ESA-ECMWF Workshop 2022

Data-driven wildfire predictions at regional and global scales

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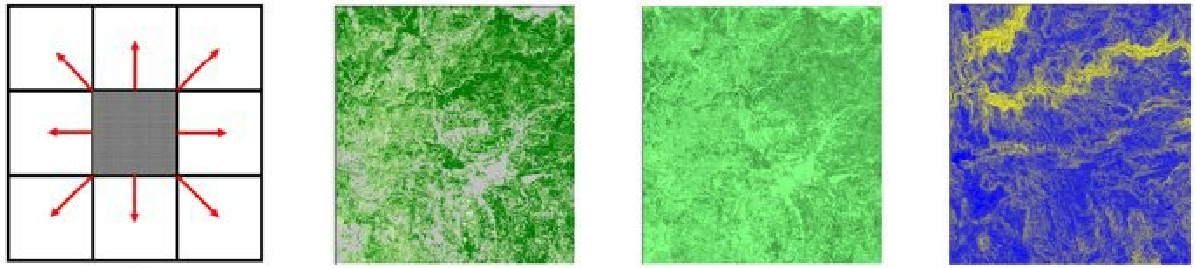
Study area and CA simulation

Cellular Automata

Canopy cover Canopy density Landscape slope



(a) (b) (c) (d)

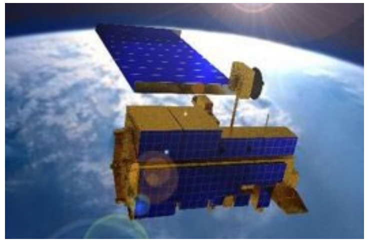
Other fire simulators/algorithms

- Rothermel equation
- Flammap
- SPARK
- CA

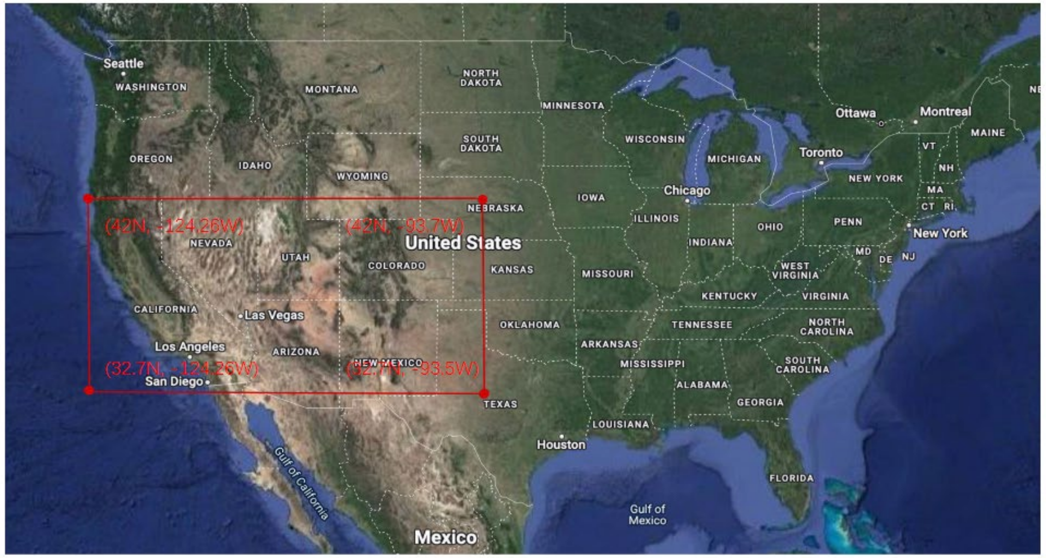
It is time consuming to simulate large fires

Alexandridis, A., Vakalis, D., Siettos, C.I. and Bafas, G.V., 2008. A cellular automata model for forest fire spread prediction: The case of the wildfire that swept through Spetses Island in 1990. *Applied Mathematics and Computation*, *204*(1), pp.191-201.

