JENSEN HUGHES

Making Our World
SAFE, SECURE + RESILIENT

FASTER-THAN-REAL-TIME FIRE FORECASTING

JONATHAN L HODGES, PH.D. | June 2023

Our Global Reach

90+ *Offices* WORLDWIDE

40,000+
GLOBAL PROJECTS
across 100+ countries

1,500+
EMPLOYEES
providing innovative solutions

PEOPLE
We are committed to a culture of trust, inclusion, integrity and professional growth.

CLIENTS
We serve as trusted advisors to our clients, value our relationships with them, strive to exceed their expectations and deliver world-class technical solutions.

INDUSTRY
We lead by championing best practices, advancing innovation and shaping the standards that keep our world safe, secure and resilient.

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330+
NFPA Committee Positions

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200+
PUBLISHED TECHNICAL PAPERS, ARTICLES AND JOURNALS SINCE 2018

Faster-Than-Real-Time Fire Forecasting

Outline

+ Data Science Background
+ Fire Forecasting Background
+ Improving Faster-Than-Real-Time Fire Forecasting
+ Emerging Concepts
+ Conclusions

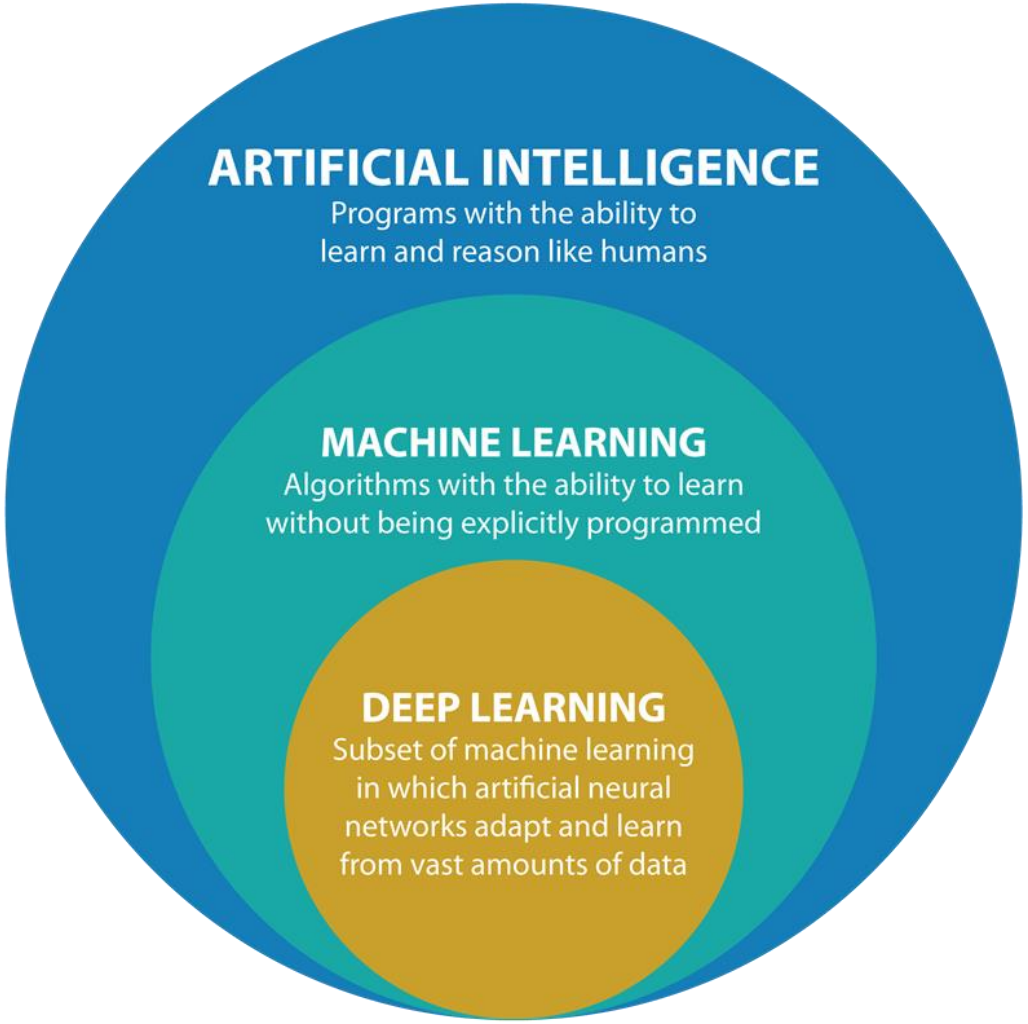
(1)

Data Science Background

+ Key Definitions
+ Types of Data
+ Data Assimilation
+ Machine Learning

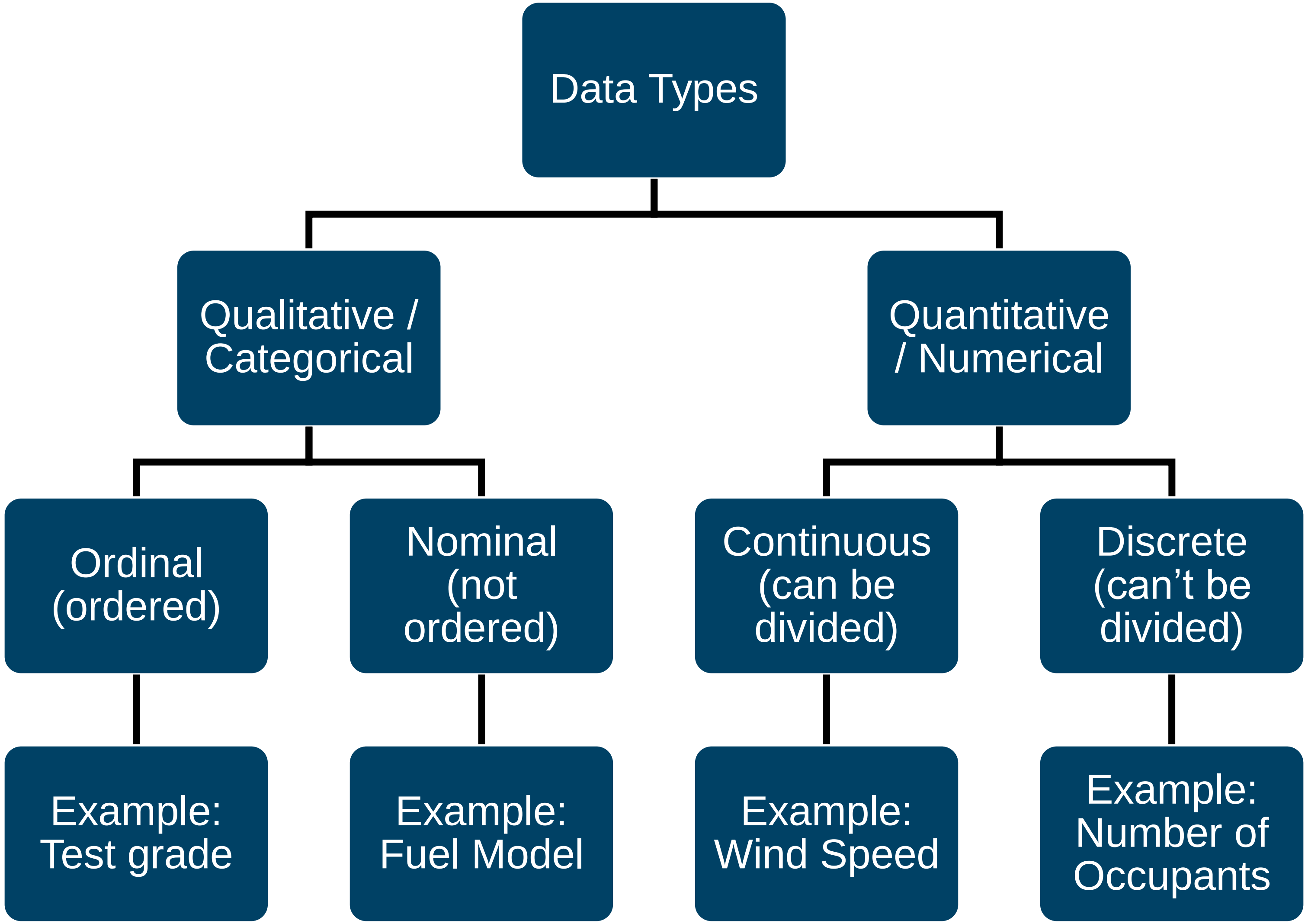
Key Definitions in Data-Driven Modeling

- Artificial Intelligence
  - Focuses on making decisions based on data
- Machine Learning
  - Form of applied statistics to estimate complicated functions
  - Set of tools to develop correlations and identify trends in data
- Neural Networks / Deep Learning
  - Uses a high number of free parameters to develop correlations
  - High complexity makes it difficult to track why a prediction is made
- Data Assimilation
  - Approximation of the true state of a random variable by combining data/observations with a model predictions in a specific scenario



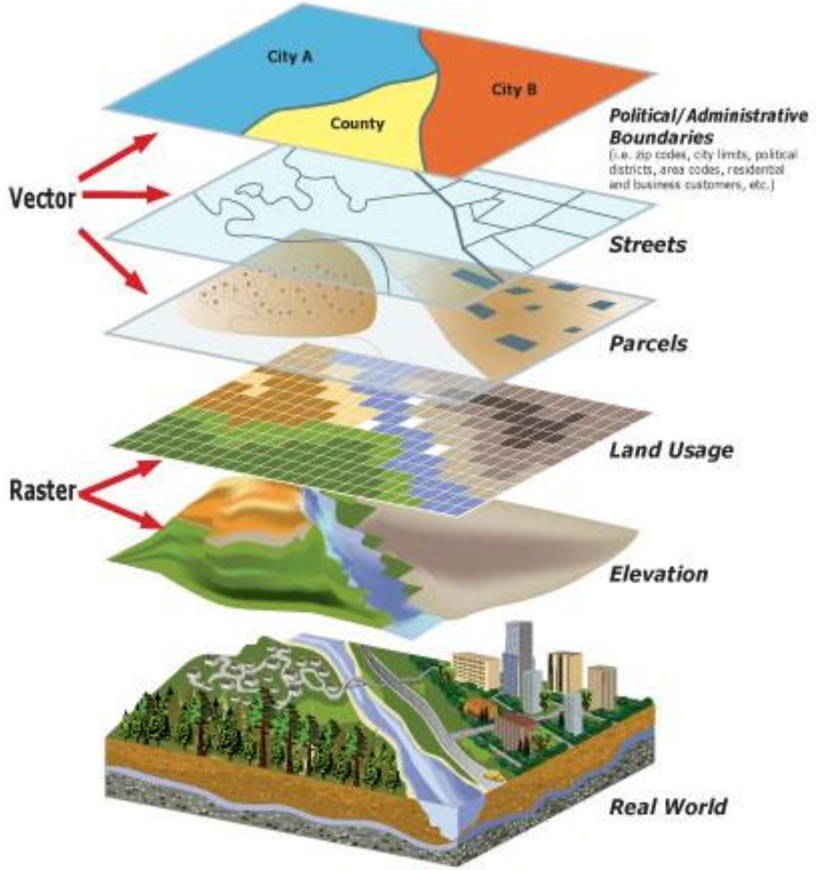
R. Nuzzi, G. Boscia, P. Marolo, F. Ricardi, The Impact of Artificial Intelligence and Deep Learning in Eye Diseases: A Review, Front. Med. 8 (2021) 1–11. doi:10.3389/fmed.2021.710329.

