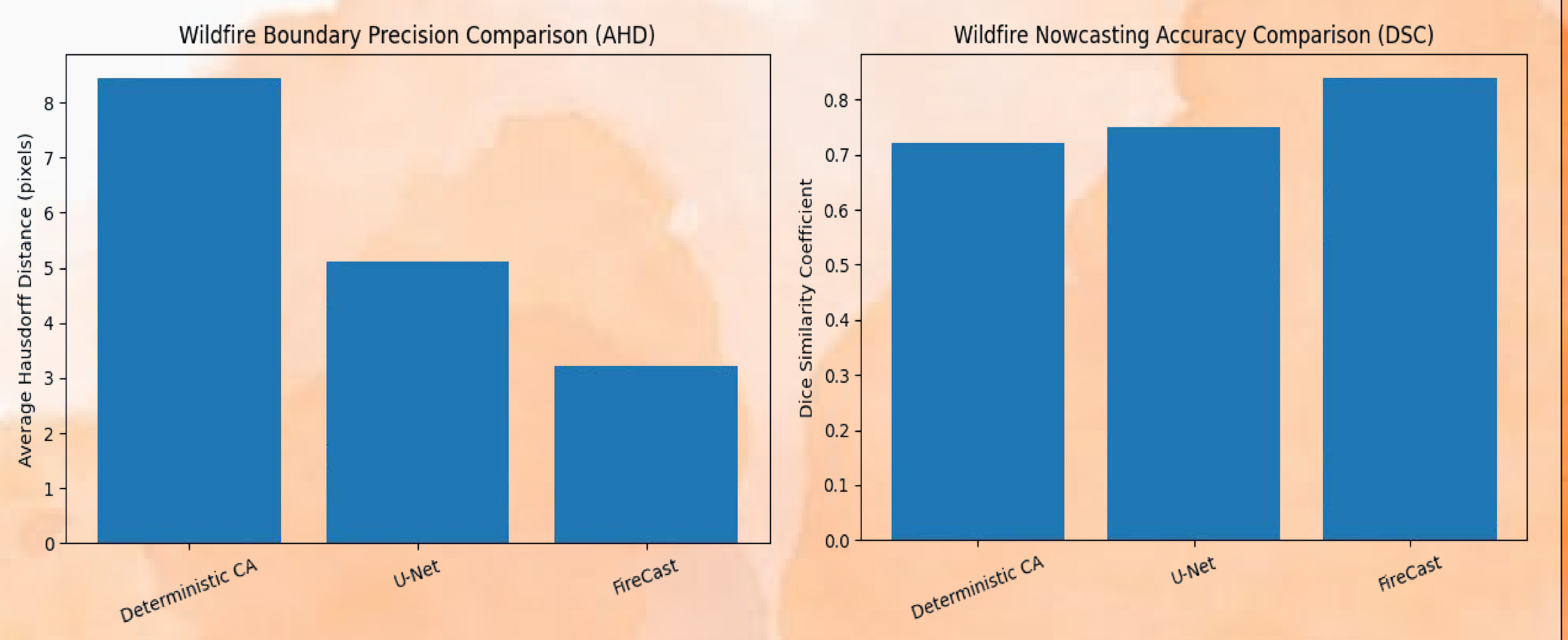

Figure 2. Quantitative comparison of FireCast against Deterministic Cellular Automaton and U-Net baselines using Dice Similarity Coefficient for spatial overlap accuracy and Average Hausdorff Distance for boundary precision in 120-minute wildfire now-casting.

CONCLUSIONS

- FireCast integrates physics informed cellular automaton modeling with conditional diffusion refinement for high fidelity wildfire now-casting.
- The hybrid deterministic stochastic framework improves spatial accuracy and boundary realism while preserving physical consistency.

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