MODIS Satellite



Launched by NASA in 1999
Daily image at 1km resolution



Surrogate modelling

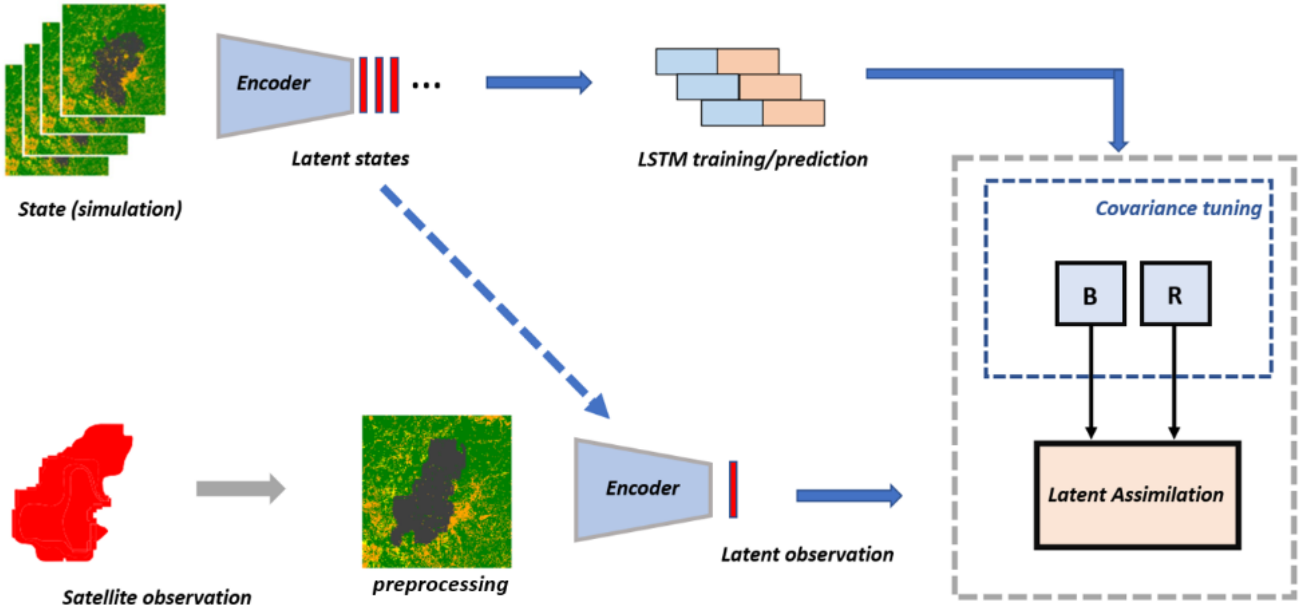
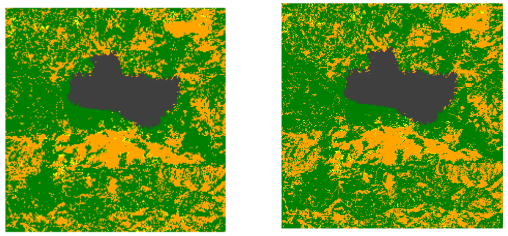


Figure 1: Flowchart of deep latent assimilation with information-based observation compression and error covariance tuning

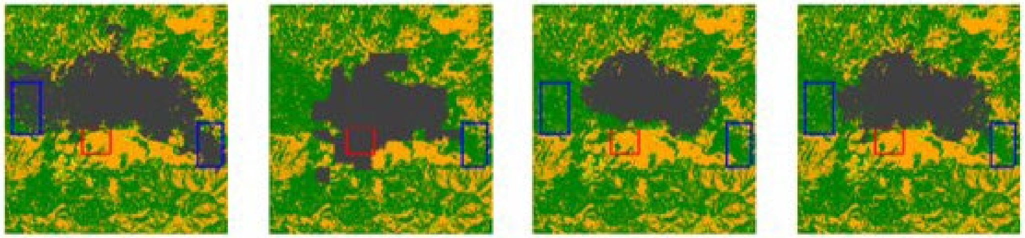
Cheng, S., Prentice, I.C., Huang, Y., Jin, Y., Guo, Y.K. and Arcucci, R., 2022. Data-driven surrogate model with latent data assimilation: Application to wildfire forecasting. Journal of Computational Physics, p.111302.

Simulation ***Surrogate***



Motivation of DA

- Integrating satellite data
- Accumulation of prediction error

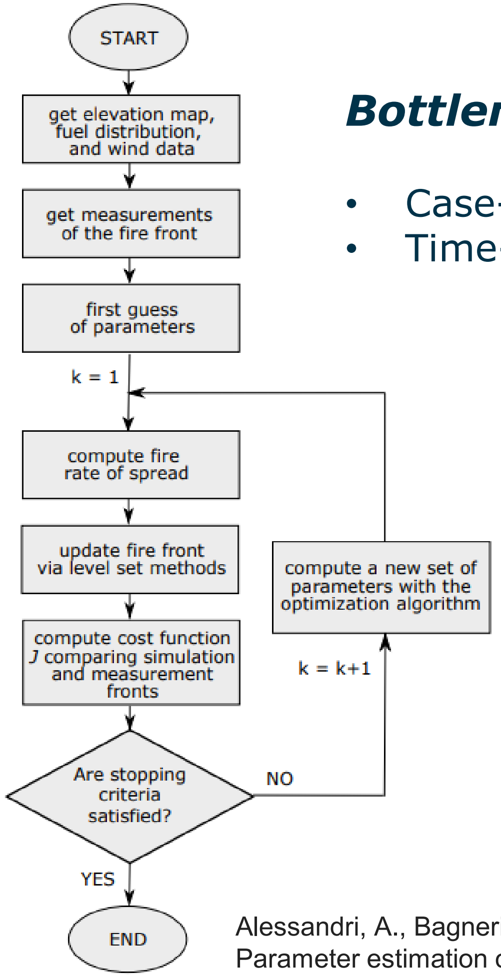


(m) LSTM(day 4) (n) obs(day 4) (o) LSTM+DA(day 4) (p) DA(day 4)