Types of Data – Quantity Types



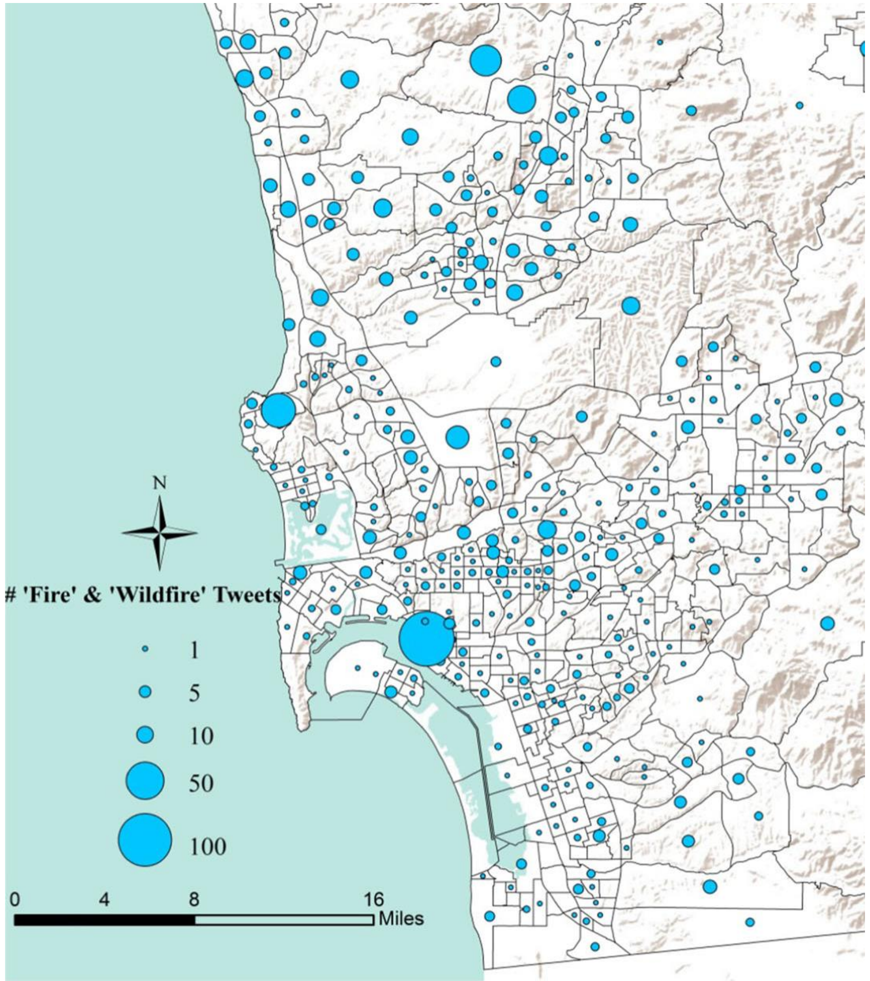
Types of Data – Geospatial Types

Structured



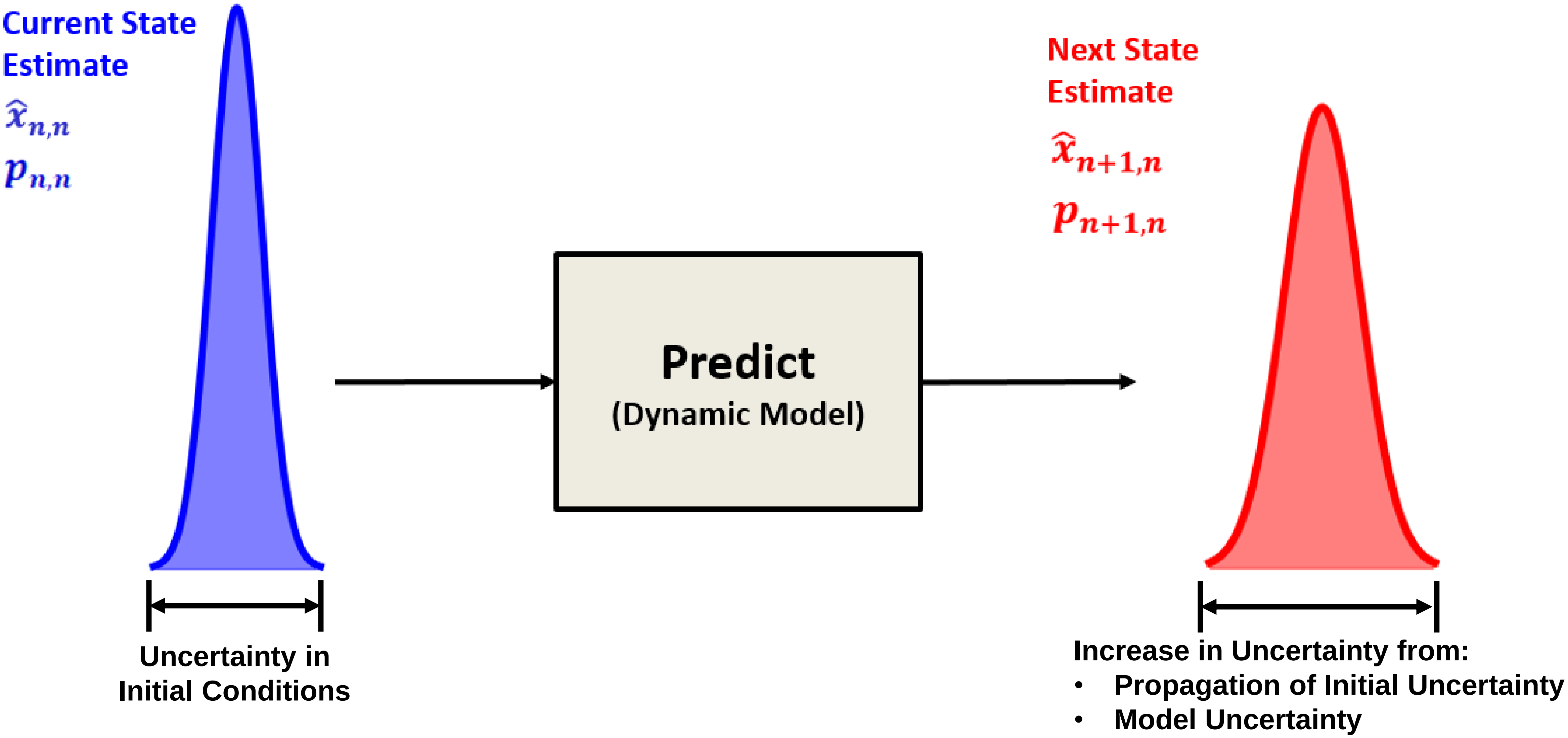
https://guides.lib.uw.edu/research/gis

Unstructured



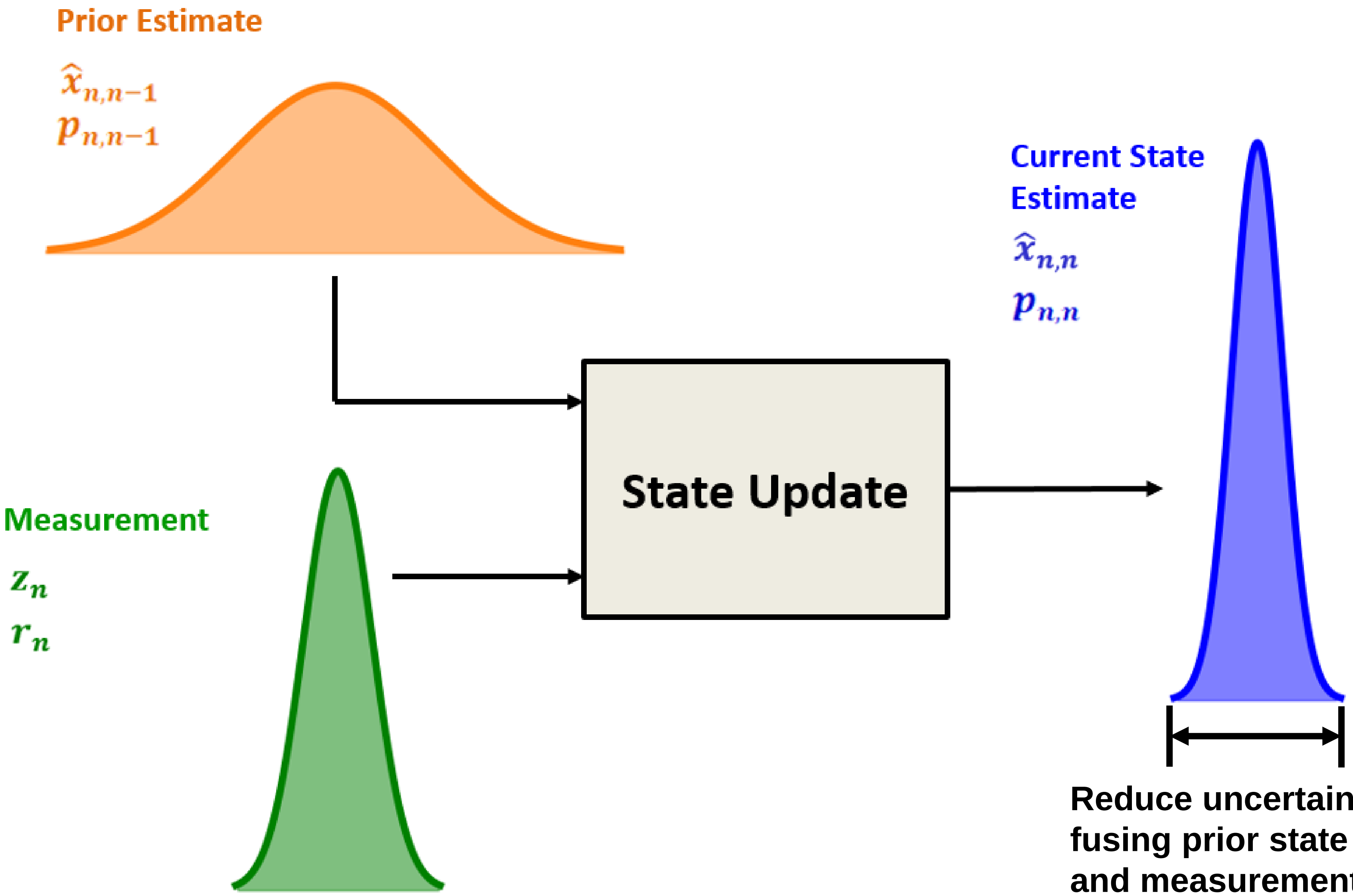
Z. Wang, X. Ye, M.H. Tsou, Spatial, temporal, and content analysis of Twitter for wildfire hazards, Nat. Hazards. 83 (2016) 523–540.

Data Assimilation Background – Traditional Modeling Without Data Assimilation



https://www.kalmanfilter.net/kalman1d.html

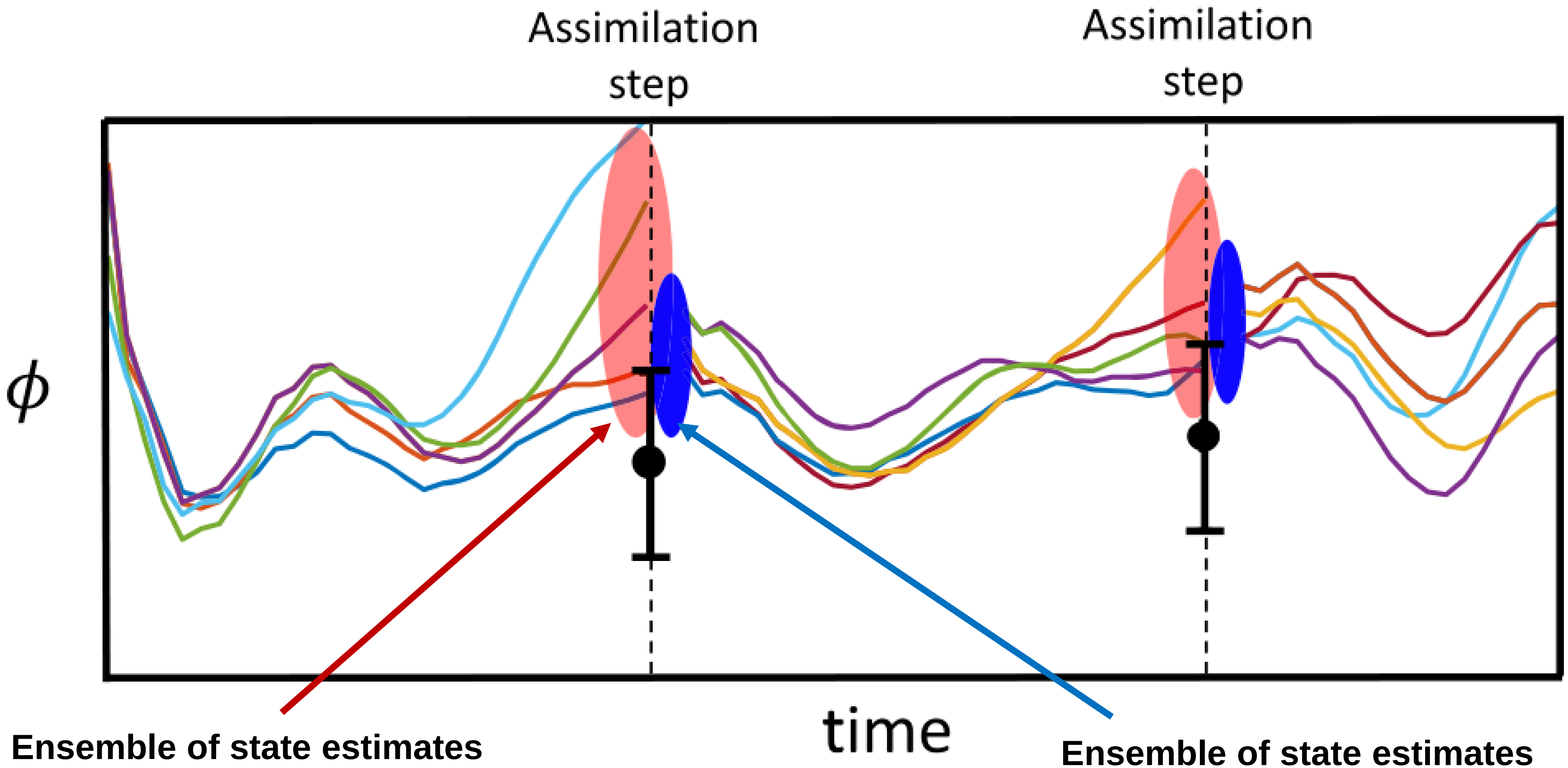
Data Assimilation Background – State Estimation



Reduce uncertainty by fusing prior state estimate and measurement

https://www.kalmanfilter.net/kalman1d.html

Data Assimilation – Ensemble of States



Ensemble of state estimates prior to assimilation

Ensemble of state estimates after assimilation

J.W. Labahn, H. Wu, S.R. Harris, B. Coriton, J.H. Frank, M. Ihme, Ensemble Kalman Filter for Assimilating Experimental Data into Large-Eddy Simulations of Turbulent Flows, Flow, Turbul. Combust. 104 (2020) 861–893. doi:10.1007/s10494-019-00093-1.

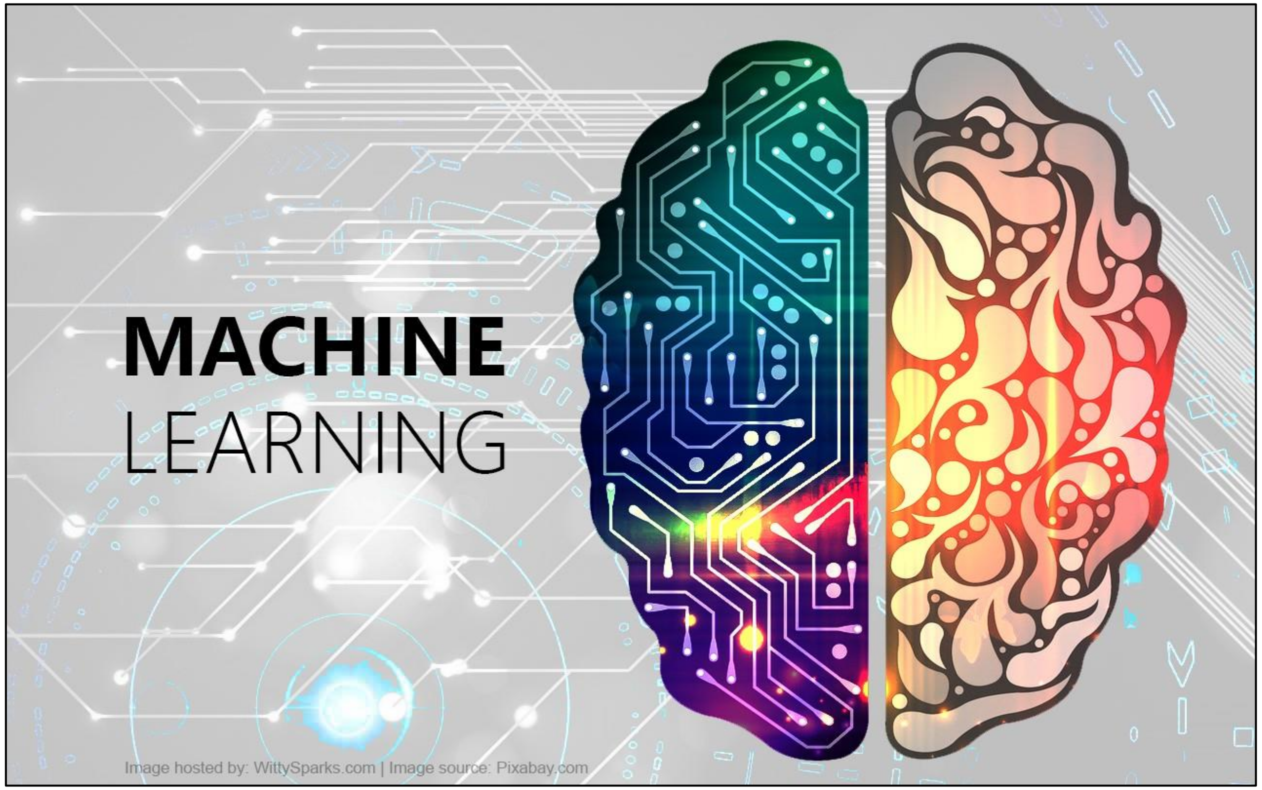
Fundamental Concepts of Machine Learning

Learning Algorithms

+ Formal definition

  A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E. – Mitchell 1997

+ Following slides provide examples of tasks, performance measures, and experience



https://towardsdatascience.com/introduction-to-machine-learning-for-beginners-eed6024fdb08

Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016. See the Deep Learning book freely available online for more detail on these topics: https://www.deeplearningbook.org/

Fundamental Concepts of Machine Learning

Tasks

1. Classification Identify type of items	What type of hazard? What type of object? What type of report?
2. Clustering Group similar items	How similar are these materials? Which fire in the NFIRS database is the most similar to this? What are the common characteristics of these hazards?
3. Regression Estimate numeric results	What is the probability of failure? What is the worst-case scenario? How quickly can a space be evacuated?
4. Anomaly Detection Detect atypical conditions	Is this report similar to others in the training set? Is this equipment operation changing over time / negatively trending? What equipment receives disproportionate amounts of maintenance?
5. Transcription Transform unstructured data	Interpreting an audio signal into textual sentences Converting images of text into textual content Auto-generating summary text / too-long didn't read (TLDR)

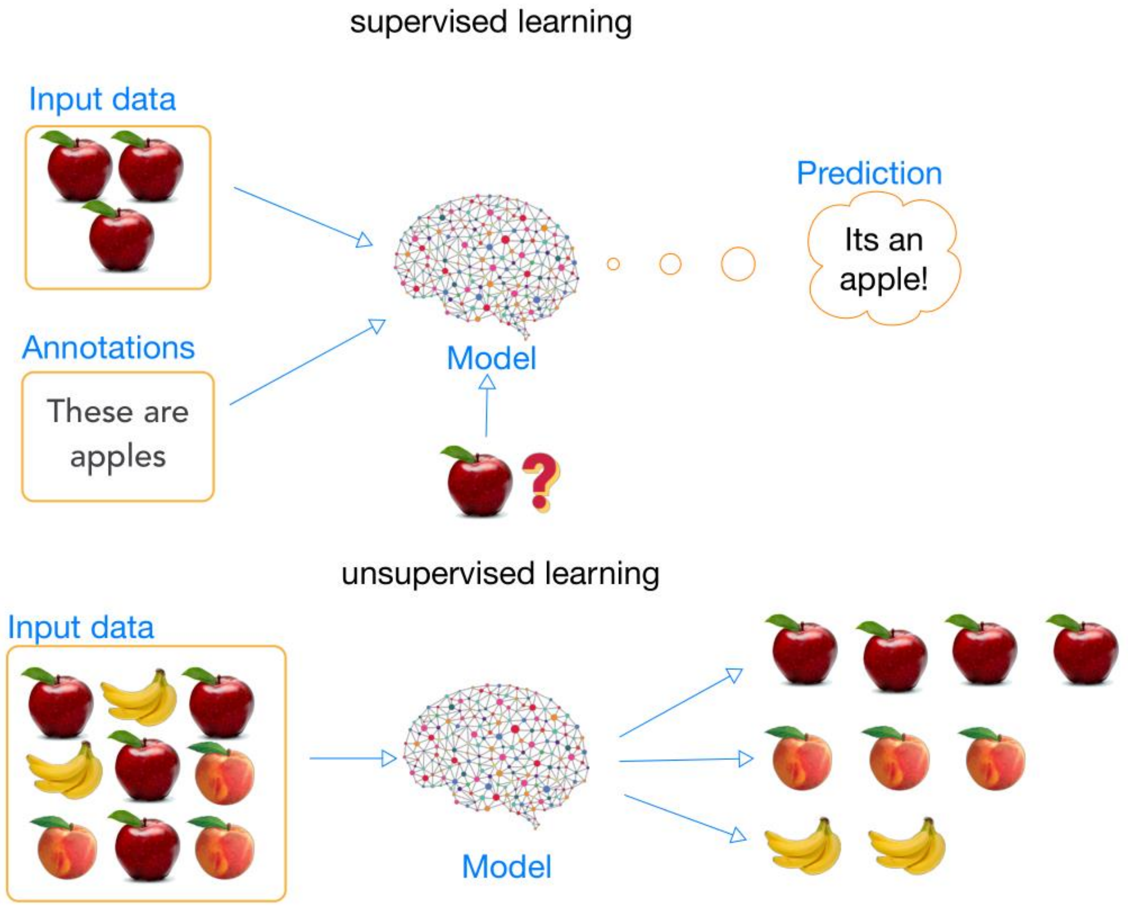
Fundamental Concepts of Machine Learning

Experience

+ Type of experience varies between supervised and unsupervised learning

+ Supervised learning
  - Learn to predict a specific target based on input
  - Human acts as the instructor to the algorithm

+ Unsupervised learning objectives
  - Determine the probability density function from which the random samples were drawn
  - Identify interesting properties of the underlying distribution
  - Algorithm acts as an instructor to the human



Y. Ma, K. Liu, Z. Guan, X. Xu, X. Qian, and H. Bao, “Background augmentation generative adversarial networks (BAGANs): Effective data generation based on GAN-augmented 3D synthesizing,” *Symmetry (Basel).*, vol. 10, no. 12, 2018.

