Adaptation Through Learning: Using Machine Learning to Improve Forest Wildfire Management

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Nice Problems vs Important Problems

- Playing Chess - cool
- Classifying cat videos - surprising
- Alpha go – amazing!
- Text and speech recognition, translation - so handy!
- Advertisement Ranking – profit!!!
- …no seriously though, how about something important?
- Some of these can be important, but they also have low risk if you're wrong.

Luckily, somebody made us a handy list

AI for (Something Good)

- United Nations Sustainable Development Goals (UN-SDGs)
  - 2nd AI For Good Summit 2018, Geneva – ITU/UN Initiative
  - Using AI to tackle Equality, Social, Economic, Infrastructure, Energy, Environmental issues
  - **Sustainable Development Network (SDSN) (Canadian SDSN hosted at UWaterloo)**
- **AI for Social Good Workshop at 2018 NeurIPS** *(co-organizer)*
- Growing number of corporate and non-profit initiatives
  - AI4Good.org
  - Microsoft – AI for Earth (Azure cloud computing) *(awardee)*
  - IBM Watson AI XPrize *(judge)*
  - Google AI Impact Challenge
  - AI for Social Good (Intel)
- Computational Sustainability
  - Institute for Computational Sustainability (Cornel, OSU) NSF <$10M – 2008, $??M 2016>, tracks at international AI conferences: AAAI, IJCAI, …
- Fire Workshops (and these are just the ones *I've* attended!)
  - Forest and Wildland Fire Management: a Risk Management Perspective. Banff, BIRS 2017
  - Wildland Fire Appropriate Response Workshop, Western U, Feb 2018.
  - **"Not the New Normal" – BC Wildfire Symposium, July 2018.**

AI for Social Good

IBM Watson AI XPRIZE

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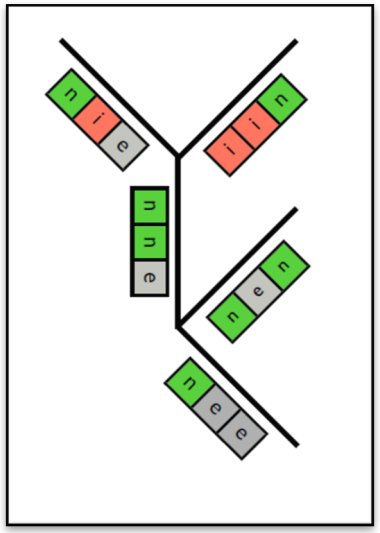
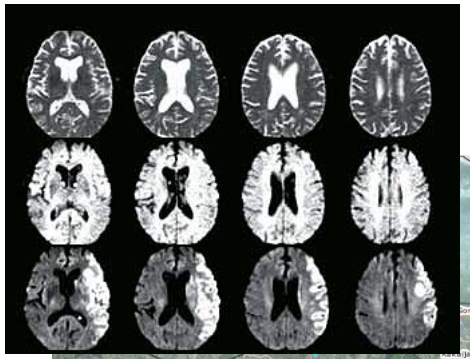
Spatially Spreading Processes in Natural Systems