Fire	simulation	LSTM	DA	DI01	Flammap
Bear 2020	3.85s	$3.1e^{-3}s$	$5.8e^{-3}s$	$8.7e^{-2}s$	$10 \sim 30$s
Buck 2017	2.96s	$5.26e^{-3}s$	$4.26e^{-3}s$	$2.12e^{-2}s$	$5 \sim 20$s
Pier 2017	8.28s	$6.28e^{-3}s$	$5.36e^{-3}s$	$2.68e^{-2}s$	$10 \sim 30$s

Table 5: Averaged computational time for one time-step using different approaches

Model parameter identification



Bottleneck

- Case-by-case tuning
- Time-consuming

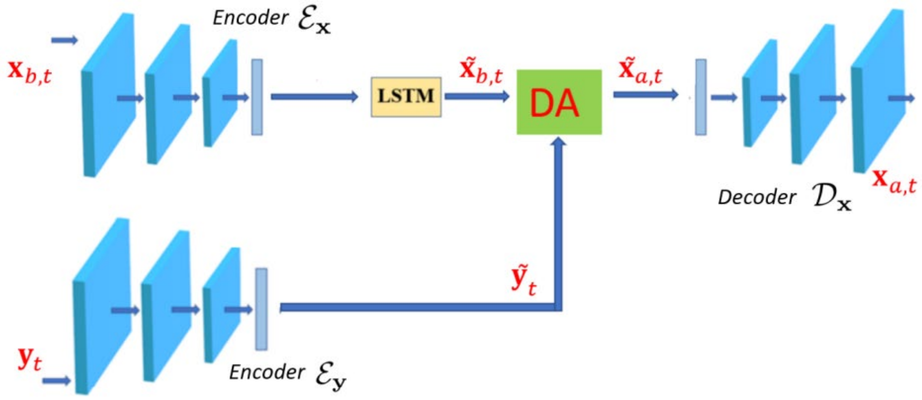
Idea

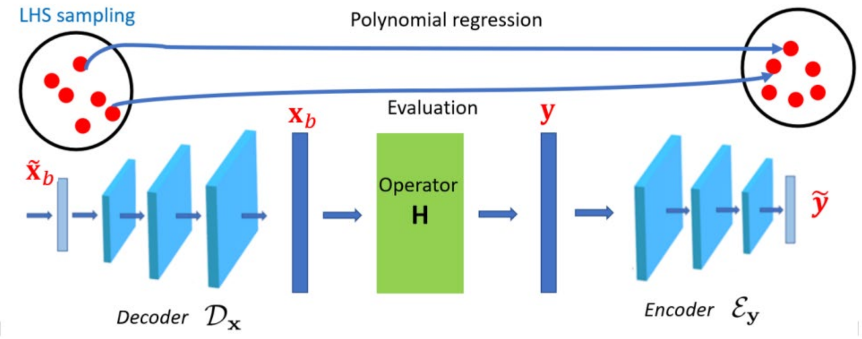
- Use fast ROM and ML forward models
- DA for parameter estimation

Alessandri, A., Bagnerini, P., Gaggero, M. and Mantelli, L., 2021. Parameter estimation of fire propagation models using level set methods. *Applied Mathematical Modelling*, *92*, pp.731-747.

Our solution

Generalised Latent Assimilation





Cheng, S. et al., 2022. Generalised Latent Assimilation in Heterogeneous Reduced Spaces with Machine Learning Surrogate Models, accepted in Journal of scientific computing

