Improve wildfire predictability driven by extreme water cycle with interpretable physically-guided ML/AI

Qing Zhu [1], William J Riley [1], James Randerson [2]
[1]Lawrence Berkeley National Laboratory
[2] University of California, Irvine

Focal Area(s)
Predictive modeling using AI techniques and AI-derived model components; use of AI and other tools to design a prediction system comprising of a hierarchy of models (Primary); insight gleaned from complex data (both observed and simulated) using AI, big data analytics, and other advanced methods, including explainable AI and physics- or knowledge-guided AI (Secondary).

Science Challenge
Wildfires modify land surface characteristics, such as vegetation composition, soil and litter carbon stocks, and surface albedo, with significant consequences for the regional carbon cycle. For example, tropical regions (i.e., African and South America) are particularly vulnerable to wildfire, account for more than 80% of the global burned area, and emit ~1.4 PgC y^{-1} into the atmosphere together with other dust and aerosols that strongly affect regional climate.

Globally, wildfire burned area has declined in recent decades due to changes in population density, cropland fraction, and livestock density (Andela et al., 2017). However, projections of increases in temperature and regional drought will likely outweigh these human impacts and result in an unprecedentedly fire-prone environment over a large fraction of the land surface, highlighting the need for better management of those critical fire regions (Walker et al., 2019). Therefore, prediction of wildfire dynamics, improved understanding of wildfire controllers, risk, and the effectiveness of potential management practices will become increasingly important for forest and savannah projections, regional carbon conservation, and sustainable land use decision-making.

In order to tackle the above-mentioned wildfire related science challenges, two categories of models are often used: process-based wildfire models and data-driven machine learning models. Physical models can often capture long-term wildfire trends, but not responses to seasonal and inter-annual variability (Li et al., 2019). Data driven

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wildfire models need to expand interpretability and physical principle explanations for short-term and extreme event interactions with wildfire (Zhu et al. 2021).

Rationale

The occurrence, spread, and impacts of wildfire are highly dependent on dry-wet conditions and the extreme water cycle of the system. For example, wildfire is sensitive to extremely dry fire seasons (hot and dry fuel) and extremely wet non-fire seasons (vegetation growth and accumulated biomass). Classic process-based models simulate dry-wet seasons carbon and water dynamics, but generally fail in seasonal wildfire prediction due to biases in process representation, model structure uncertainty, and parametric uncertainty. Also, classic process-based models have difficulties making use of existing diverse datasets of wildfire activities. To this end, ML/AI approaches are critical to effectively integrate the very large observational datasets of fires with the short-term observations under various water cycle conditions (e.g., dry, wet).

To utilize large datasets, process based models, and physical understanding of wildfire dynamics, physically guided ML/AI models are needed for high-accuracy wildfire predictions in response to previous and concurrent extreme water events. Also, ML/AI infrastructure needs to be designed to predict wildfire several months ahead of the fire season that can support planning and management of wildfire, regional carbon conservation, and sustainable climate decision-making.

Narrative

Coupled process models and machine learning models are needed for predicting wildfire activities, ecosystem vulnerability to wildfire, and assessing the impacts of wildfire and potential management activities on ecosystem carbon cycling. The coupling between process and ML/AI models could be implemented in various ways. Figure 1 is one example of a successful coupling, which provides pre-training datasets for ML/AI models based on process-based model simulations, and provides the basis for physical constraints and guidance that need to be considered in ML/AI architecture (Figure 1). Also, the coupling could effectively utilize large datasets (e.g., remote sensing based GFED burned area and emissions dataset Giglio et al., 2013). The coupled framework could provide high accuracy prediction with reasonable physical considerations. As a result, the interpretability of the coupled model is largely improved compared with a traditional ML/AI model.

The integrated infrastructure that combines data, ML/AI model, and process-based model could be automated to perform real-time forecasting. The infrastructure could (1) collect near real-time remote sensing data about surface climate, fire ignition, fuel availability, and combustibility; (2) continuously fine-tune machine learning models to predict wildfire activity in the next few months; (3) generate feasible management scenarios over regions with high vulnerability to wildfire and feed information to process based models; (4) assess management practices and uncertainty quantification; (5) aid planning and management of wildfire over critical regions; and (6) inform observational needs regarding wildfire predictions (e.g., large-scale observational campaigns, remote sensing). For example, it could be used to answer science questions such as: How do ecosystem vulnerabilities to wildfire change through time and space? How do physical environments (e.g., soil moisture), fuel conditions, and ignition processes interactively affect wildfire activities over different ecosystems? How do various management practices contribute to wildfire control, carbon stock conservation, and regional vegetation growth? In addition, the automated workflow of this physically-guided ML/AI wildfire model could be applied to many other earth system predictability problems.

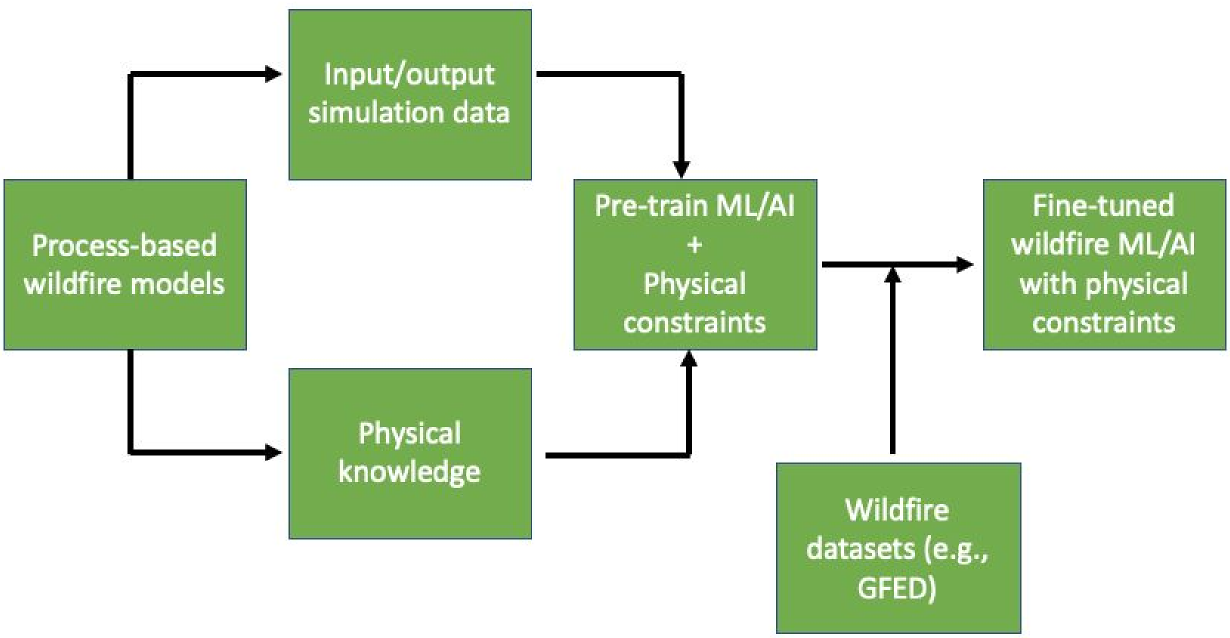

Figure 1. Workflow diagram for combining process-based wildfire model, ML/AI model, and large datasets and achieve physically-guided wildfire ML/AI model.

Reference

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