“Being the fire”

A CNN-Based Reinforcement Learning Method to Learn How Fires Behave Beyond the Limits of Physics-Based Empirical Models

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SCHOOL OF EARTH, ENERGY & ENVIRONMENTAL SCIENCES

The problem in 2020/21

4M
acres burnt

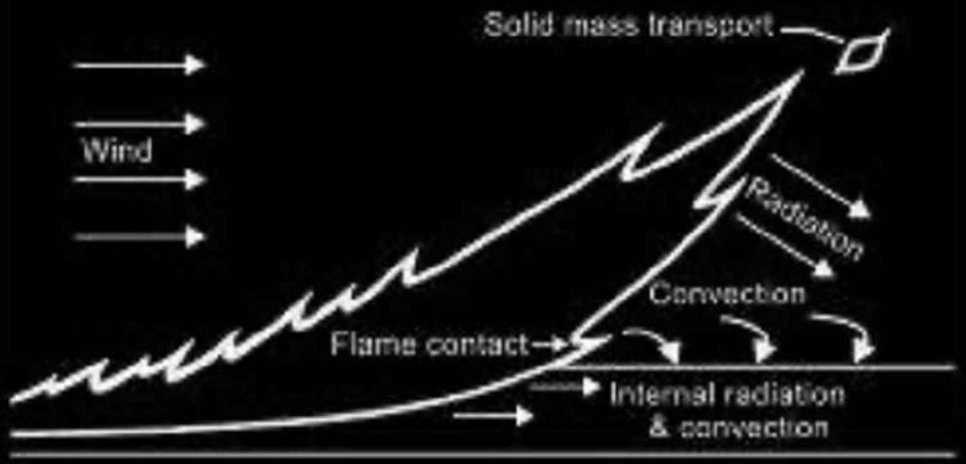
31
fatalities

$10B
damages

Prediction | Mitigation | Evacuation | Insurance

All of this innovation depends on one model

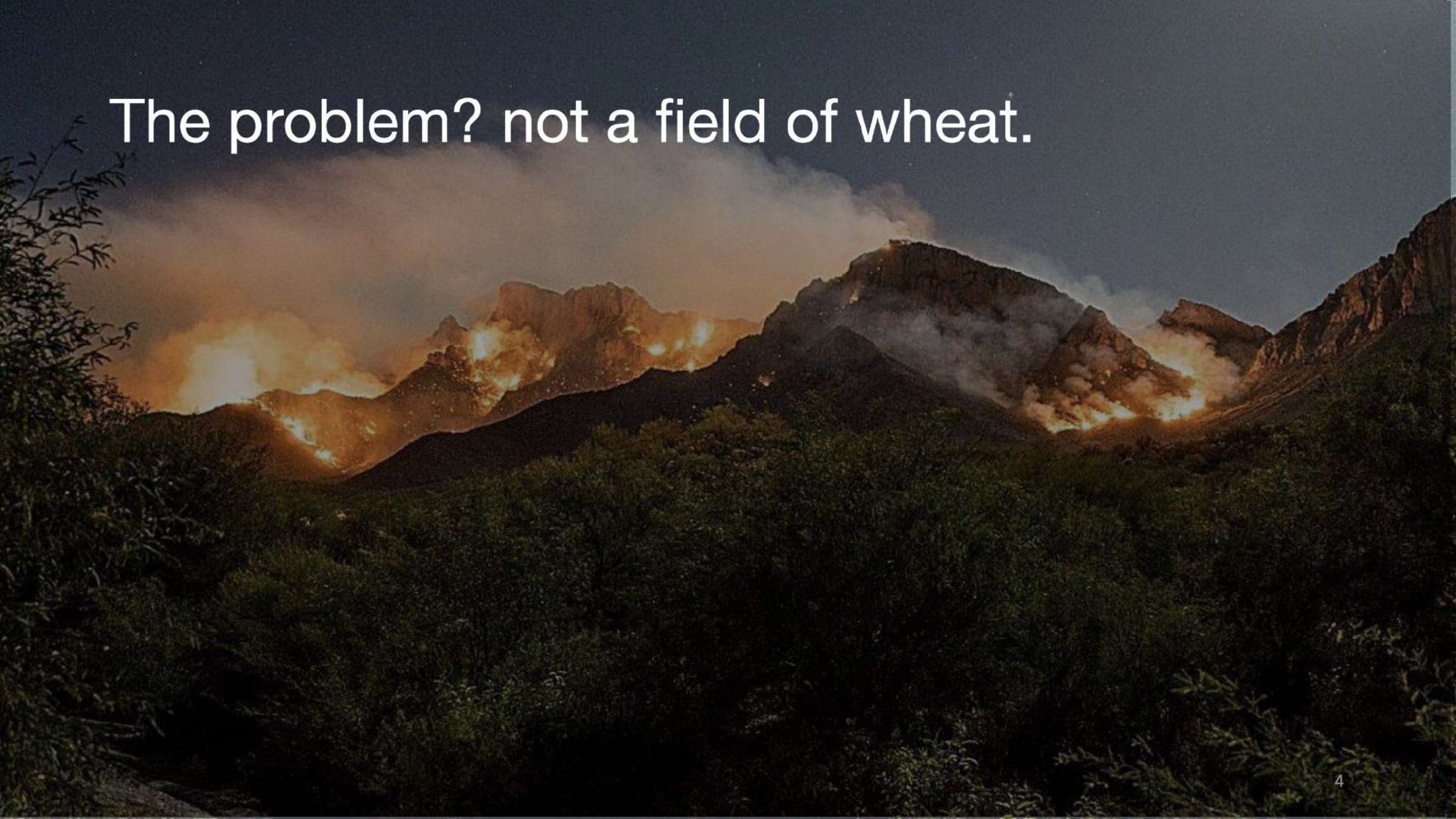
$$R = \frac{I_R \xi (1 + \phi_W + \phi_s)}{\rho_b \epsilon Q_{ig}}$$