GLA for model parameter identification

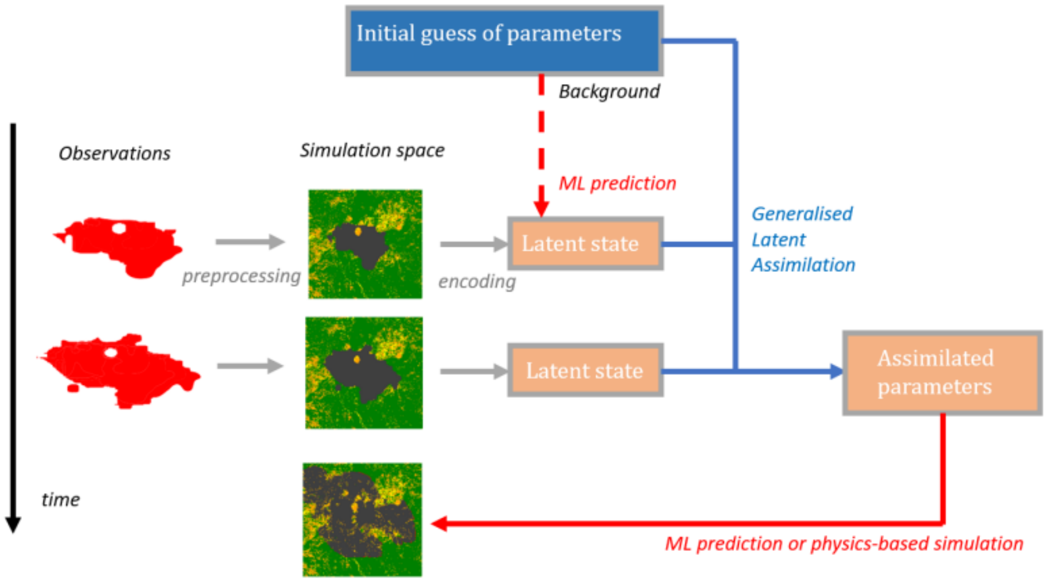
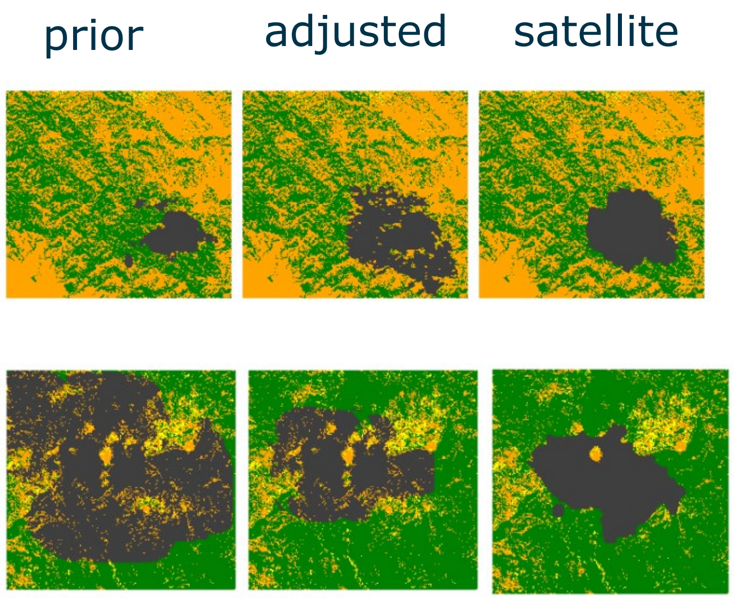


Figure 3. Flowchart of the inverse model for parameter identification using GLA.