Example Performance Measures

+ Confusion Matrix
  - Shows the ratio of correct and incorrect predictions in binary classification

		Ground Truth: Ignition	Ground Truth: No Ignition
Model	Ignition	True Positive (TP)	False Positive (FP)
Model	No Ignition	False Negative (FN)	True Negative (TN)

+ Accuracy
  - Bad metric for skewed data
  - 99% accurate by predicting NO ignition

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)}$$

+ False Negative Rate (FNR)
  - Fraction of ignitions which are not detected (i.e., number of fires which reach a critical size prior to discovery)

$$FNR = \frac{FN}{(TP+FN)}$$

+ False Discovery Rate (FDR)
  - Fraction of false alarms to be investigated by fire service (i.e., measure of nuisance)

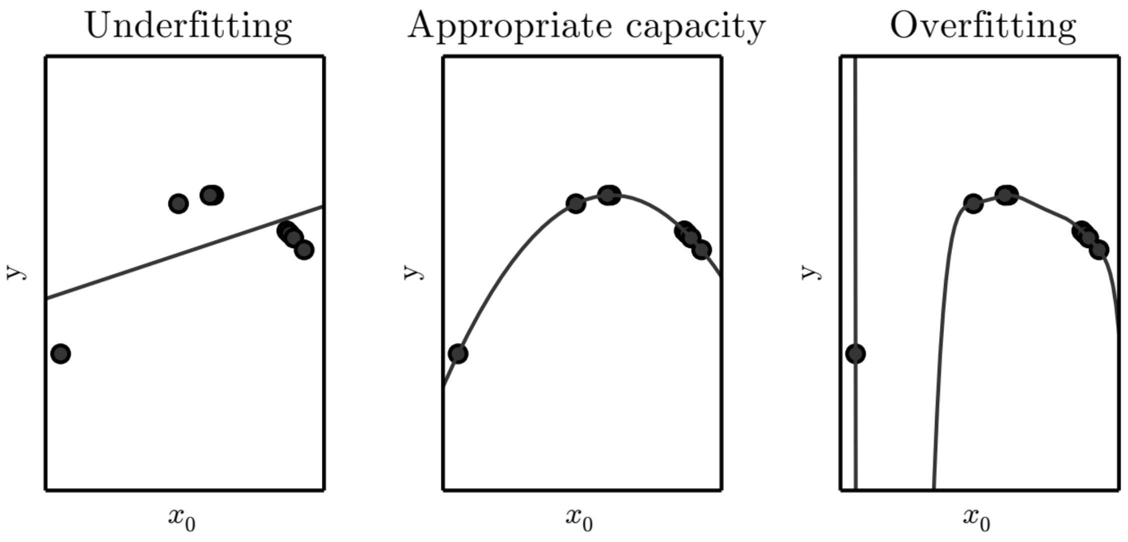
$$FDR = \frac{FP}{(TP+FP)}$$

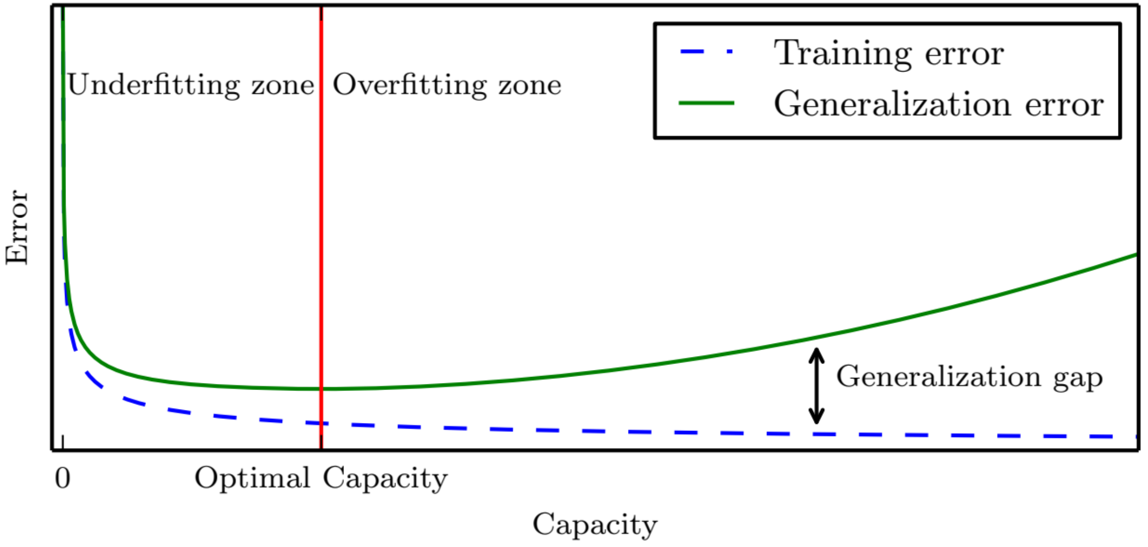
Generalization, Capacity and Regularization

- Generalization
  - Ability to perform well on *new, previously unseen* inputs
  - Difference between training and testing errors

- Capacity
  - Ability of a model to store information
  - High-capacity models will memorize the training set
  - Low-capacity models will fail to fit the training set

- Regularization
  - Increasing the difficulty to train a model to force the system to learn more robust relationships
  - Objective to reduce generalization error without impacting training error



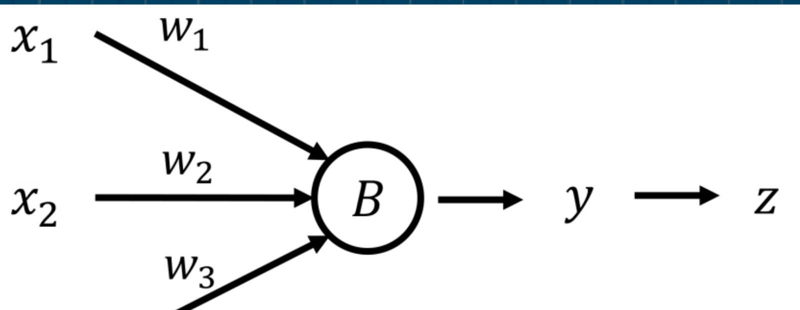


A. C. Ian Goodfellow, Yoshua Bengio, “The Deep Learning Book,” *MIT Press*, vol. 521, no. 7553, p. 785, 2017.

Fundamental Concepts of Machine Learning

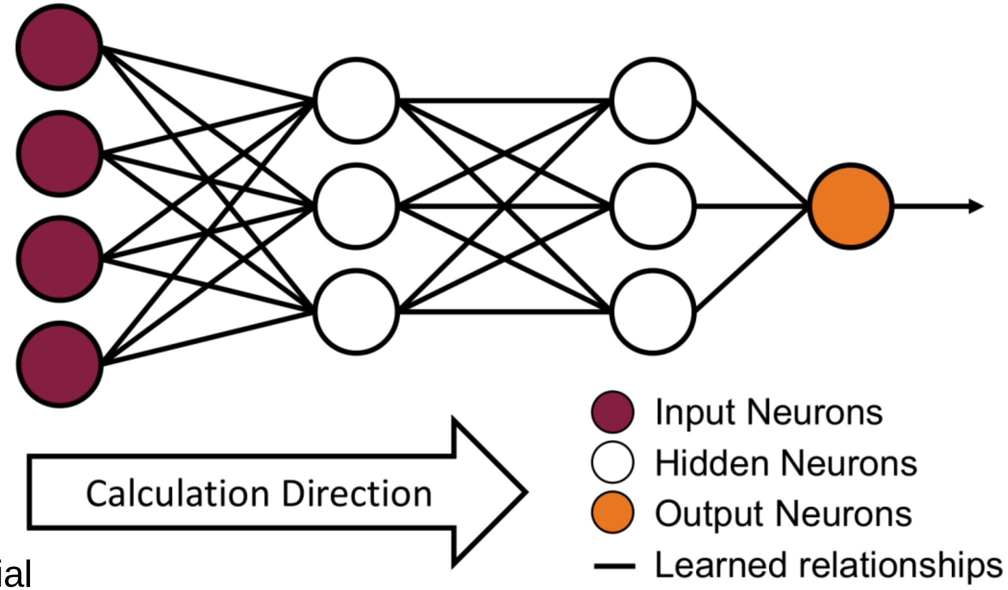
Artificial Neural Networks

+ Massively parallel system of equations
+ Weights and biases are solved by the computer using known data during training
+ Perceptron/neuron: Represents a single equation
  - Trained parameters: One weight per input, and one bias
  - Activation function: Remaps the raw output to capture non-linearities
+ Layer: Group of neurons which are processed simultaneously
+ Network Architecture: Functional form of the model, overall system



$$w_1x_1 + w_2x_2 + w_3x_3 + B = y$$
$$z = f(y)$$

Example neuron



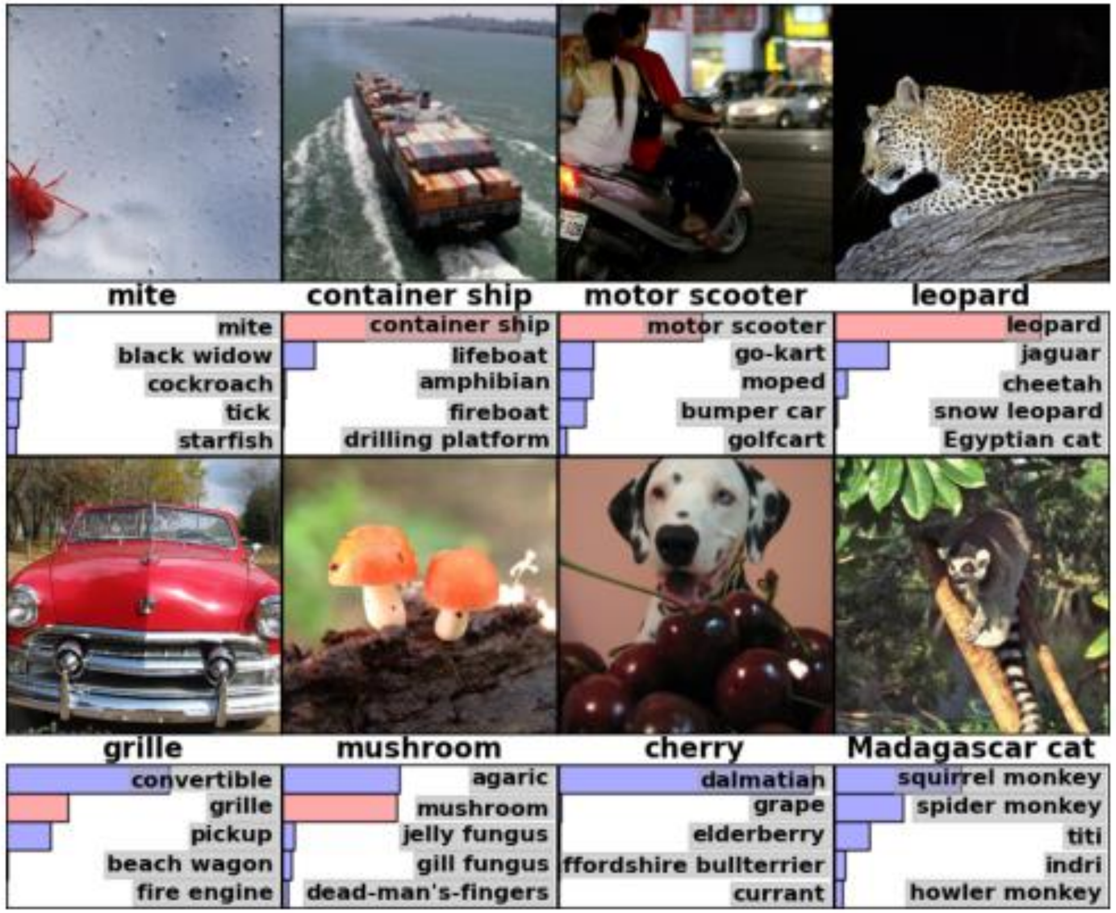
Example Neural Network

J.L. Hodges, Predicting Large Domain Multi-Physics Fire Behavior Using Artificial Neural Networks, Virginia Polytechnic Institute and State University, 2018.

Convolutional Neural Networks

- Inputs are images
  - Size: (pixels x pixels x number of channels)

- Convolutional Layers (CNN)
  - Assumes features are spatially related
  - Neurons are arranged into volumetric filters
  - Filters are small spatially, but extend through all input channels
  - Example: 5x5x3 or 10x10x3 for an RGB image
  - Inputs are convolved with each filter
  - Response to each filter is a measure of importance of that feature at a pixel



Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

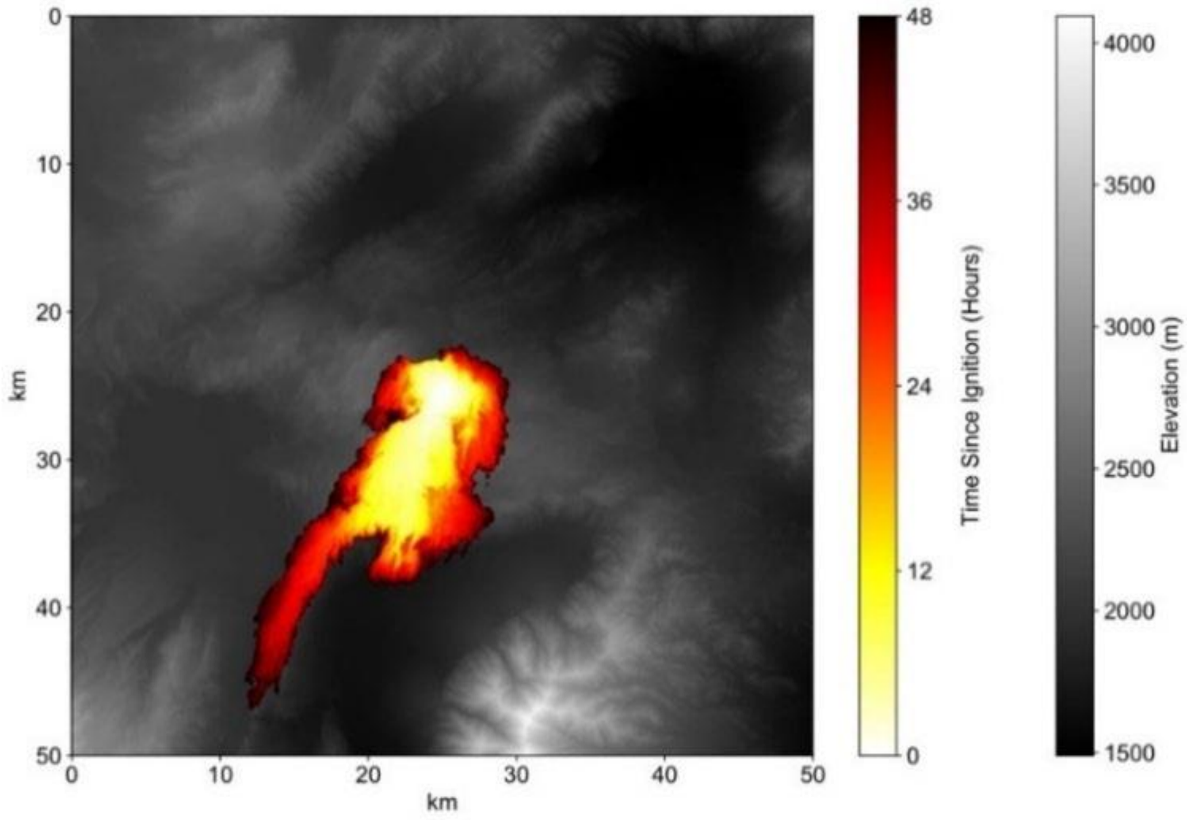
(2)