Invasive Species Control

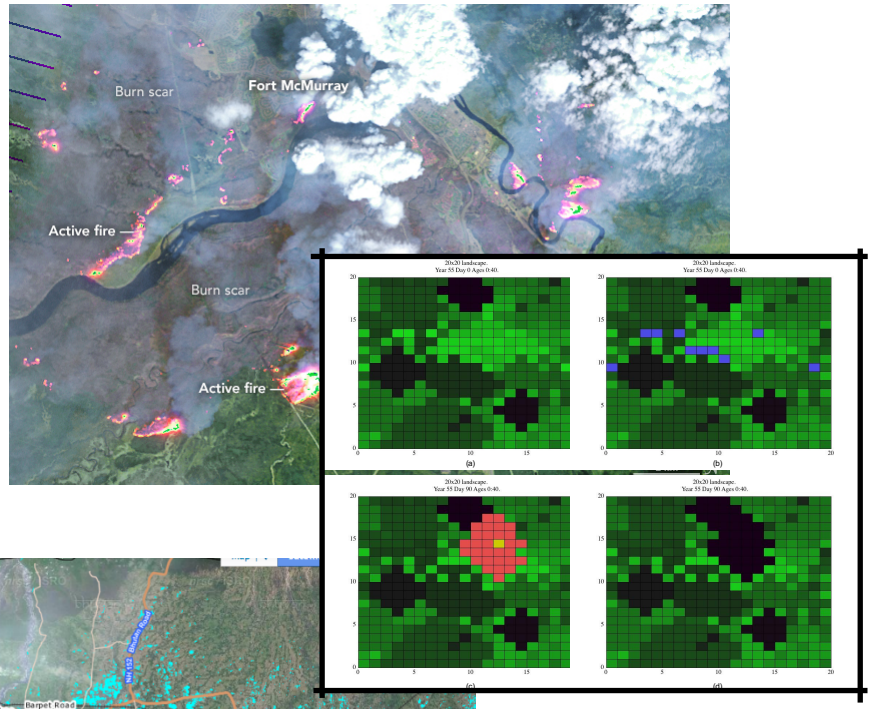


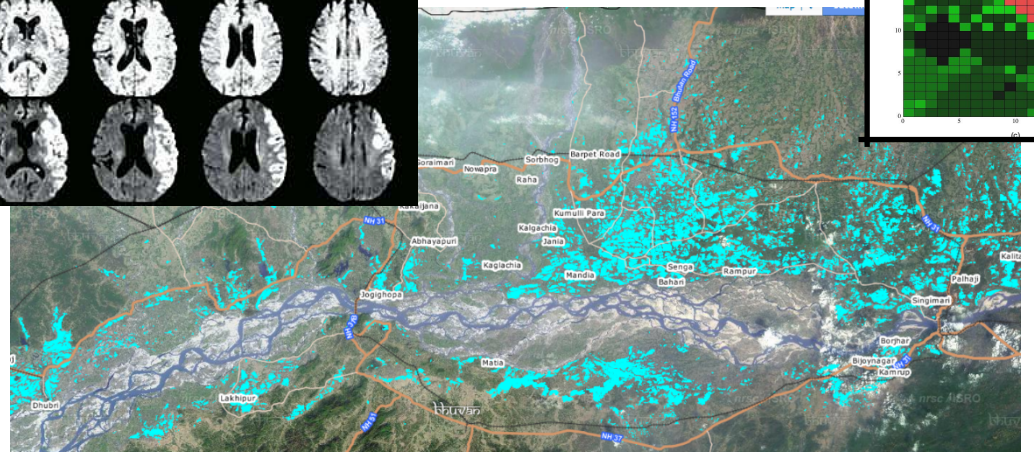
Sustainable Forest Management

Medical Imaging



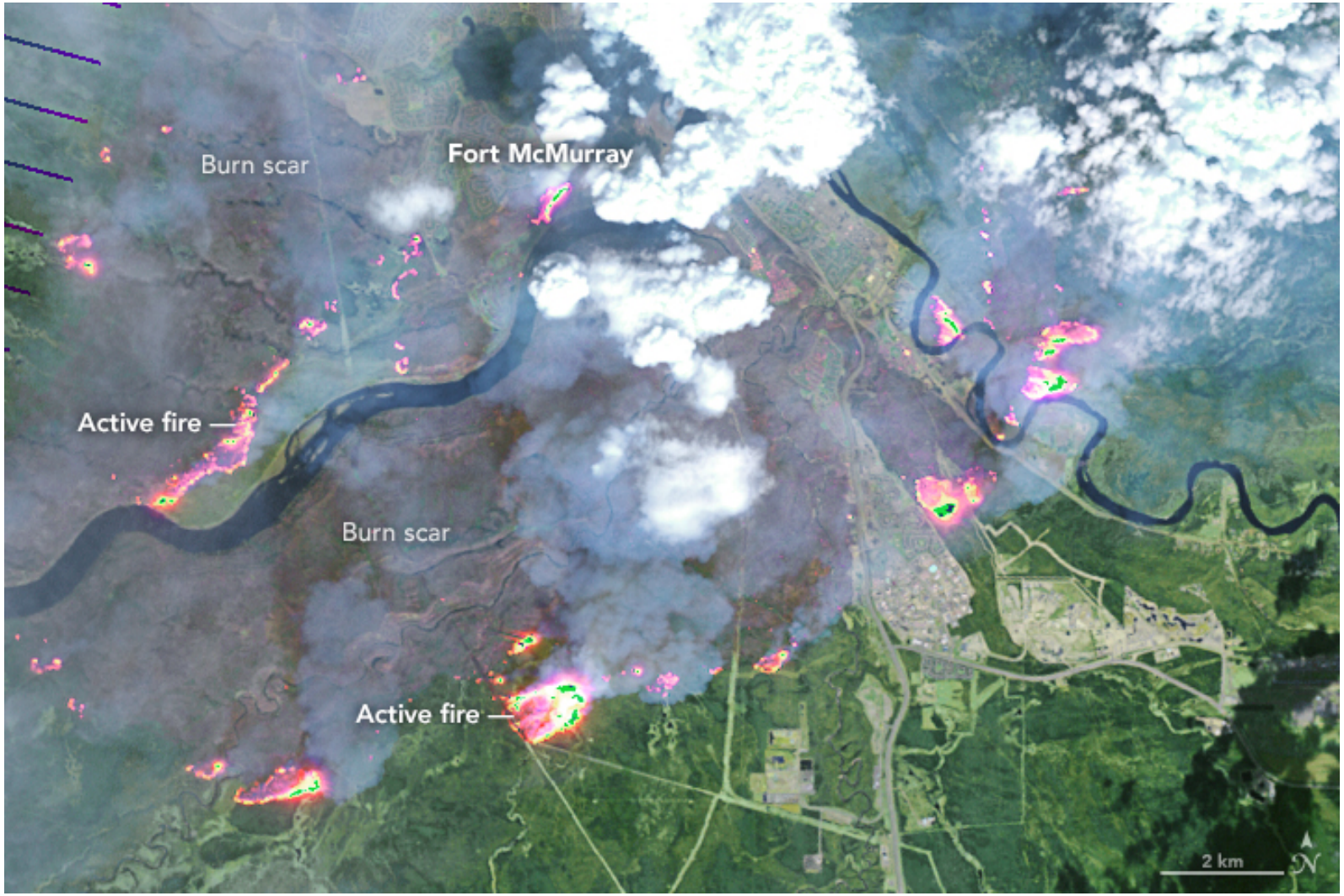
Predicting and Managing Forest Wildfires





Flood Prediction

Forest Fire Management



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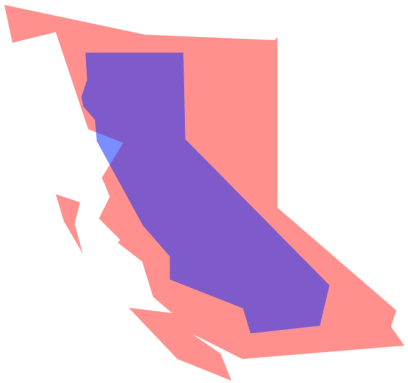
Rising Costs of getting it wrong on Forest Fires



- Cost and impact of wildfires is rising
  - California Camp Fire 2018 : **86 dead; $16B damage; $4B uninsured; 62,000 ha burned**
  - Eg. Thomas Fire Flooding (2017)
    - Well known that loose soil worsens floods dramatically after fire
    - Rain 4x higher than any model predicted few months after major fire
  - Fort McMurray, Alberta 2016 – 90,000 people evacuated, $9B (CND) damage, 590,000 ha burned
  - BC and Ontario 2018 had historic fire year
    - *1985:* 2 million ha *2018:* 8 million ha
    - **4% of entire province in burned in past two years** (BC is 2.2 x the size of California)
  - Australia (bushfire) 18M hectares – lasted 1 year – 34 deaths – >9000 buildings destroyed
- Current simulation methods have high precision but:
  - They often underestimate the scale of fires and risk
  - Computationally expensive to run many times (manual modelling)
  - Hard to adapt to changing climate conditions or poor regions of the world

A Review of ML in Wildfire Science and Management

- What has been done and what methods were used?
- Do ML methods work better than other methods and for what tasks?
- Can we make use of existing success stories here in Canada?
- Identify gaps and challenges
- Find opportunities for future research

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We gratefully acknowledge support from the Simons Foundation and member institutions.