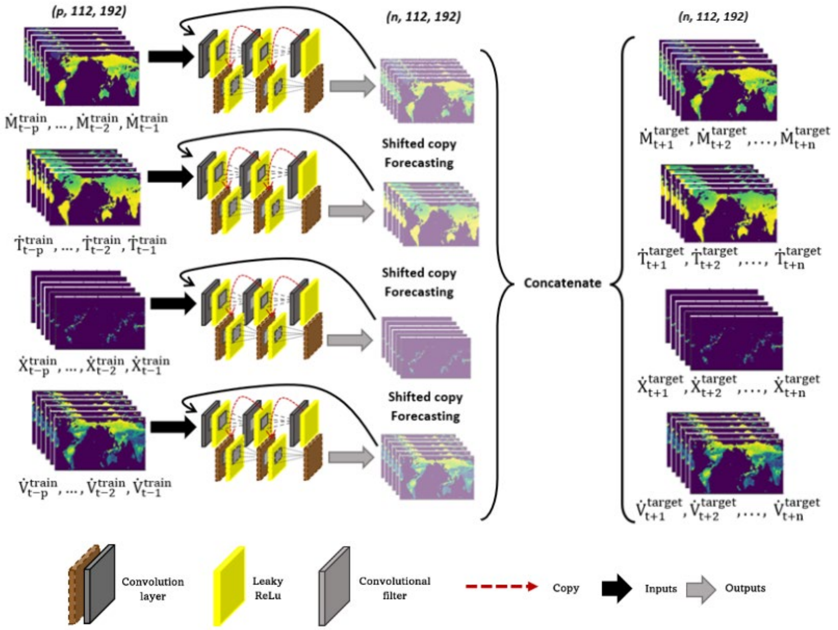
Prediction

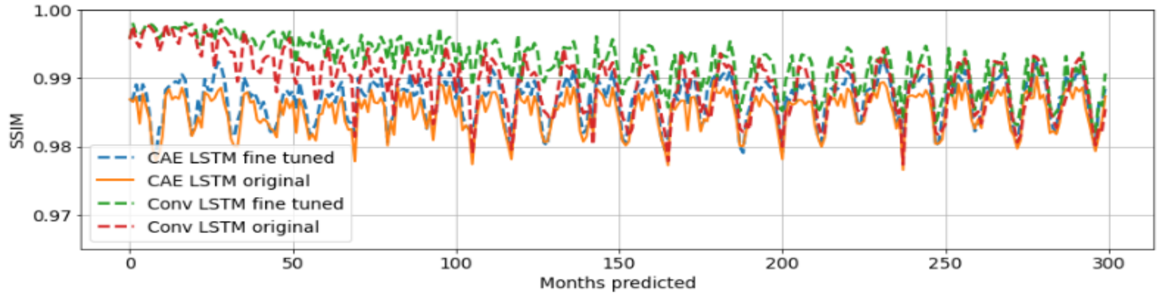
after parameter estimation

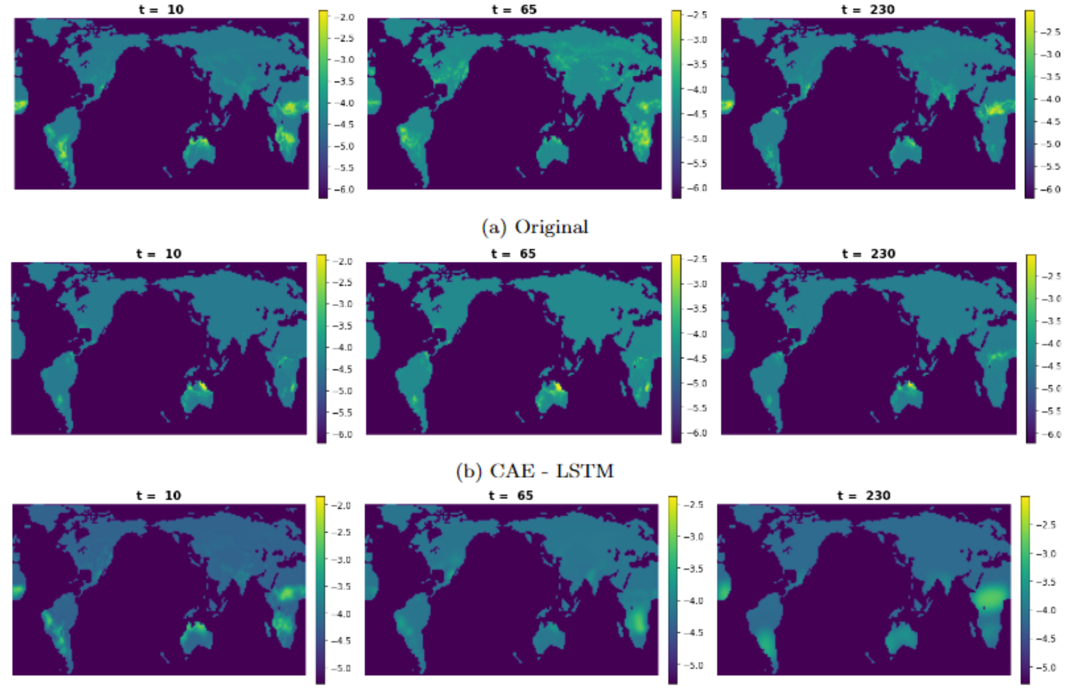


Cheng, S. et al., 2022. Parameter flexible wildfire prediction using machine learning techniques: Forward and inverse modelling. *Remote Sensing*, *14*(13), p.3228.

Surrogate model for JULES-INFERNO With a fine-tuning strategy







(a) Original

(b) CAE - LSTM

(c) ConvLSTM

	best CAE - LSTM		best ConvLSTM	
Metric	*Original*	*Fine tuned*	*Original*	*Fine tuned*
RE	2.13×10^{-3}	2.01×10^{-3}	1.73×10^{-3}	1.51×10^{-3}
mean SSIM	98.52%	98.70%	98.96%	99.24%
Prediction time (s)	2.29	2.34	7.31	6.53

Zhang, C., Cheng, S., Kasoar, M., and Arcucci, R.: Reduced order digital twin and latent data assimilation for global wildfire prediction, EGUsphere [preprint], 2022.