Fire Forecasting Background

- Forecast Objectives
- Types of Simulations
- Forecasting and Lead-Time
- Physics of Flame Spread and Simplifications

Forecast Objectives

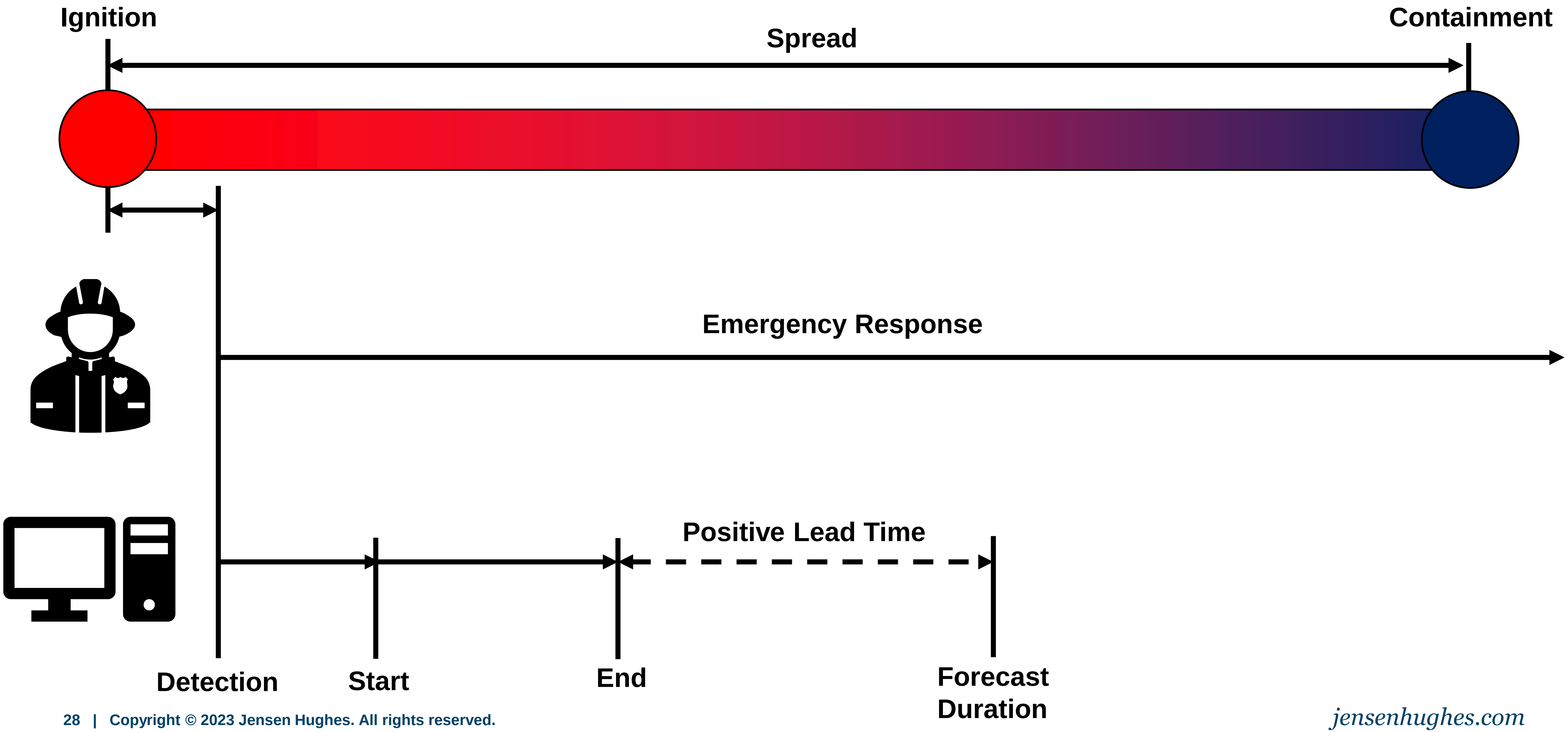
- Situational awareness
  - Evolution over time from discrete ignition point / current fire perimeter
  - Public evacuation
  - Prioritize emergency response
- High uncertainties
  - Current state (vegetation, moisture, fire perimeter)
  - Future weather (wind speed and direction)
- Technologies
  - Empirical models, physical models, data-driven models



Example Deterministic Simulated Fire Perimeter

J.L. Hodges, B.Y. Lattimer, Wildland Fire Spread Modeling Using Convolutional Neural Networks, Fire Technol. 55 (2019). doi:10.1007/s10694-019-00846-4.

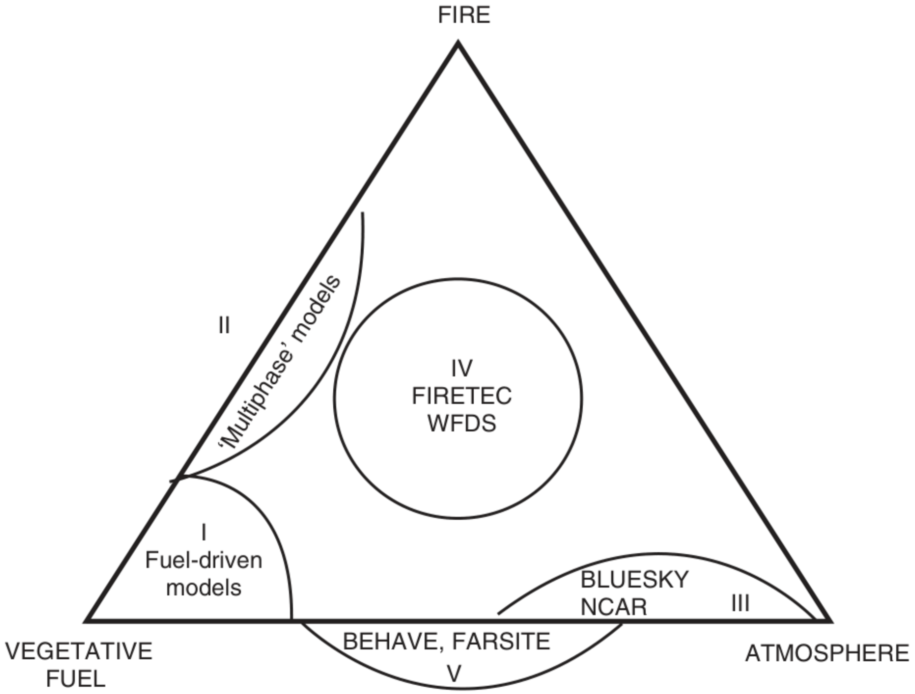
Forecasting and Lead-Time



Simplifications

+ Operational tools
  - Empirical atmosphere, fire, and vegetation
  - Fast simulations, high uncertainty in predictions

+ Research tools
  - Incorporate physics in one or more formulations
  - Physical atmosphere, empirical fire
    - CAWFE, WRF-SFIRE
  - Physical fire, empirical atmosphere
    - FDS
  - Slow simulations, lower uncertainty



Emphasis of different wildfire models

W. Mell, M.A. Jenkins, J. Gould, P. Cheney, A physics-based approach to modelling grassland fires, Int. J. Wildl. Fire. 16 (2007) 1–22.

How can we use modern technology to improve these models and make accurate, faster-than-real-time simulation possible?

(3)

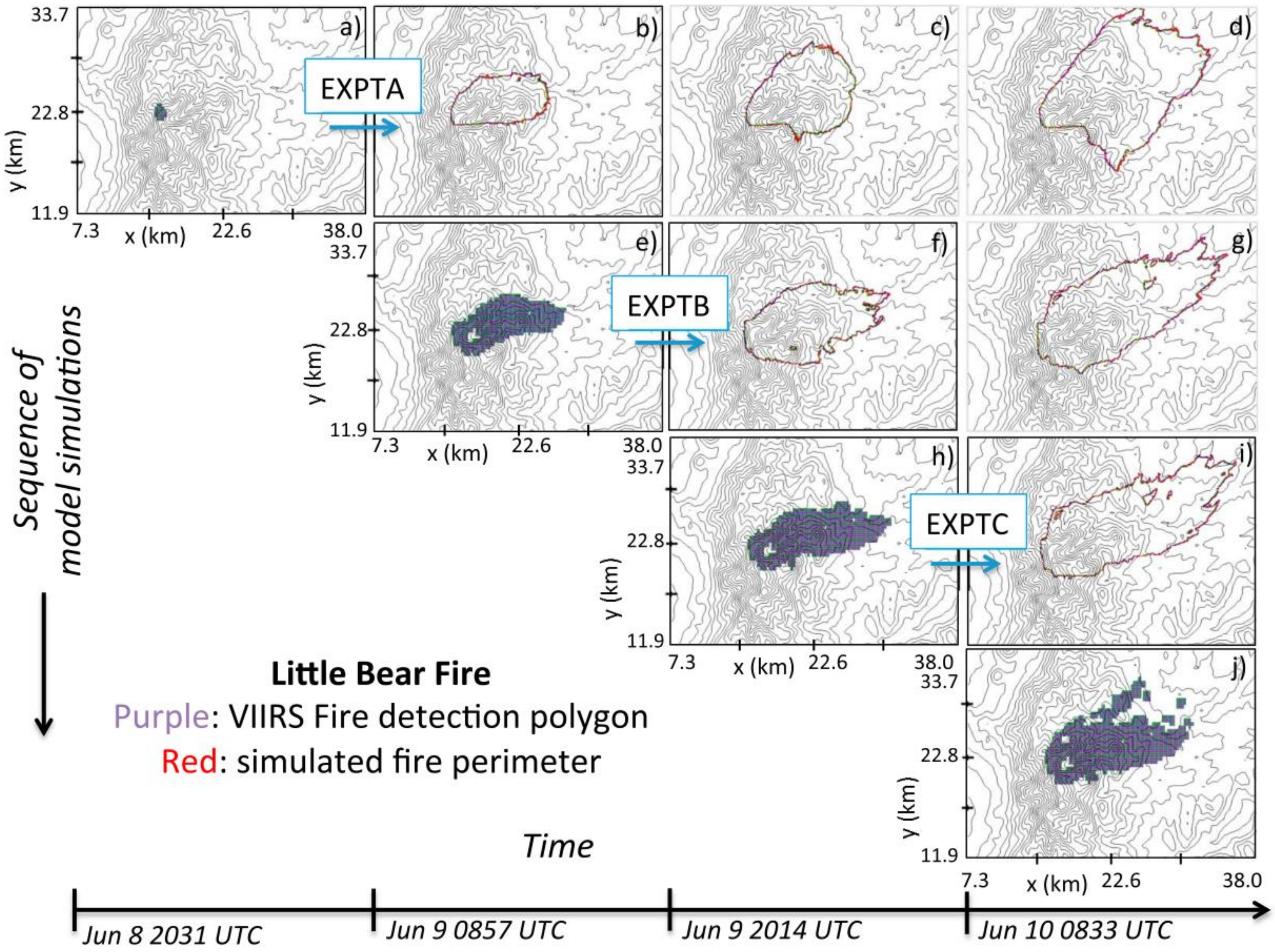
Improving Faster-Than-Real-Time Fire Forecasting

+ Data Assimilation
+ Inverse Analysis
+ HPC Parallelization
+ Machine Learning – Surrogate Modeling

Data Assimilation – Re-Initialization (1/2)

- Restart simulation based on observation from current perimeter
  - Satellite
  - Drones
  - Ground personnel identified

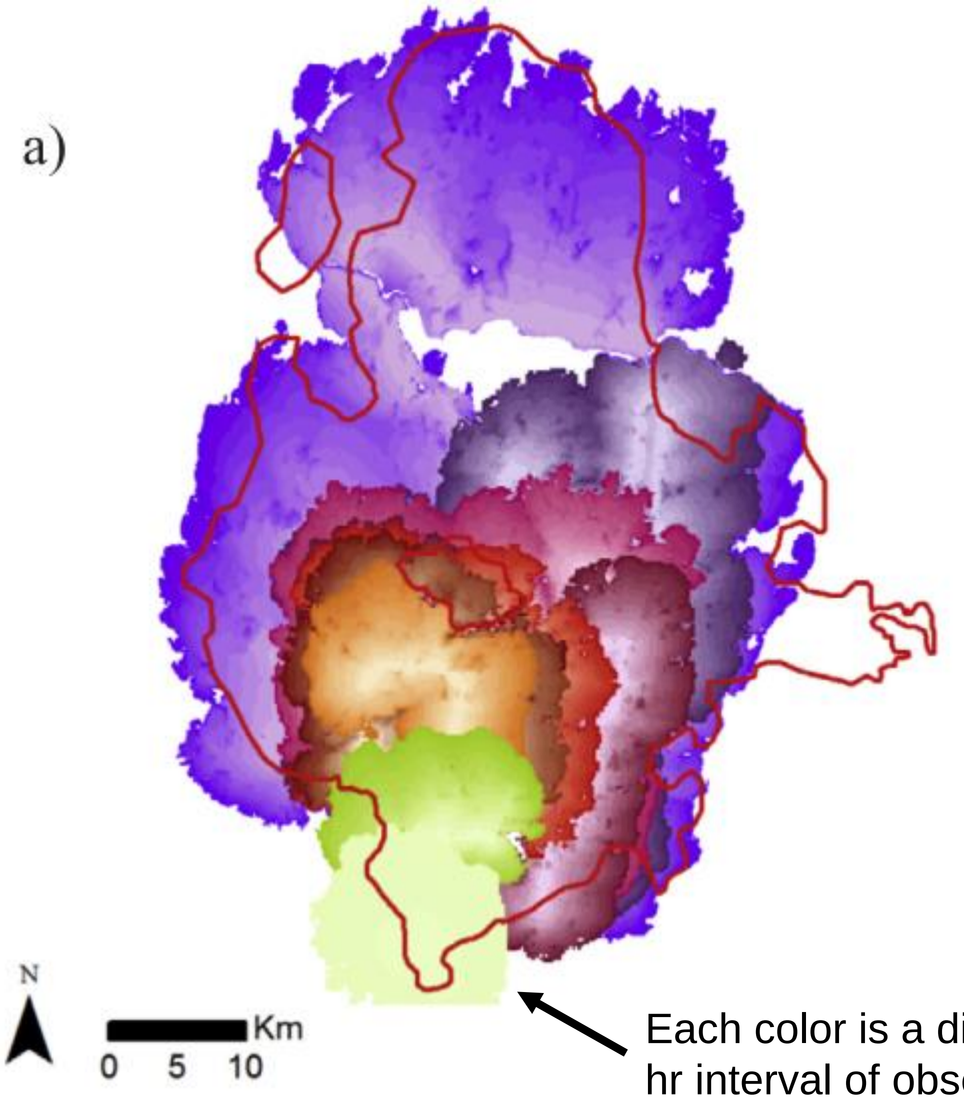
- Results
  - Limits final error in forecast by resetting to a known condition
  - Does not drastically improve forecasts



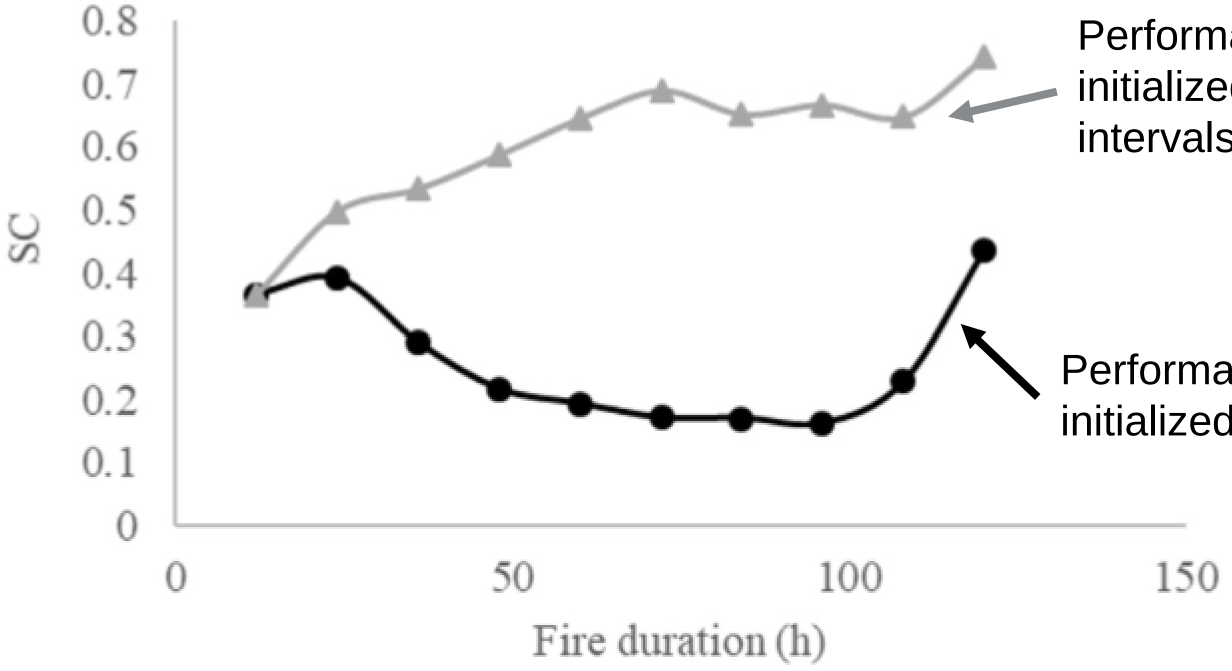
J.L. Coen, W. Schroeder, Use of spatially refined satellite remote sensing fire detection data to initialize and evaluate coupled weather-wildfire growth model simulations, Geophys. Res. Lett. 40 (2013) 5536–5541. doi:10.1002/2013GL057868.

