

# 1 Reply to referee 2

## General comment

The manuscript presents an interesting and valuable comparison of machine learning (ML) methods for wildfire prediction and introduces the integration of permanent and temporary firebreaks. This is an important first step toward understanding how suppression strategies influence fire spread. However, some sections and the figures need clarification and expansion to strengthen the work.

Thank you for the positive assessment and for highlighting the contribution of integrating permanent and temporary firebreaks into the predictive framework. We appreciate your constructive feedback. In response, we have revised and expanded several sections of the manuscript to improve clarity, particularly in the description of model states, suppression mechanisms, and methodological assumptions. We have also updated multiple figures and captions to enhance interpretability and visual consistency, including adding clearer explanations, scale references, and zoomed-in views where appropriate. These revisions strengthen both the presentation and the discussion of results.

## Technical comments

1. The complexity of wildfire behaviour depends on multiple environmental variables. While the study includes vegetation density, canopy cover, slope, and wind, future development of training datasets should incorporate additional critical factors such as fuel type (not just vegetation density, but species-specific combustibility) and moisture content of soil/vegetation (highly variable across seasons and strongly influences ignition and spread).

Thank you for this insightful suggestion. We agree that incorporating additional environmental drivers, such as species-specific fuel characteristics and soil/vegetation moisture content, would improve the physical realism of the model. The Cellular Automata (CA) simulator adopted in the present study is intentionally simplified and does not explicitly distinguish between fuel types or moisture variability, as the primary objective was to demonstrate the feasibility of learning fire–firebreak interactions within a controlled framework. However, the proposed surrogate modelling approach is not limited to this simplified CA formulation. In future work, more physically detailed wildfire simulators that explicitly account for heterogeneous fuel types and moisture dynamics can be used to generate training data. We have expanded the Future Work section to acknowledge these factors and to outline their potential integration into future training datasets to enhance predictive performance under varying seasonal and environmental conditions.

2. CA uses States 1–15, while ConvLSTM uses States 0–12. This difference may be confusing to the reader. Recommendation is to include a table comparing or brief explanation of CA and ConvLSTM state definitions and why/how numbering differs.

Thank you for this helpful suggestion. We have added a table (table 1) comparing the CA and ConvLSTM state definitions and clarified the rationale for the different state numbering in Section 2.2.

*The difference in state numbering between the CA simulator and the ConvLSTM model (Table 1) arises from their distinct modelling objectives. The CA simulator employs a more detailed state representation (States 1–15) to explicitly track physical fire processes and firebreak degradation. In contrast, the ConvLSTM surrogate model adopts a simplified and compact state encoding (States 0–12) to reduce the complexity of the multi-class classification task, improve training stability, and focus on the dominant fire and firebreak dynamics relevant for prediction. Temporary firebreaks in both models follow the same*

Concept	CA States	ConvLSTM States
Non-burnable (no fuel)	State 1: No fuel, cannot burn	State 0: Unburned
Unburned (Fuel present)	State 2: Contains fuel but has not ignited	State 0: Unburned
Burning	State 3: Actively burning	State 1: Burning or burned cells
Burned	State 4: Burned out	State 1: Burning or burned cells
Permanent firebreak	State 5: Permanent firebreak	State 2: Permanent firebreak
Temporary firebreak	States 15 $\rightarrow$ 6: Temporary firebreak degrading over 10 time steps	States 12 $\rightarrow$ 3: Temporary firebreak degrading over 10 time steps

Table 1: Comparison of states used in the CA simulator and the ConvLSTM surrogate model.

*binary suppression logic and degrade over ten time steps; however, their numerical labels differ due to this abstraction.*

- The manuscript states “100% suppression for 10 time steps,” but does not clarify whether suppression weakens progressively or remains full until expiration. Explicitly state if suppression is binary or gradual during degradation.

Thank you for this helpful comment. We clarify that the suppression effect of a temporal firebreak is binary rather than gradual. Specifically, a temporal firebreak provides complete (100%) suppression throughout its effective duration and then ceases entirely after 10 time steps, at which point the cell reverts to its original burnable state and fire spread may resume if conditions permit. There is no progressive weakening during the degradation process.

For clarification, we have updated the following sentence in Section 2.1 to avoid ambiguity and to ensure that the temporal dynamics of firebreak effectiveness are clearly defined.

*In the CA simulator, these temporary firebreaks provide complete (100%) suppression throughout their effective duration of 10 time steps, after which they revert to their original state, allowing fire spread to resume if conditions permit.*

- Section 2.2 mentions the second channel for landscape data but notes it is zero-filled. Is this topography? Explain “Currently, the second channel is unused, limiting the model’s ability to incorporate terrain features. Future work should populate this channel with detailed landscape data to improve predictive accuracy.”