Chassagnon, H., Cheng, S., Kasoar, M., Guo, Y., and Arcucci, R.: Deep learning surrogate models of JULES-INFERNO for wildfire prediction on a global scale,submitted, 2022.

How to generalize the surrogate models?

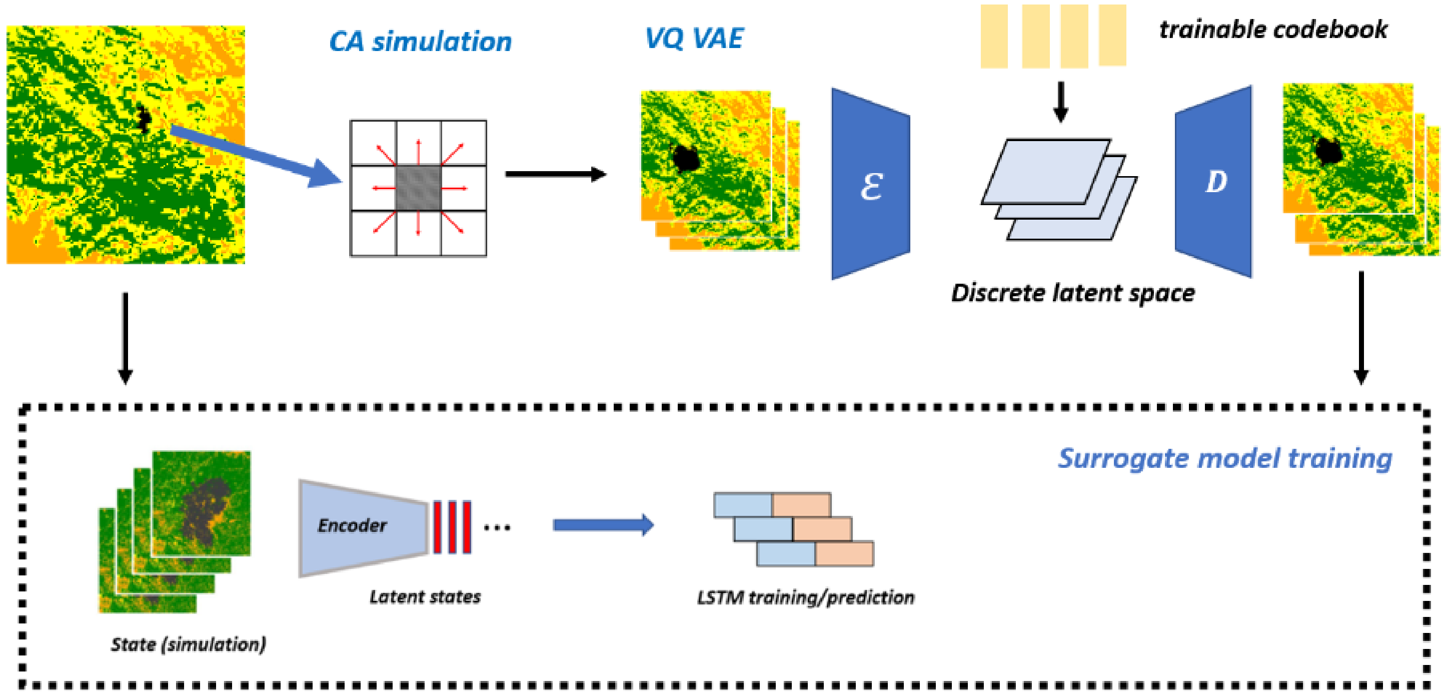
Challenges

Surrogate models are specific to ecoregions

Many simulations need to the performed to form the training set

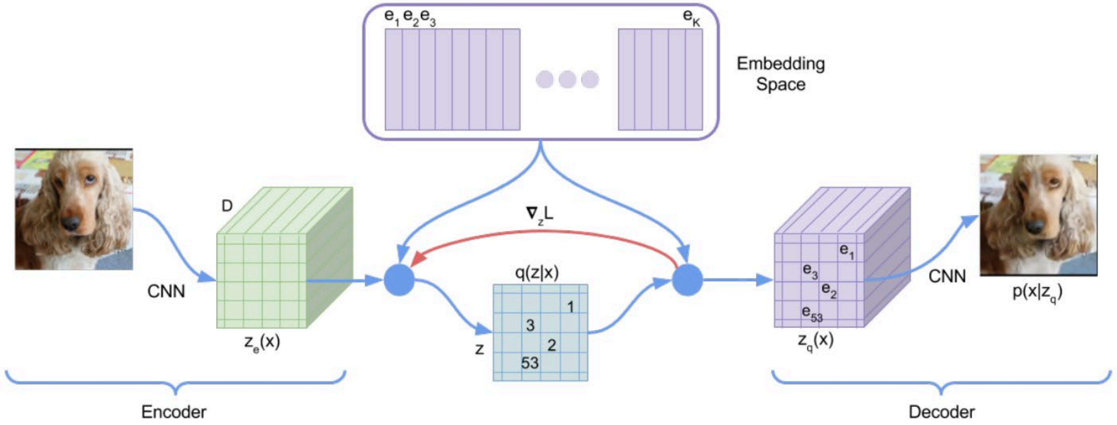
Our idea

Generative models



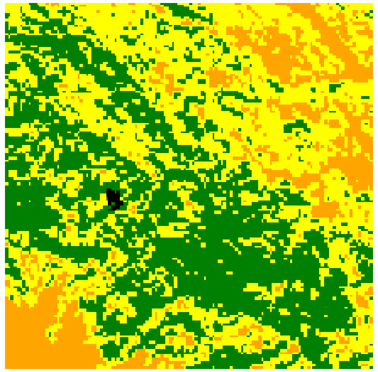
Generative model