"The model describes very well a fire burning in a field of wheat. As you get further away from that uniformity, the less accurate it becomes."

Richard Rothermel

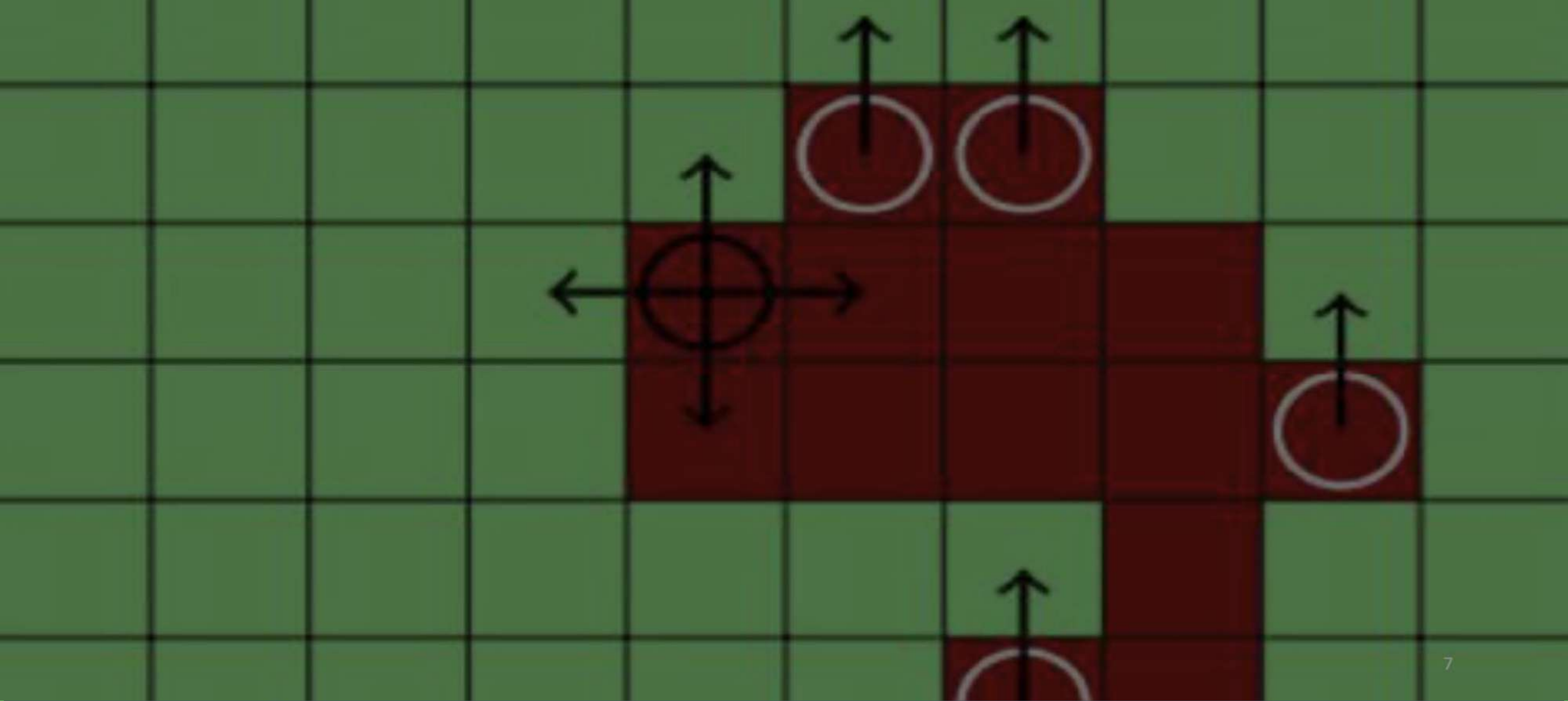
The problem? not a field of wheat.