Data Assimilation – Re-Initialization (1/2)

$$SC = \frac{2 \times TP}{2 \times TP + FN + FP}$$



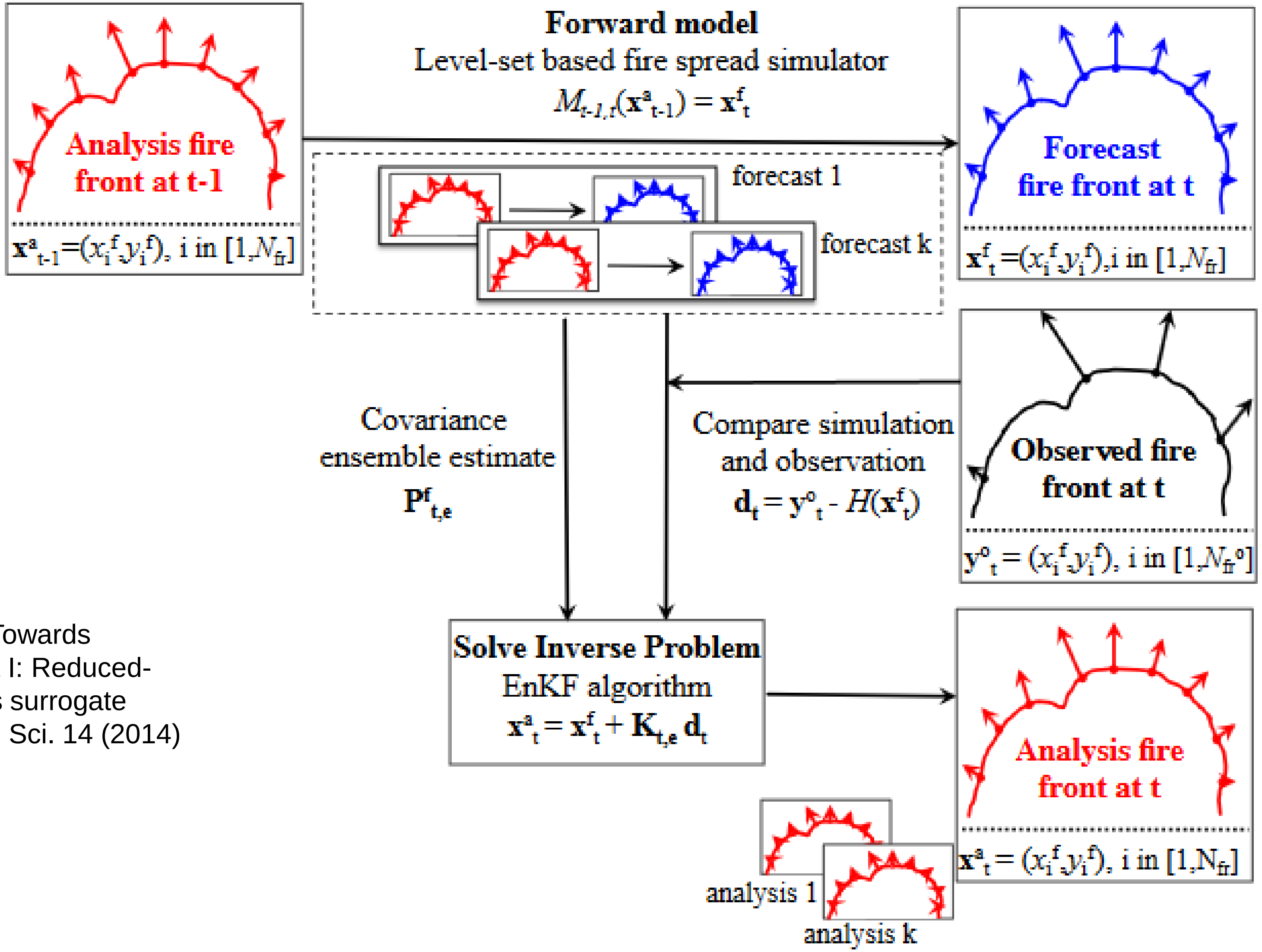
Each color is a different 12-hr interval of observations



A. Cardil, S. Monedero, J. Ramírez, C.A. Silva, Assessing and reinitializing wildland fire simulations through satellite active fire data, J. Environ. Manage. 231 (2019) 996–1003. doi:10.1016/j.jenvman.2018.10.115.

Data Assimilation – Ensemble Filter (1/2)

- Ensemble of empirical weather forecasts used to propagate fire front
- Observations fused with ensemble state estimate

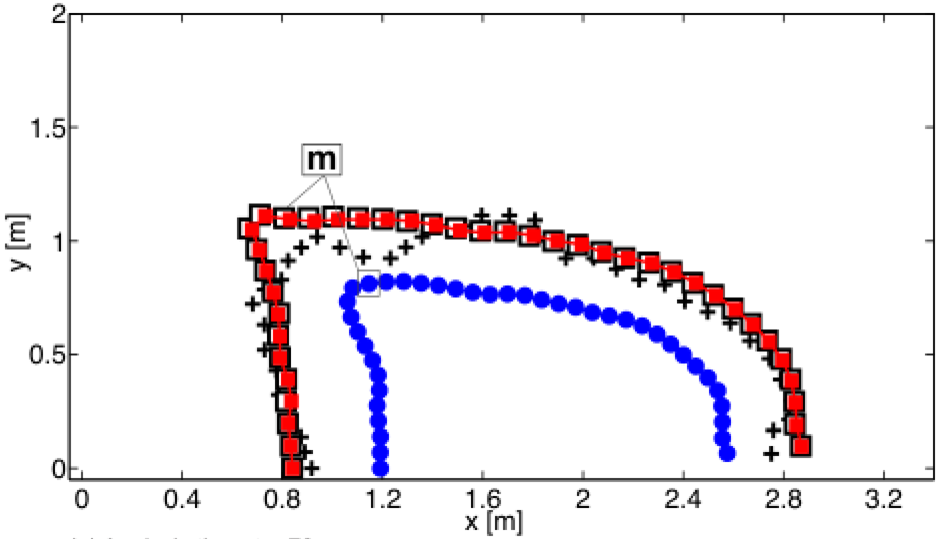


M.C. Rochoux, S. Ricci, D. Lucor, B. Cuenot, A. Trouvé, Towards predictive data-driven simulations of wildfire spread - Part I: Reduced-cost ensemble Kalman filter based on a polynomial chaos surrogate model for parameter estimation, Nat. Hazards Earth Syst. Sci. 14 (2014) 2951–2973. doi:10.5194/nhess-14-2951-2014.

Data Assimilation – Ensemble Filter (2/2)

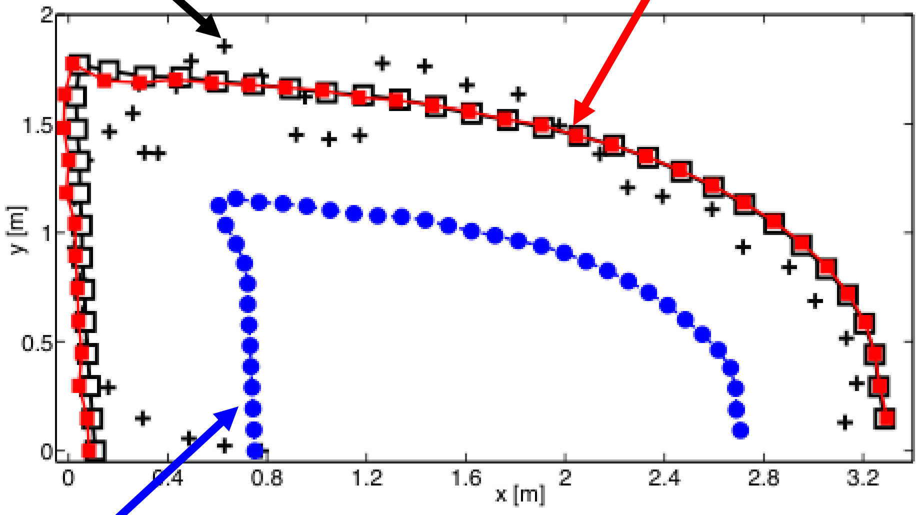
Observations (not assimilated on right)

Forecasted perimeter with assimilation



(a) Analysis time, $t_1 = 78$ s.

Assimilation Time Step



(b) Forecast time, $t_2 = 106$ s.

Forecasted perimeter with no data assimilation

Forecasted Time Step

M.C. Rochoux, S. Ricci, D. Lucor, B. Cuenot, A. Trouvé, Towards predictive data-driven simulations of wildfire spread - Part I: Reduced-cost ensemble Kalman filter based on a polynomial chaos surrogate model for parameter estimation, Nat. Hazards Earth Syst. Sci. 14 (2014) 2951–2973. doi:10.5194/nhess-14-2951-2014.

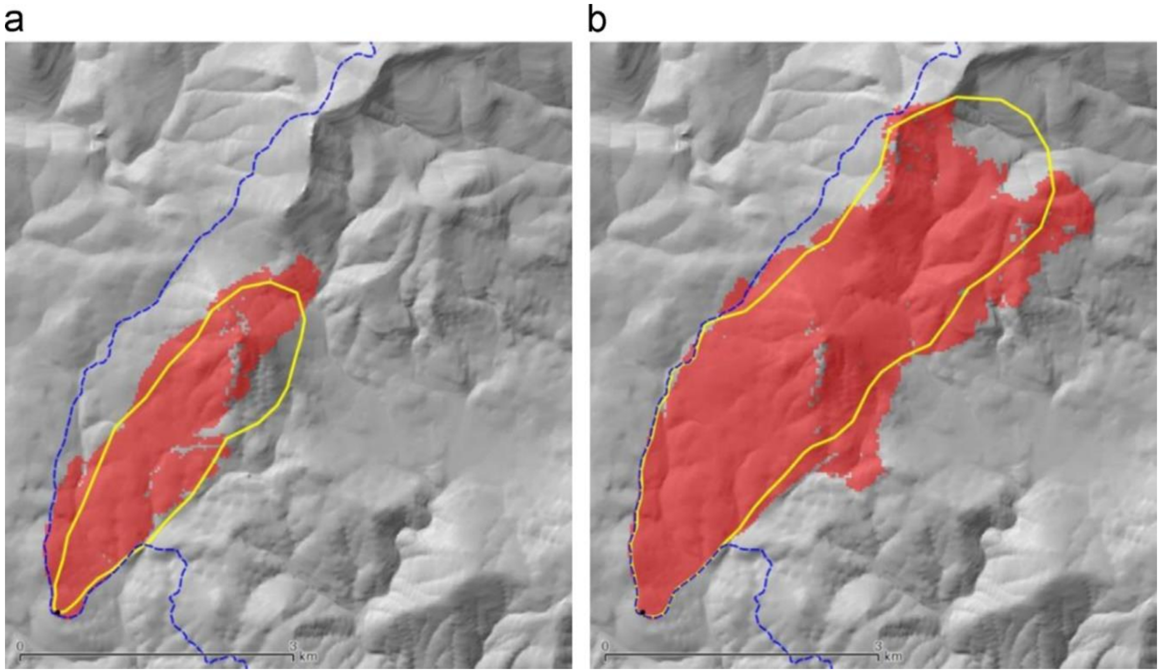
Data Assimilation – Re-Initialization & Ensemble Filter Summary

- Both approaches can limit the propagation of error over time in wildfire forecasts
- Adds some computational overhead to fully empirical models, but much less than coupling with a weather model
- Straightforward approach to integrate structured data (e.g., fixed weather stations, satellite data, etc.)

- Limitations
  - Data acquisition
    - Potential for occlusion of remote sensing
    - Not straightforward to integrate unstructured data (drones, fire service perimeters, crowd sourced data)
  - Accuracy
    - Does not address the accuracy of the forecast itself, just resets the perimeter periodically
    - Inherits same accuracy limitations due to uncertainties in the rate of spread calculation and weather forecast

Inverse Analysis (1/3)

- Use observed fire perimeters to reduce uncertainty in model input parameters
- Does not (always) update the fire perimeter directly
- Split input parameters into two groups:
  - Fixed parameters – Assumed to be known and not optimized
  - Free parameters – Assumed to be unknown and included in the optimization.
    - Generally assumed to be invariant in time
- Optimization
  - Forecast generated with an ensemble of free parameter sets
  - Forecast compared to observation at available times
  - Free parameters established based on minimum error

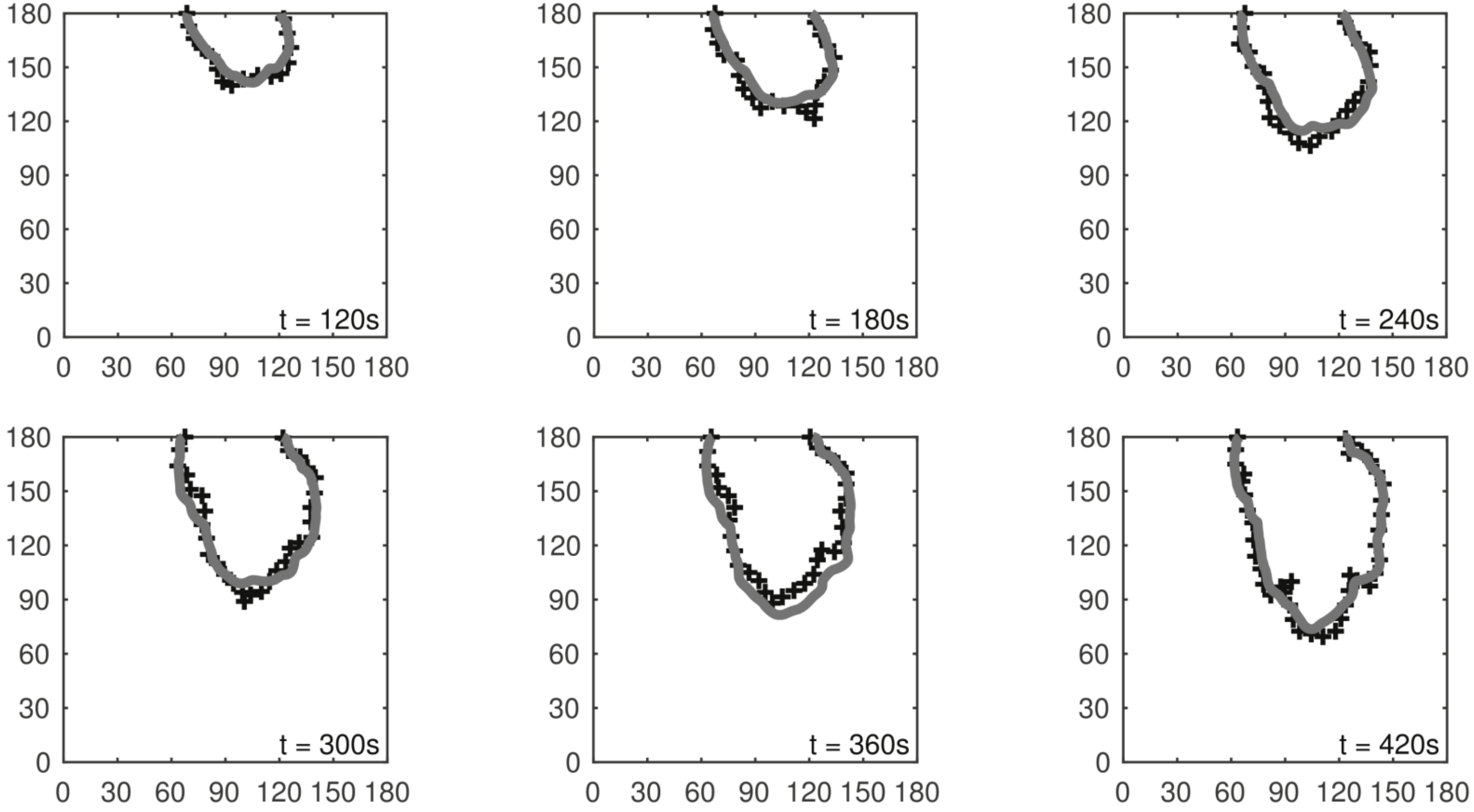


Comparison of target perimeters (yellow) with model forecasts after inverse analysis (red).