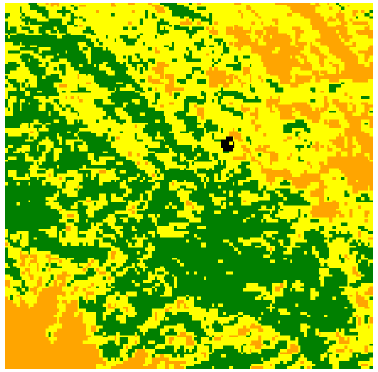
VQ-VAE

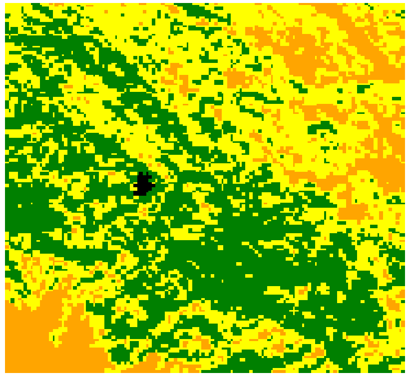


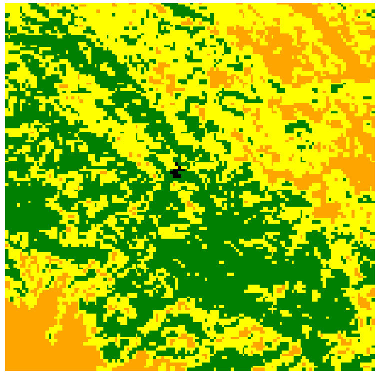
Van Den Oord, A. and Vinyals, O., 2017. NeurIPS

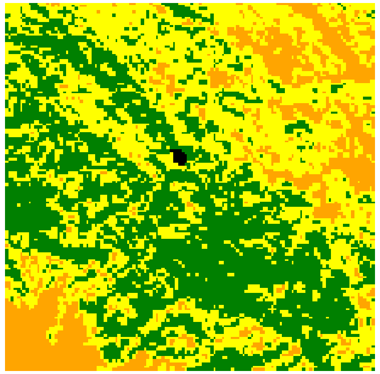
- Most of the generations are reasonable
- The generative model ‘understand’ the impact of vegetation density and slope









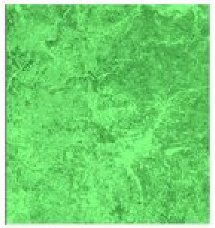


Fire-Image-Densenet

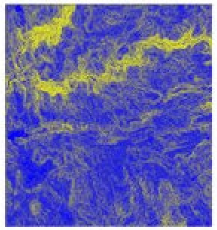
Objective：predicting the final burned area