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Computer Science > Machine Learning

[Submitted on 2 Mar 2020]

A review of machine learning applications in wildfire science and management

Piyush Jain, Sean C P Coogan, Sriram Ganapathi Subramanian, Mark Crowley, Steve Taylor, Mike D Flannigan

Artificial intelligence has been applied in wildfire science and management since the 1990s, with early applications including neural networks and expert systems. Since then the field has rapidly progressed congruently with the wide adoption of machine learning (ML) in the environmental sciences. Here, we present a scoping review of ML in wildfire science and management. Our objective is to improve awareness of ML among wildfire scientists and managers, as well as illustrate the challenging range of problems in wildfire science available to data scientists. We first present an overview of popular ML approaches used in wildfire science to date, and then review their use in wildfire science within six problem domains: 1) fuels characterization, fire detection, and mapping; 2) fire weather and climate change; 3) fire occurrence, susceptibility, and risk; 4) fire behavior prediction; 5) fire effects; and 6) fire management. We also discuss the advantages and limitations of various ML approaches and identify opportunities for future advances in wildfire science and management within a data science context. We identified 298 relevant publications, where the most frequently used ML methods included random forests, MaxEnt, artificial neural networks, decision trees, support vector machines, and genetic algorithms. There exists opportunities to apply more current ML methods (e.g., deep learning and agent based learning) in wildfire science. However, despite the ability of ML models to learn on their own, expertise in wildfire science is necessary to ensure realistic modelling of fire processes across multiple scales, while the complexity of some ML methods requires sophisticated knowledge for their application. Finally, we stress that the wildfire research and management community plays an active role in providing relevant, high quality data for use by practitioners of ML methods.

Comments: 79 pages, 4 figures, 3 tables
Subjects: **Machine Learning (cs.LG)**; Machine Learning (stat.ML)
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- Sean C P Coogan
- Sriram Ganapathi Subramanian
- Mark Crowley
- Steve Taylor
- Mike D. Flannigan

https://arxiv.org/abs/2003.00646

(under revision and review)

Review paper for ML in Wildfire (Under revision)