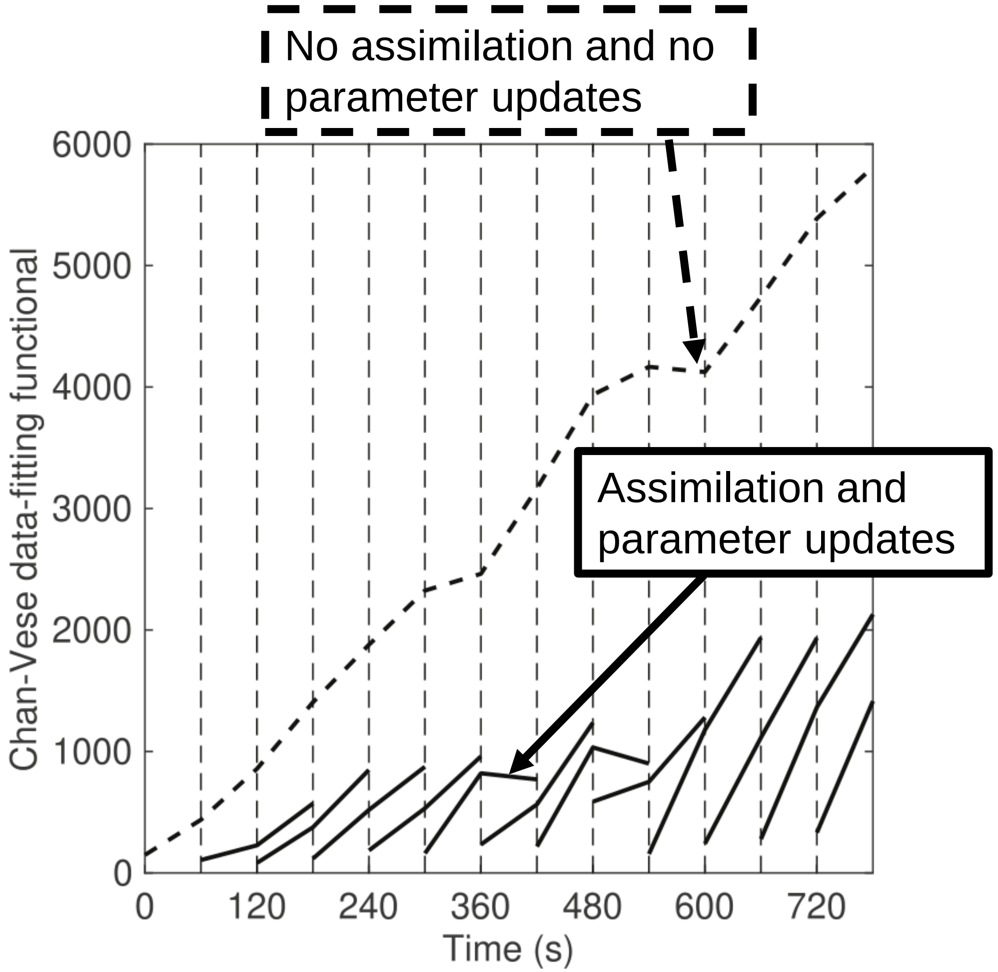
C. Lautenberger, Wildland fire modeling with an Eulerian level set method and automated calibration, Fire Saf. J. 62 (2013) 289–298. doi:10.1016/j.firesaf.2013.08.014.

Inverse Analysis (2/3)

+ Mixing data assimilation and inverse analysis



120 second forecasts



Shape similarity, low is better

C. Zhang, A. Collin, P. Moireau, A. Trouvé, M.C. Rochoux, State-parameter estimation approach for data-driven wildland fire spread modeling: Application to the 2012 RxCADRE S5 field-scale experiment, Fire Saf. J. 105 (2019) 286–299.

Inverse Analysis (3/3)

- Approach can limit the propagation of error over time in wildfire forecasts
- Approach can potentially reduce uncertainty in forecast by reducing input parameter uncertainty
- Adds some computational overhead to fully empirical models, but much less than coupling with a weather model
- Straightforward approach to integrate structured data (e.g., fixed weather stations, satellite data, etc.)
- Limitations
  - Data acquisition
    - Potential for occlusion of remote sensing
    - Not straightforward to integrate unstructured data (drones, fire service perimeters, crowd sourced data)
  - Accuracy
    - Assumes the free parameters are invariant over the forecast window
    - Assumes the errors are due to inaccurate inputs rather than not-included physics
    - Limited case shows forecast error steadily increases.
    - Has only been validated on small duration fires.

HPC Parallelization (1/3)

+ IRIS Project (Greece)
  - WRF-SFIRE implementation

+ Case Study
  - Deterministic simulation
  - Spatial domain
    - Weather mesh 1km x 1km cells ~150 km x 150 km domain
    - Fire 1501x1501 cells ~0.1km resolution
  - Positive lead time
    - 24-hour forecast
    - 1 hour of real-time
    - 200 cores

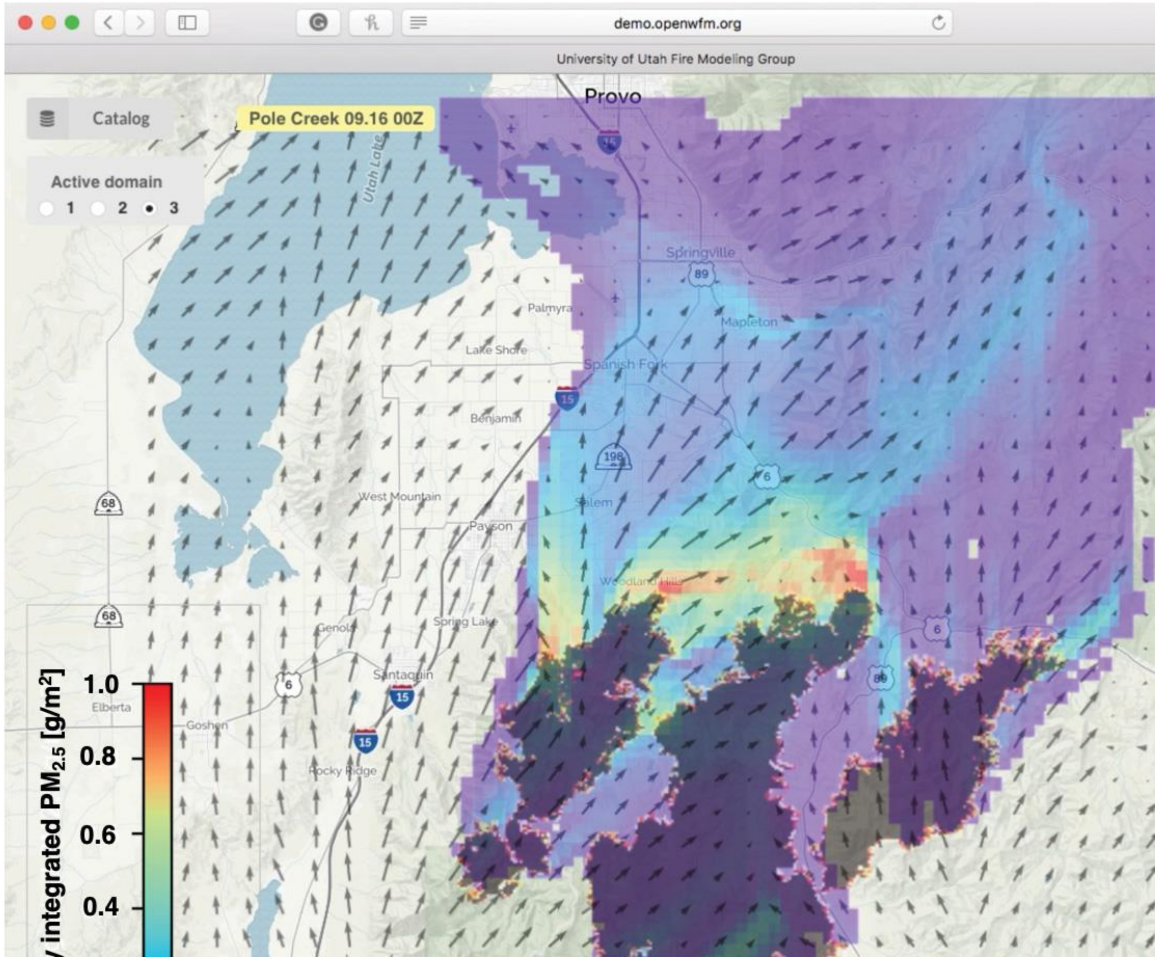
T.M. Giannaros, V. Kotroni, K. Lagouvardos, IRIS-Rapid response fire spread forecasting system : Development, calibration and evaluation, Agric. For. Meteorol. 279 (2019) 107745. doi:10.1016/j.agrformet.2019.107745.

Final perimeter comparison

HPC Parallelization (2/3)

- WRFx Project
  - WRF-SFIRE implementation

- Case Study
  - Deterministic simulation
  - Spatial domain
    - Weather mesh 0.33-0.55km cells 20-90 km domain
    - Fire ~600-3000 x 600-3000 cells
    - 0.028km-0.033km resolution
  - Positive lead time
    - 36-84-hour forecast
    - 4-6 hours of real-time
    - 196 cores



Simulated fire perimeter and PM2.5 concentration

J. Mandel, M. Vejmelka, A. Kochanski, A. Farguell, J. Haley, D. Mallia, K. Hilburn, An interactive data-driven HPC system for forecasting weather, wildland fire, and smoke, Proc. Urgent. 2019 1st Int. Work. HPC Urgent Decis. Mak. - Held Conjunction with SC 2019 Int. Conf. High Perform. Comput. Networking, Storage Anal. (2019) 35–44. doi:10.1109/UrgentHPC49580.2019.00010.

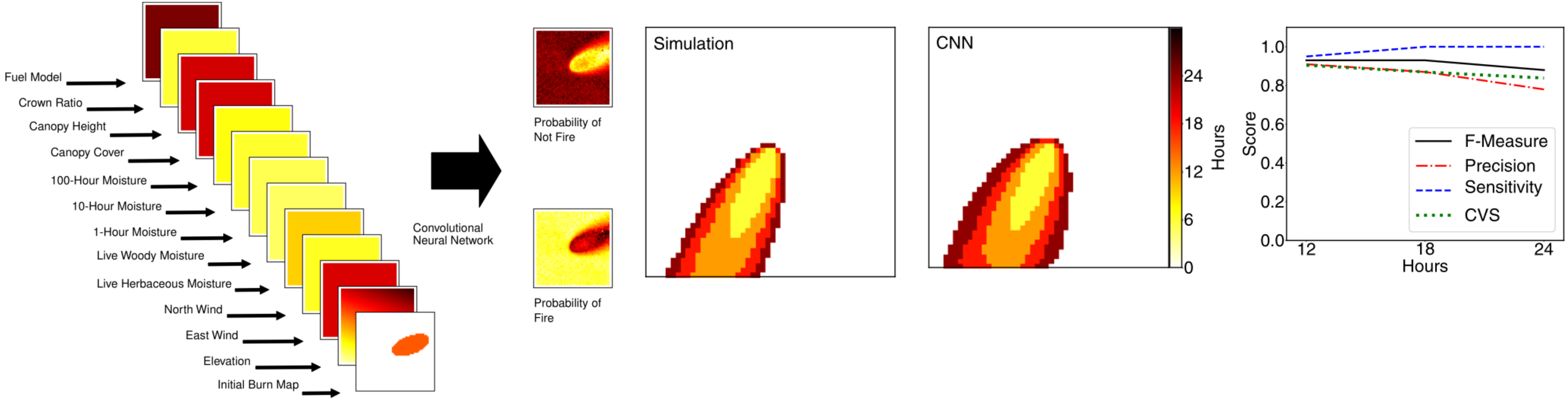
HPC Parallelization (3/3)

- Faster-than-real-time simulation is possible with physical atmosphere model and empirical fire model

- Limitations
  - Domain size
    - Current studies limited to 1500-3000 grid cells in each direction in the fire domain
    - Need ~100m resolution for large fires without complex canyons, valleys, etc. (150-300km)
    - Need ~30m resolution with complex terrain (45-90km)
  - Cores required
    - ~200 cores per 24 hours of positive lead time per simulation (not a linear function)
    - Limiting factor for broader use with ensembles of weather forecasts, multiple fire locations, etc.
  - Accuracy
    - Known use cases of WRF which underpredict local flow velocities in complex terrain
    - Fire forecast accuracy limited due to high uncertainties in the rate of spread calculation

Machine Learning – Surrogate Modeling (1/3)

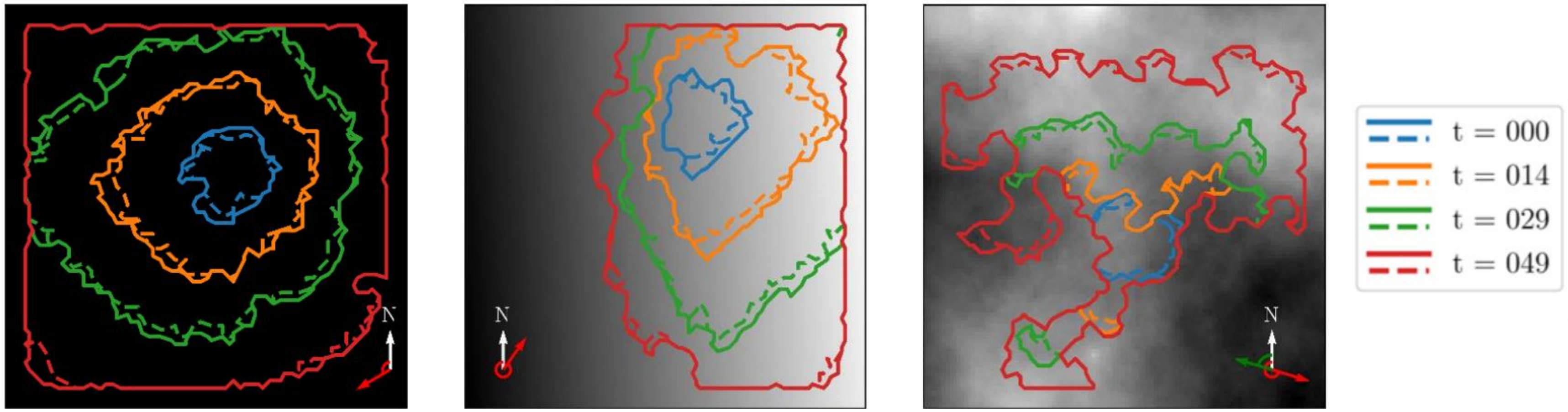
- Front-load simulation time prior to an event
  - Develop database of fire simulations using a high-resolution modeling tool
  - Train a machine learning model to approximate the high-resolution modeling tool
- During an event
  - Rapid predictions using machine learning-based surrogate

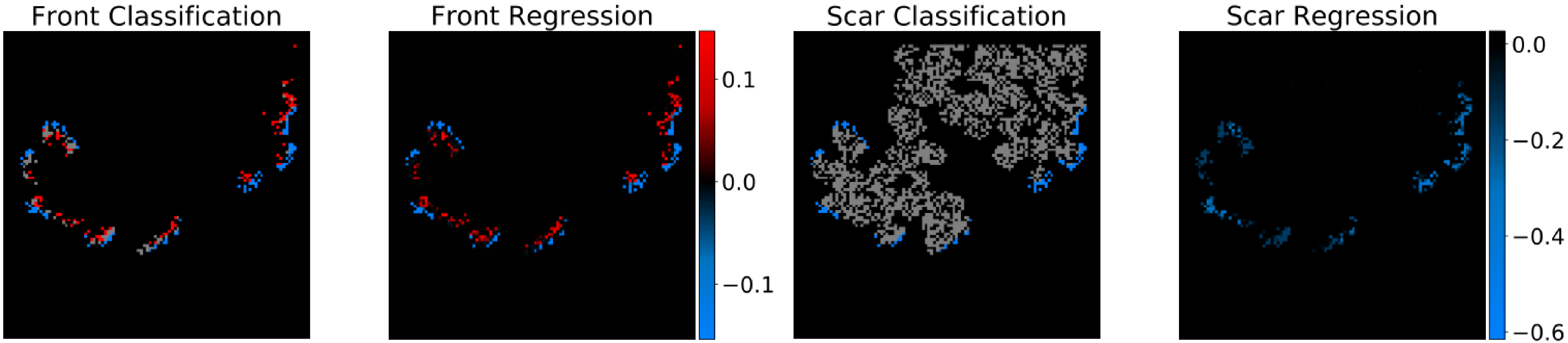


Hodges, Jonathan L., and Brian Y. Lattimer. "Wildland fire spread modeling using convolutional neural networks." Fire technology 55.6 (2019): 2115-2142.