Thank you for pointing out the need for clarification. The ConvLSTM model architecture is designed with two input channels: the first channel encodes fire and firebreak states, while the second channel is intended to represent landscape-related information, such as topography and other static environmental features. In the present study, although landscape data are available for the selected case studies, the number and diversity of landscapes are insufficient to train a single, well-generalized model that effectively learns across different terrain configurations. Consequently, the second channel is zero-filled in the current implementation. As a result, each ConvLSTM model is trained separately for a specific landscape, making the current approach landscape-specific.

The following paragraph has been updated to the Section 2.2.

*The second channel was originally designed to include landscape-related data; however, although such data are available for the selected case studies, the limited number and diversity of landscapes are insufficient to train a single generalized model that can robustly learn across different terrains. Consequently, this channel is zero-filled in the current*

implementation. As a result, the ConvLSTM models are trained separately for each of the three landscapes used in the CA simulations, making the current approach landscape-specific.

5. The results section could benefit from a short discussion on why scenarios with firebreaks improve accuracy such as, firebreaks reduce randomness and constrain fire spread, making patterns more predictable and easier for the model to learn.

We have added the following paragraph to Section 3.1 discussing why scenarios with firebreaks lead to improved predictive accuracy:

*In Figure 7, the improved predictive accuracy observed in scenarios with firebreaks can be attributed to the reduced stochasticity and constrained fire spread dynamics introduced by suppression measures. Firebreaks limit the spatial extent and rate of fire propagation, thereby reducing the number of possible spread pathways and dampening the inherent randomness of the CA simulations. This constraint leads to more structured and predictable fire evolution patterns, which are easier for the ConvLSTM model to learn and generalize. In contrast, scenarios without firebreaks exhibit more unconstrained fire growth and higher variability, increasing the difficulty of accurately predicting long-term spread. As a result, the presence of firebreaks not only mitigates fire propagation in the simulations but also enhances the stability and learnability of the underlying spatio-temporal patterns captured by the model.*

6. Figure 2: Needs a clearer caption explaining arrows and state transitions.

Following the reordering of figures, this diagram is now presented as Figure 3 in new manuscript. We have revised the caption to explicitly explain the meaning of the arrows and the associated state transitions, as detailed below.

*Solid arrows denote deterministic state transitions, while dotted arrows indicate probabilistic transitions, with the associated probabilities shown next to each arrow. Non-burnable cells (State 1) remain unchanged. Burnable but unignited cells (State 2) ignite with probability  $P_{\text{burn}}$  and transition to the burning state (State 3) when one or more neighbouring cells are burning. Burning cells (State 3) transition to the burned-out state (State 4) with probability  $R_{\text{burned\_down}}$ . Cells within permanent firebreaks (State 5) may still ignite with probability  $P_{\text{pfb\_burn}}$ . Temporary firebreaks are initialized at State 15 upon deployment and deterministically degrade by one state at each subsequent time step, transitioning from State 15 to State 6 over 10 time steps, after which the cell reverts to its original pre-firebreak state.*

7. Figure 3: Add a scale bar for spatial reference.

As Figure 4 (formerly figure 3 in the old manuscript) is intended primarily to illustrate fire propagation patterns and firebreak behaviour rather than precise geographic positioning, we did not include an additional scale bar in the panel.

8. Figure 4: This workflow figure is important to explain the workflow. Ensure it is explicitly discussed in the text.

We have moved the workflow figure earlier in the manuscript and explicitly introduced it at the beginning of Section 2. The figure is now presented as Figure 2 in new manuscript and is accompanied by a new paragraph:

*Figure 2 provides an overview of the data generation, model training, and prediction workflow used in this study. First, a CA simulator is employed to generate spatio-temporal wildfire propagation data under various environmental conditions and firebreak deployment scenarios. These CA-generated fire spread sequences, together with firebreak information, are then used to train a ConvLSTM-based surrogate model. During inference, the*

*trained ConvLSTM model takes a sequence of previous fire states as input and predicts subsequent wildfire evolution with significantly reduced computational cost. This workflow illustrates the relationship between the physics-inspired CA simulator and the data-driven ConvLSTM model, and clarifies how the two components are integrated in the proposed framework.*

9. Colourscales: All figures should include legends and units for clarity (esp. Figure 1).

Thank you for this comment. For Figure 1, the displayed data are normalized and therefore do not have physical units. To improve clarity, we have added a legend to the figure and clarified this explicitly in the caption.

*The Ferguson 2018 fire landscape presents normalized data in slope, vegetation density, and canopy cover (Fig.(a), (b), (c), (d)). Similarly, the Bear 2020 fire depicts distinct topographical and ecological normalized data, including slope, vegetation density, and canopy distribution (Fig.(e), (f), (g), (h)). Fig (a,e) are from © Google wildfire product.*