Canopy cover

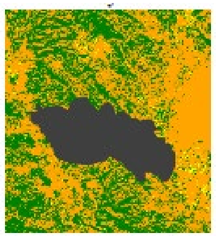
Canopy density

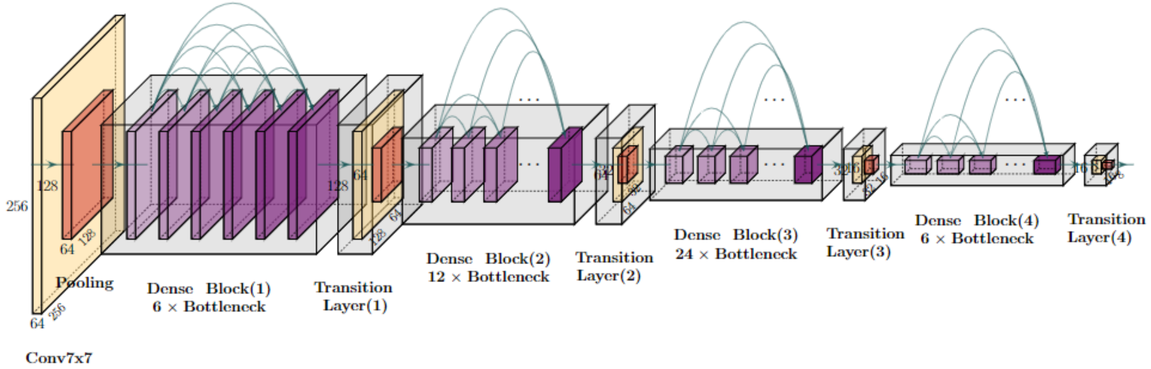


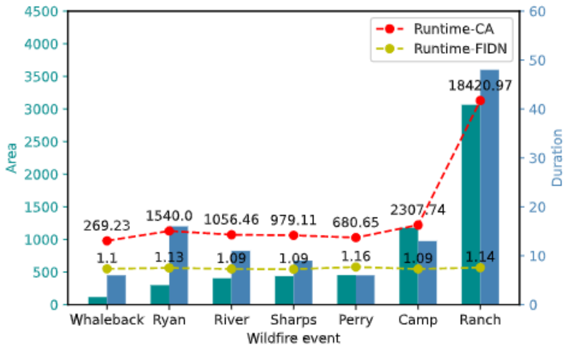
slope



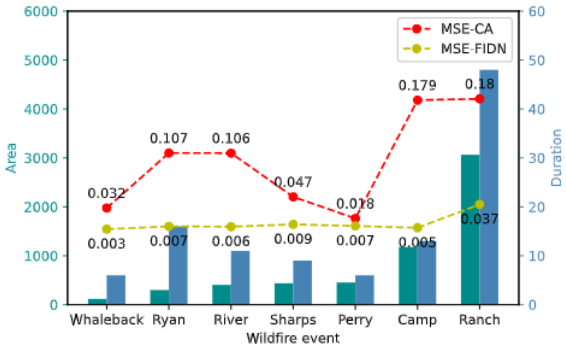
Day 1-3







(a) Runtime



(b) MSE

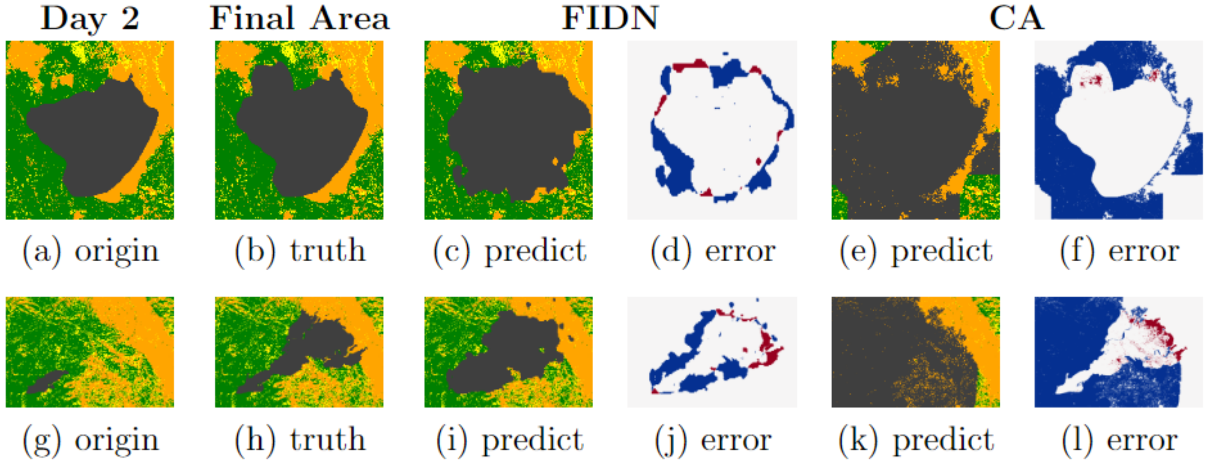


Figure 9: Predicted results for the Whaleback(2018) Fire and the Ryan(2018) Fire (from top to bottom)

Future works

- Improve the generalizability of the developed models
- Extend the current models to other natural hazards
- Self-supervised learning with remote sensing data

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ECMWF

Google DeepMind

NVIDIA

YouTube

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Every year, the DataLearning group organises a workshop on **Machine Learning and Data Assimilation for Dynamical Systems (MLDADS)**, as part of the International Conference on Computational Science (ICCS).

London - ICCS 2022 Poland - ICCS 2021 Amsterdam - ICCS 2020 Faro, Portugal - ICCS 2019

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To get access to our **codes**: **Our GitHub** https://github.com/DL-WG

GitHub

3 Open special Issues

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