Machine Learning – Surrogate Modelling (2/3)

- Adaptation to long-short term memory (LSTM) neural networks
- Inputs to the model include the state at multiple previous time steps





J. Burge, M. Bonanni, M. Ihme, L. Hu, Convolutional LSTM Neural Networks for Modeling Wildland Fire Dynamics, (2020). http://arxiv.org/abs/2012.06679.

Machine Learning – Surrogate Modeling (3/3)

- Simulation times significantly lower than traditional empirical and physics-based models
  - Can evaluate probabilistic weather scenarios to generate ensembles
  - Can be used as the forecast model in data assimilation-based approaches

- Limitations
  - Applicability
    - Based on the range of parameters included in the training dataset
    - Extrapolation beyond range of parameters does not work well
    - Can be difficult to determine if a new scenario is applicable due to the high number of variables
  - Accuracy
    - Surrogate model cannot be more accurate than the model used to develop the database

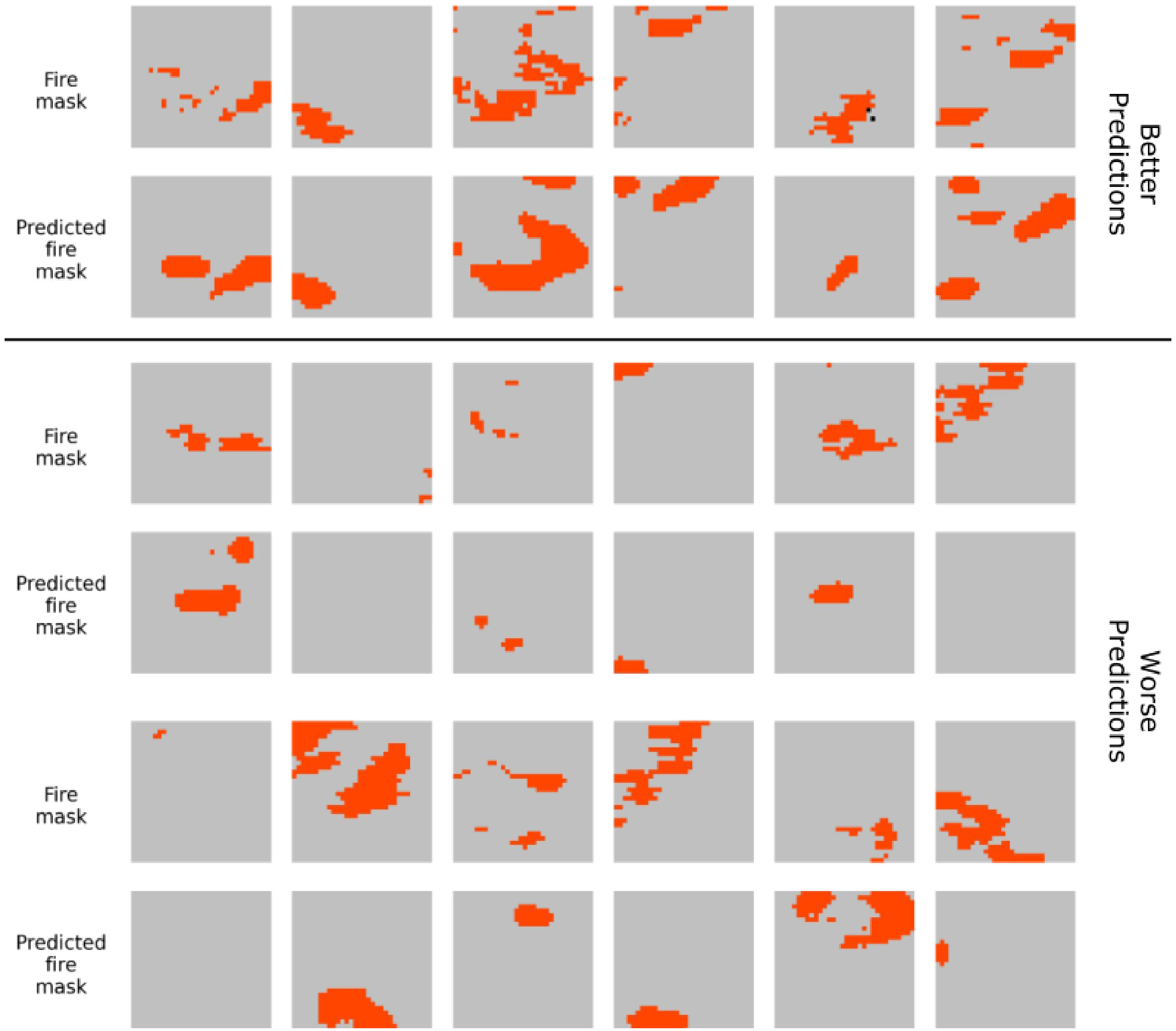
(4)

Emerging Concepts

- Machine Learning – Independent Modeling
- Machine Learning – Physics Informed Modeling
- Model Validation

Machine Learning – Independent Modeling

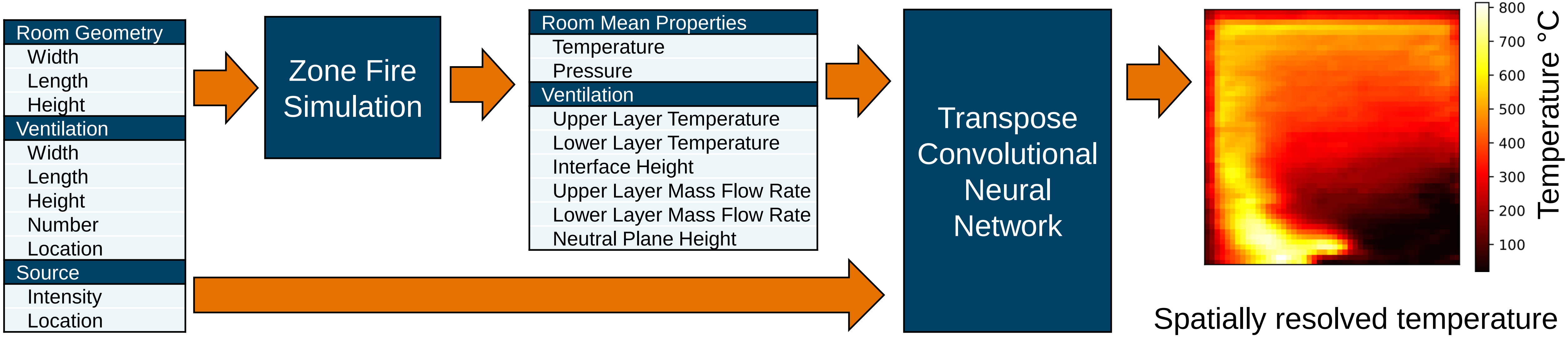
- Redesign network to use remote sensing data as inputs
- Limitations
  - Error propagation
    - Builds on remote sensing data products
    - Error in underlying products propagates to model
  - Data availability
    - Occlusion can affect data availability during an event
    - Impacts of human intervention (e.g., suppression, fire breaks, etc.) not well characterized in datasets
    - Limited to aerial observable data, which has limited correlation with surface state



F. Huot, R.L. Hu, N. Goyal, T. Sankar, M. Ihme, Y.F. Chen, Next Day Wildfire Spread: A Machine Learning Dataset to Predict Wildfire Spreading From Remote-Sensing Data, IEEE Trans. Geosci. Remote Sens. 60 (2022) 1–13. doi:10.1109/TGRS.2022.3192974.

Machine Learning – Physics Informed (1/4)

+ Coarse model predictions as inputs to the model
  - Geometry and mean flow properties can be represented as a vector of model inputs (high level descriptions)
  - Spatially resolved thermal flow field can be represented as a series of 2-D slices (image channels)
  - Calculate spatially resolved intensive properties from rapid coarse predictions

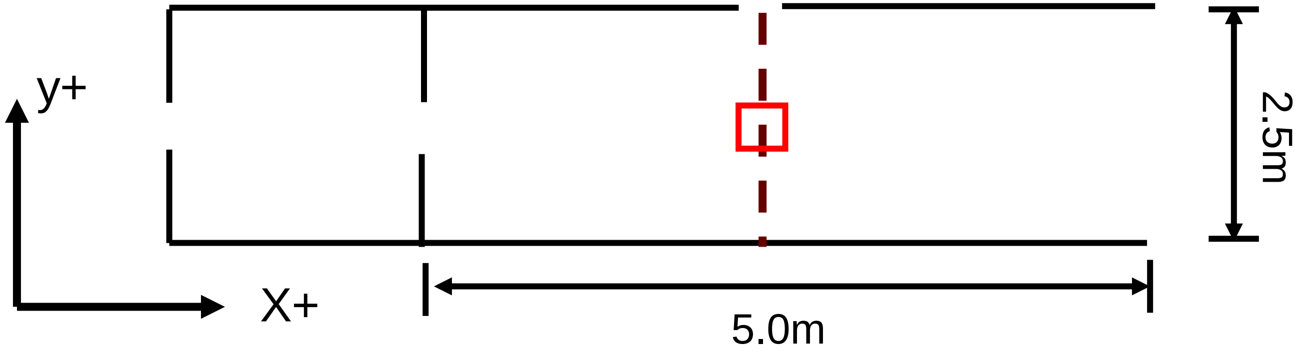


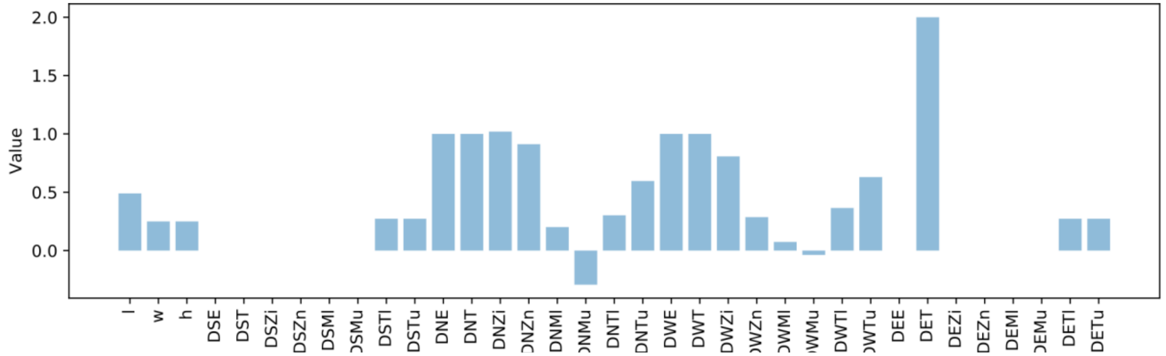
Spatially resolved temperature and velocity predictions

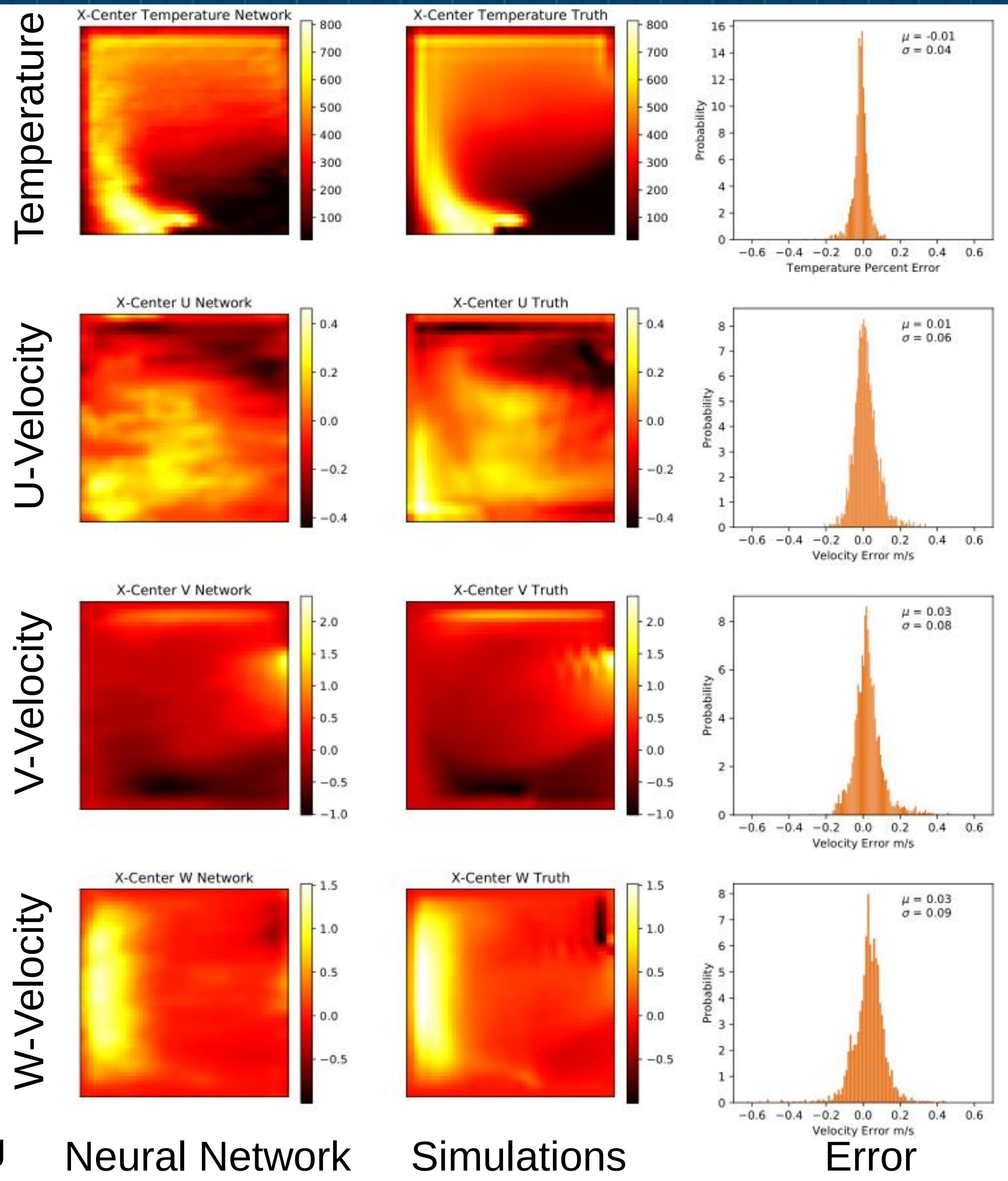
J.L. Hodges, B.Y. Lattimer, K.D. Luxbacher, Compartment fire predictions using transpose convolutional neural networks, Fire Saf. J. 108 (2019) 1–22. doi:10.1016/j.firesaf.2019.102854.