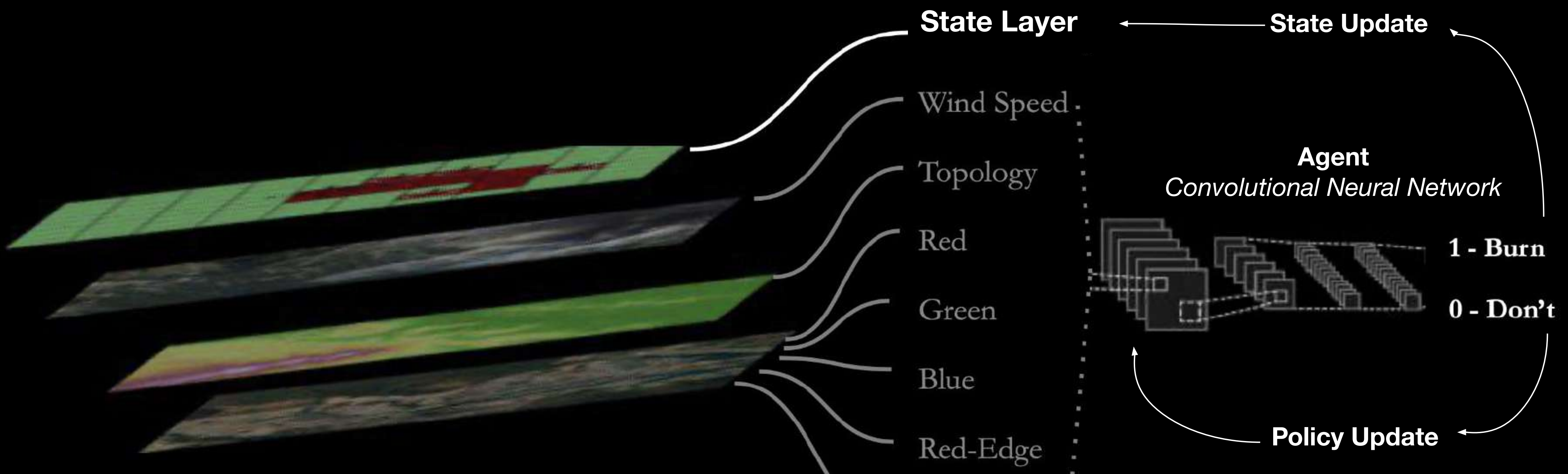
Innovation 1: geolocalized wind speeds

Innovation 2: high resolution remote sensing

Innovation 3: ML-driven fire spread modeling



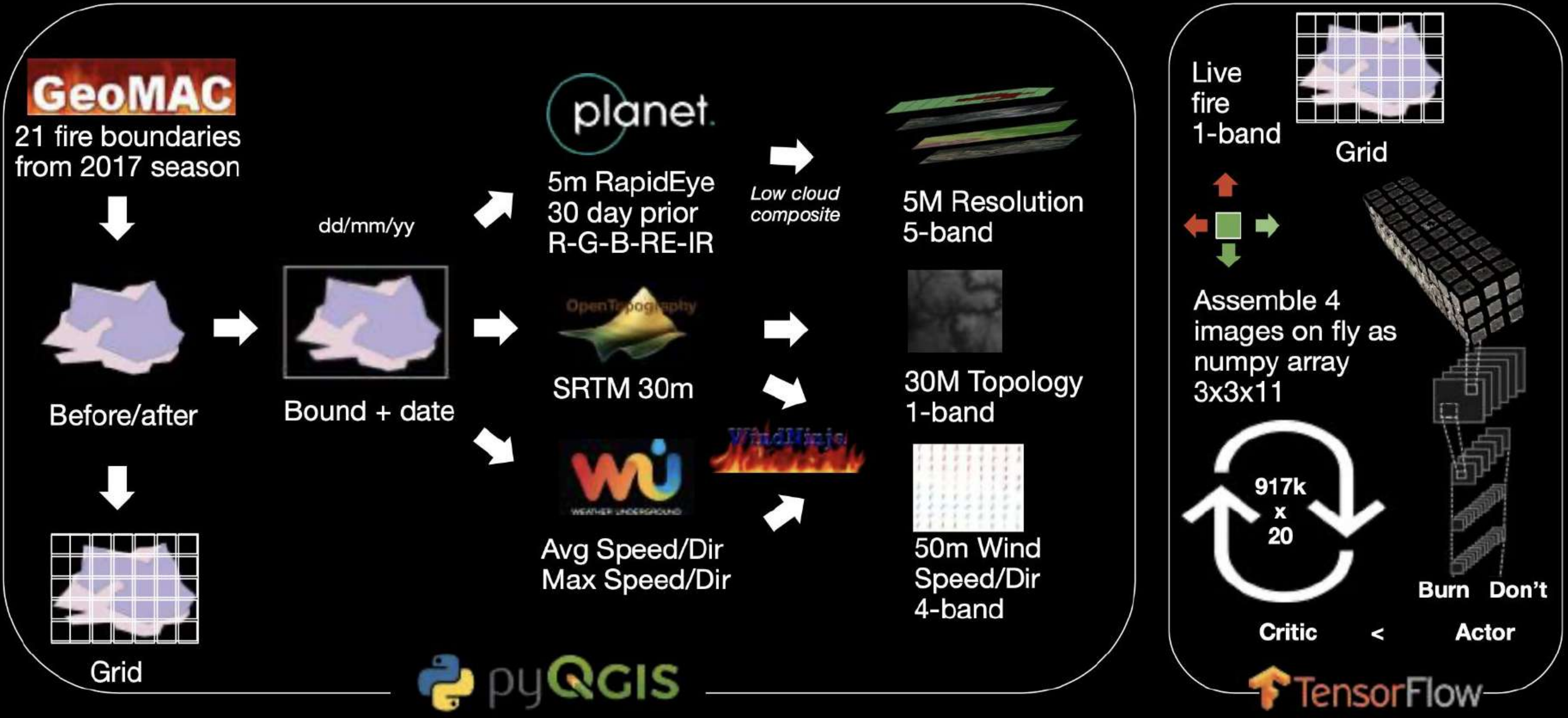
Research Direction



$$Q(s,a) = (1-\alpha)\,Q(s,a) + \alpha\,Q_{obs}(s,a)$$

$$\text{where, } Q_{obs}(s,a) = r(s,a) + \gamma \max_{a'} Q(s',a')$$

Methods

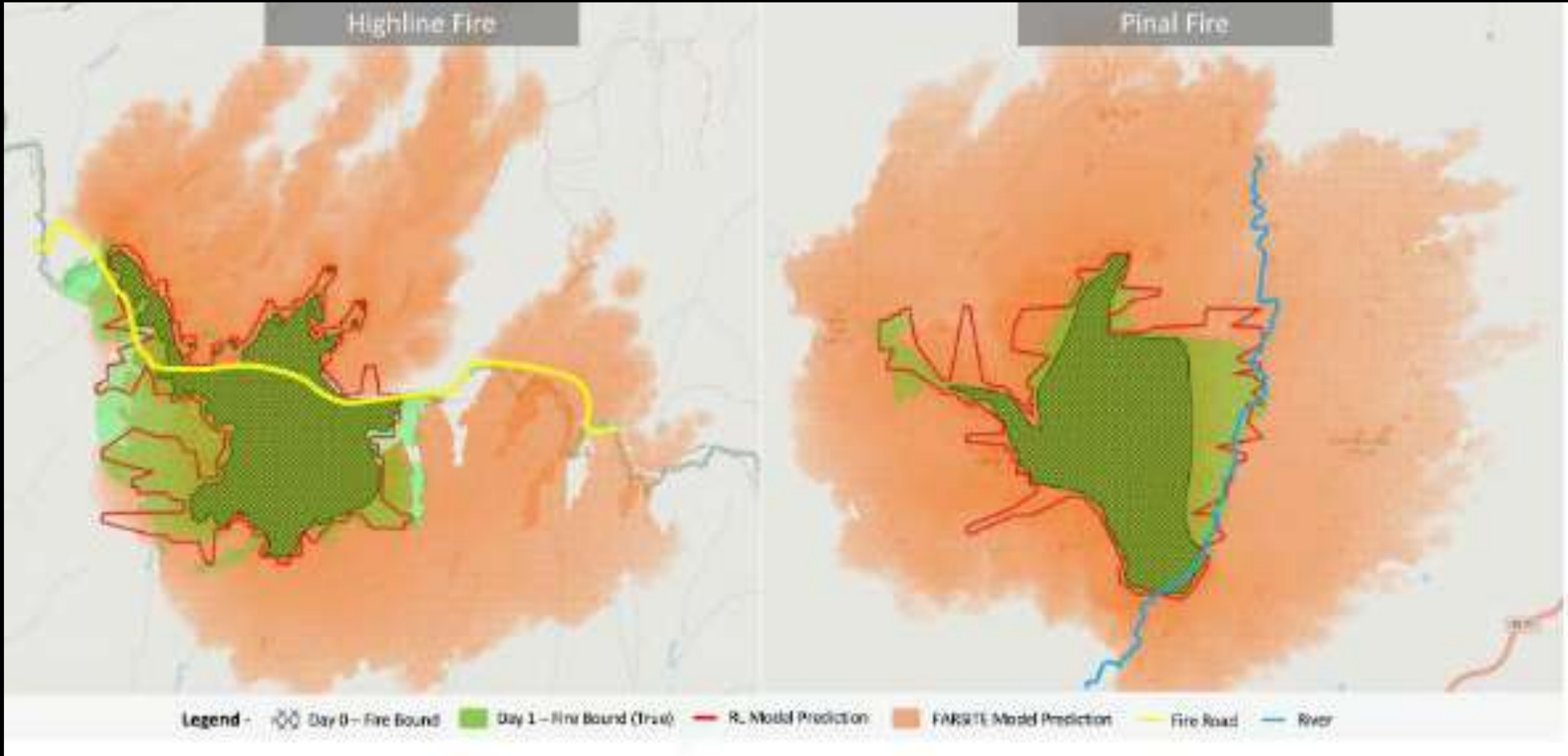

GeoMAC
21 fire boundaries
from 2017 season
Before/after
Grid
dd/mm/yy
Bound + date
planet.
5m RapidEye
30 day prior
R-G-B-RE-IR
SRTM 30m
Avg Speed/Dir
Max Speed/Dir
Low cloud
composite
5M Resolution
5-band
30M Topology
1-band
50m Wind
Speed/Dir
4-band
pyQGIS
Live
fire
1-band
Grid
Assemble 4
images on fly as
numpy array
3x3x11
917k
x
20
Burn
Don't
Critic
<
Actor
TensorFlow

Results - Quantitative Performance

Fire Name	CNN-Based RL, TD(0) Q-Learning			FARSITE Benchmark		
	Precision	Recall	F-1	Precision	Recall	F-1
Buck	.82	.78	.74	.64	.45	.44
Highline	.77	.69	.59	.62	.43	.39
Pinal	.84	.84	.81	.84	.20	.08
Sulfur	.78	.72	.64	.79	.73	.74

Weighted average F-1 of 0s and 1s in T=0 unburned sample area

Results - Qualitative Performance



Conclusions

- CNN-based RL is an important direction of research for fire spread modeling
  - Tail wind of improved data availability/resolution
  - Tail wind of ML research generally
  - Head wind of interpretability

- All methods will be challenged by reality of modeling a highly stochastic physical process
  - Existing methods performance below expectations
  - Consequences for downstream research

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