Machine Learning – Physics Informed (2/4)

- Left image is the neural network prediction
- Middle image is the CFD prediction
- Right image is the discrete probability density function of error between the two
- Contours are scaled the same



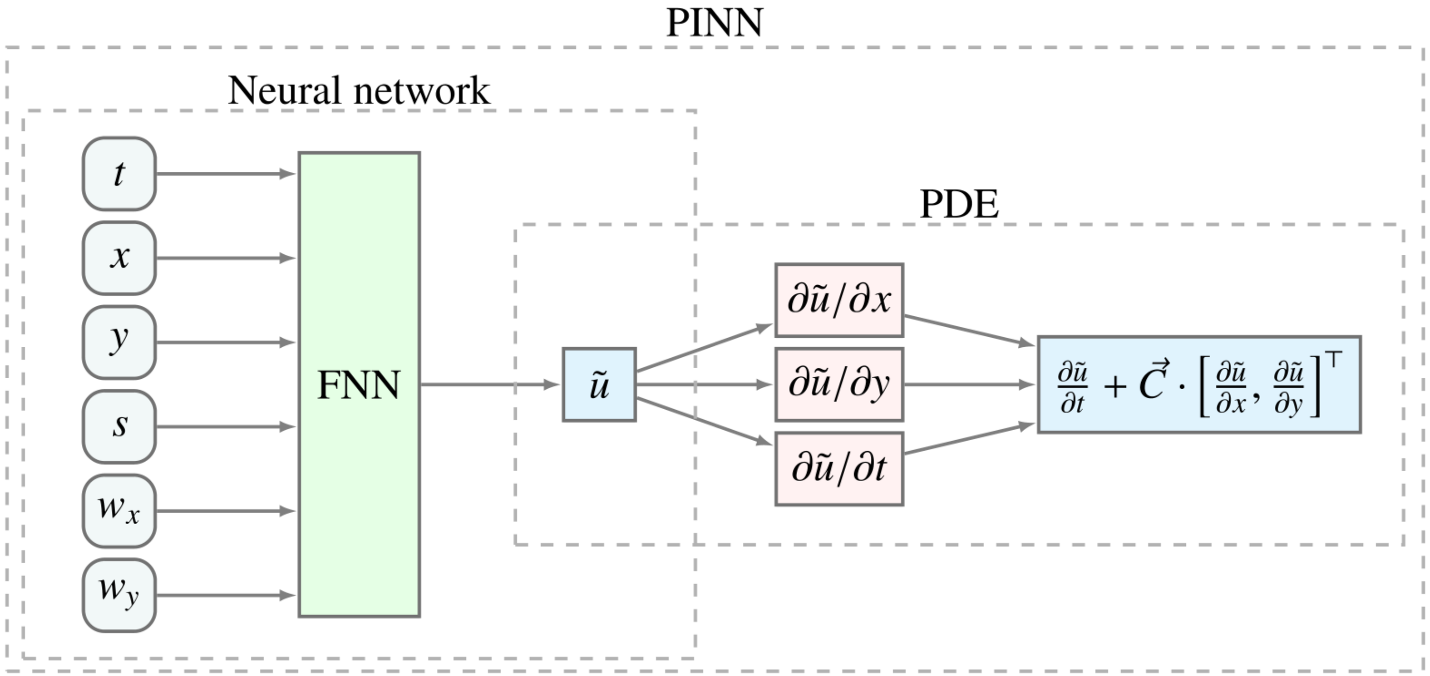




J.L. Hodges, B.Y. Lattimer, K.D. Luxbacher, Compartment fire predictions using transpose convolutional neural networks, Fire Saf. J. 108 (2019) 1–22.

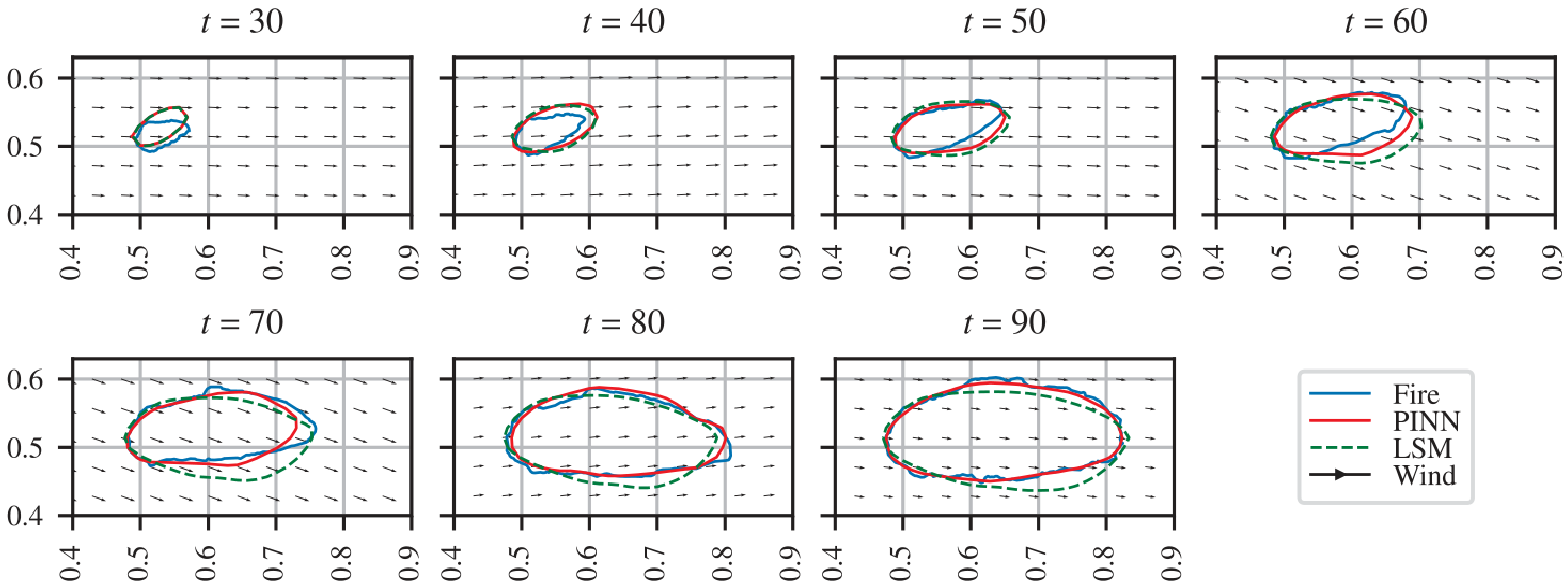
Machine Learning – Physics Informed (3/4)

+ Physics-informed neural networks (PINN)
  - Model predicts a state variable based on inputs
    - Level-set solution in this example
  - Embeds a conservation equation in the loss calculation



J.J. Dabrowski, D.E. Pagendam, J. Hilton, C. Sanderson, D. MacKinlay, C. Huston, A. Bolt, P. Kuhnert, Bayesian Physics Informed Neural Networks for Data Assimilation and Spatio-Temporal Modelling of Wildfires, Spat. Stat. 55 (2023) 100746. doi:10.1016/j.spasta.2023.100746.

Machine Learning – Physics Informed (4/4)



J.J. Dabrowski, D.E. Pagendam, J. Hilton, C. Sanderson, D. MacKinlay, C. Huston, A. Bolt, P. Kuhnert, Bayesian Physics Informed Neural Networks for Data Assimilation and Spatio-Temporal Modelling of Wildfires, Spat. Stat. 55 (2023) 100746. doi:10.1016/j.spasta.2023.100746.

Model Validation

- Fire Dynamics Simulator – Wildfire Rate of Spread
  - Describes each experiment used in the validation
  - Describes specific notes for the modeling effort
  - Source code for the software and input files for validation publicly available
- Presents statistical analysis of model performance based on 6 datasets including 354 fire rate of spread measurements
- Expresses model performance as a systematic bias and error standard deviation

3.12 CSIRO Grassland Fires

In July and August of 1986, the Commonwealth Scientific and Industrial Research Organisation (CSIRO) of Australia conducted controlled grassland fire experiments near Darwin, Northern Territory [152]. July and August are in the middle of the dry season when the grasses are fully cured (dried) and the weather is warm and dry. The experiments were conducted on flat plots measuring 100 m by 100 m, 200 m by 200 m, or 200 m by 300 m. Two cases have been simulated. Case C064 was conducted on a 100 m by 100 m plot of kerosene grass (*Eriachne burkittii*); Case F19 was conducted on a 200 m by 200 m plot of kangaroo grass (*Themeda australis*).

Modeling Notes

Two of these experiments were originally simulated with FDS by Mell et al. [153]. These simulations modeled the grass as a collection of cylindrical Lagrangian particles. The pyrolysis model assigned to the particles is described in the FDS User's Guide [1], chapter "Earth, Wind and Fire," Section 19.1, "Thermal Degradation Model for Vegetation."

Now these two experiments are also simulated using the Boundary Fuel Model (BFM) [154] and the Rothermel-Albini fire spread algorithm [155, 156]. For the experiment labelled Case C064, fuel index 1 (Short Grass) is used, with a modified moisture fraction of 0.063. For F19, fuel index 3 (Tall Grass) is used, with a modified moisture fraction of 0.058.

Measured properties for the specific types of grasses burned in the two experiments are listed in Table 3.4. Properties that were not measured are listed in Table 3.5. These assumed properties are typically for wood or cellulosic fuels. The moisture is modeled as water. The grass is assumed to be composed primarily of cellulose.

Snapshots of the Lagrangian particle simulation of Case F19 is shown in Fig. 3.7. The computational domain in this case is 240 m by 240 m by 20 m. The grid cells are 0.5 m cubes. The domain is subdivided into 36 individual meshes and run in parallel. The grass is represented 1 simulated blade per grid cell. The radius of the cylinder is derived from the measured surface area to volume ratio. Each simulated blade of grass represents many more actual blades of grass. The weighting factor is determined from the measured bulk mass per unit area. The fires in the experiments were ignited by two men carrying drip torches walking in opposite directions along the upwind boundary of the plot (the red strip in Fig. 3.7). In FDS, this action was modeled using a specified spread rate along the strip.

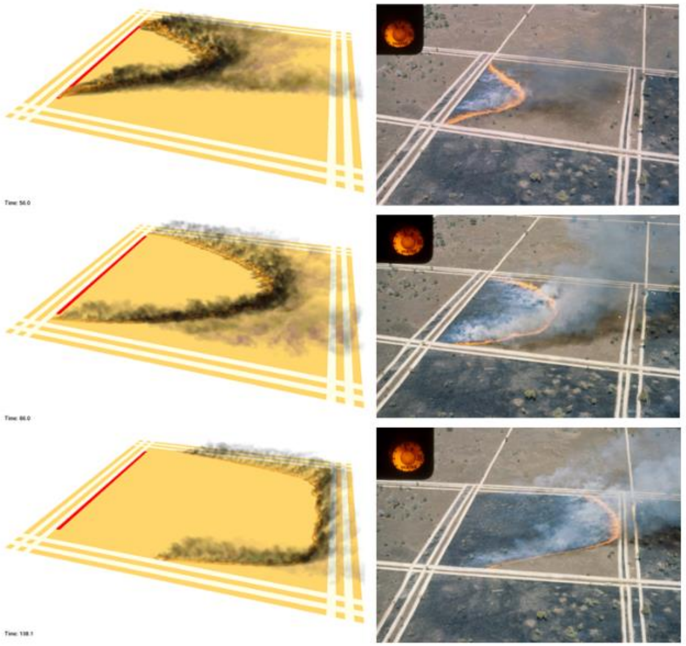
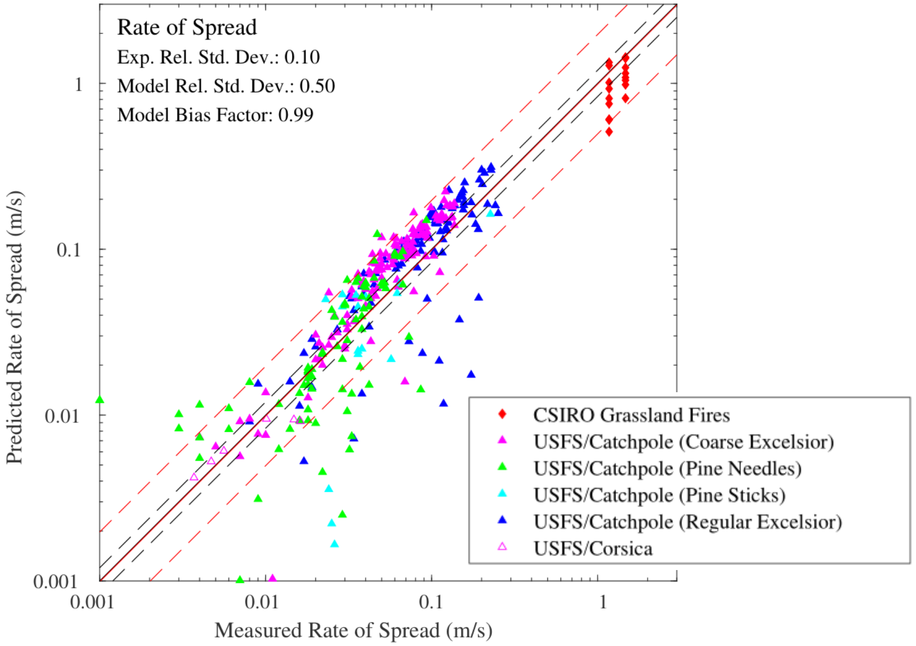


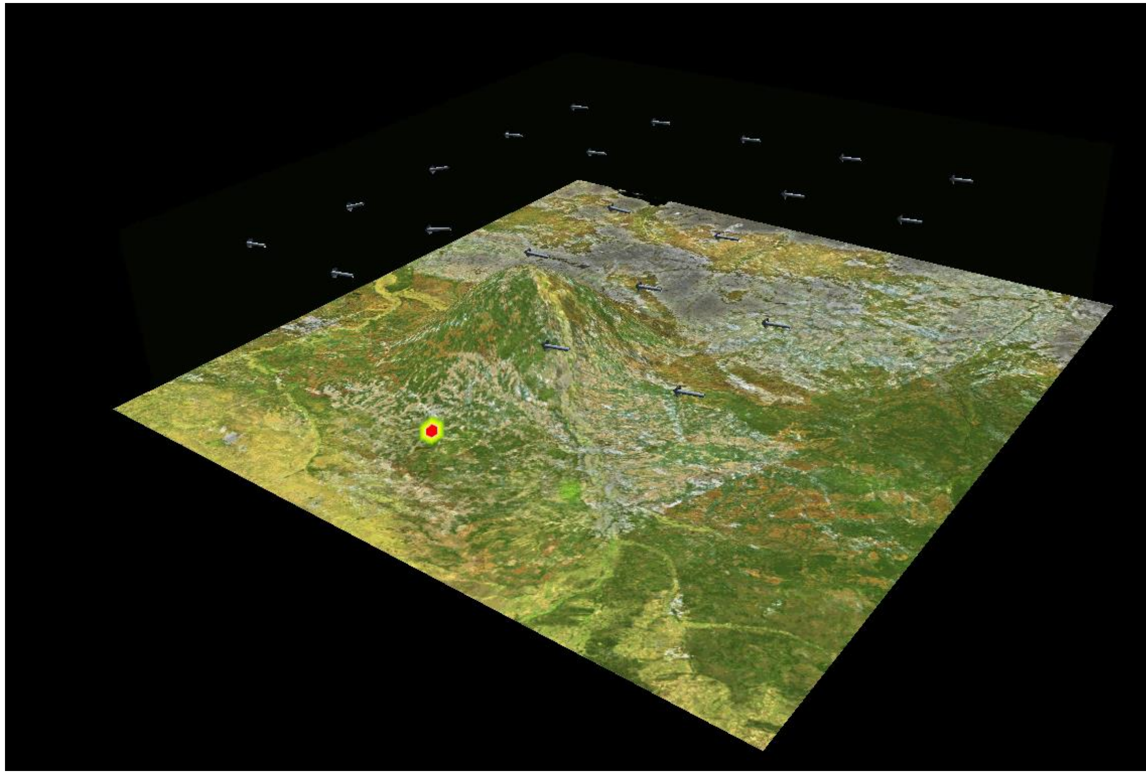
Figure 3.7: Snapshots of the simulation of CSIRO Grassland Fire F19 compared to photographs of the fire.



Conclusions

+ Several approaches exist for faster-than-real-time forecasts of wildfires
  - Different pros and cons with each approach
  - Data can be used to improve operational forecasts in several ways

+ Looking to the future
  - Increasing need for accurate data collection and scenario reconstruction methodologies
  - Common databases are needed to train, and to benchmark developed models



Data-driven models can allow us to leverage the accuracy of high-fidelity simulations at the time requirements of operational tools

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