https://arxiv.org/abs/2003.00646

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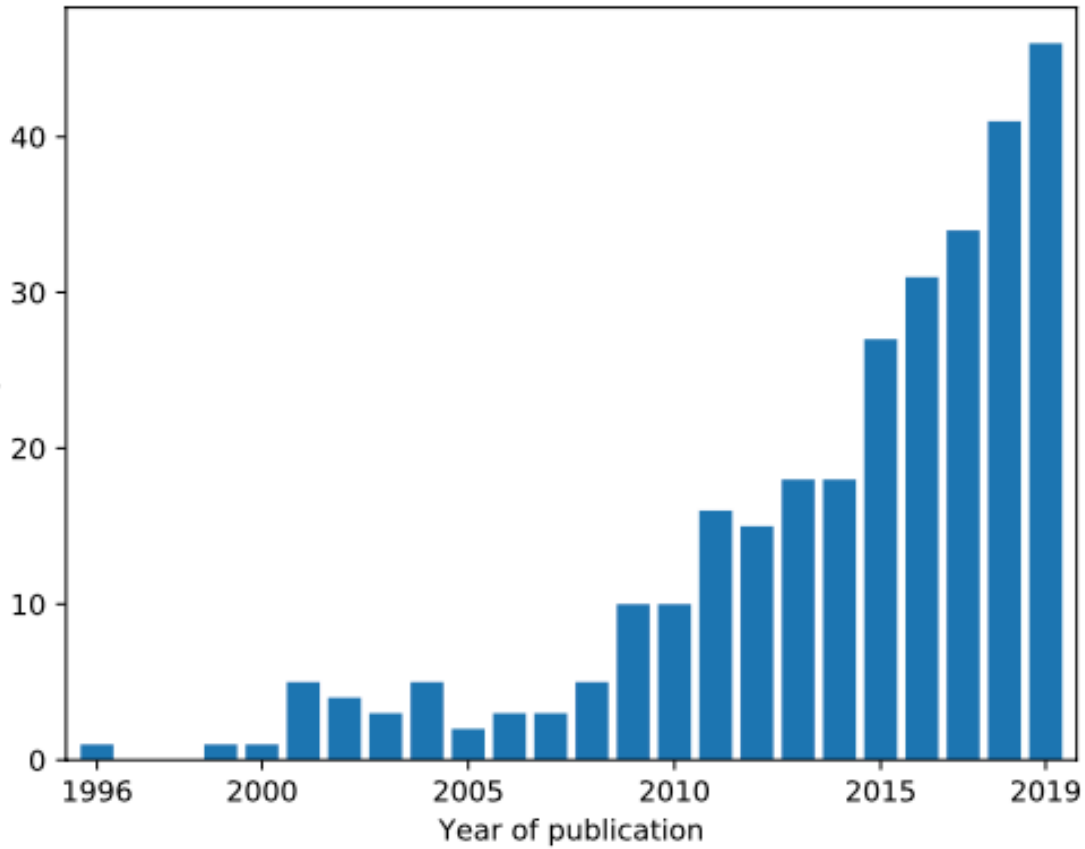
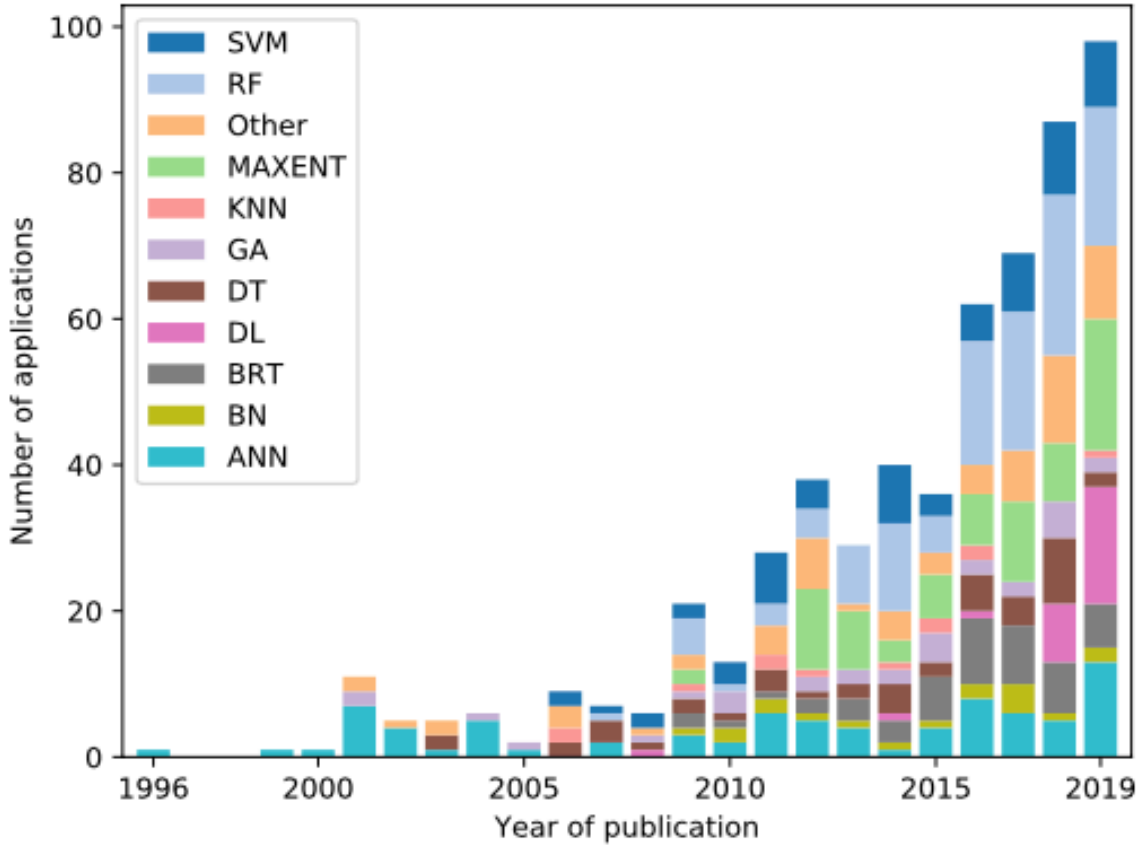
Review summary (currently 298 papers)



Number of publications by year for 298 publications on topic of ML and wildfire science and management as identified in this review.



Number of ML applications by category and by year for 298 publications on topic of ML and wildfire science and management as identified in this review.

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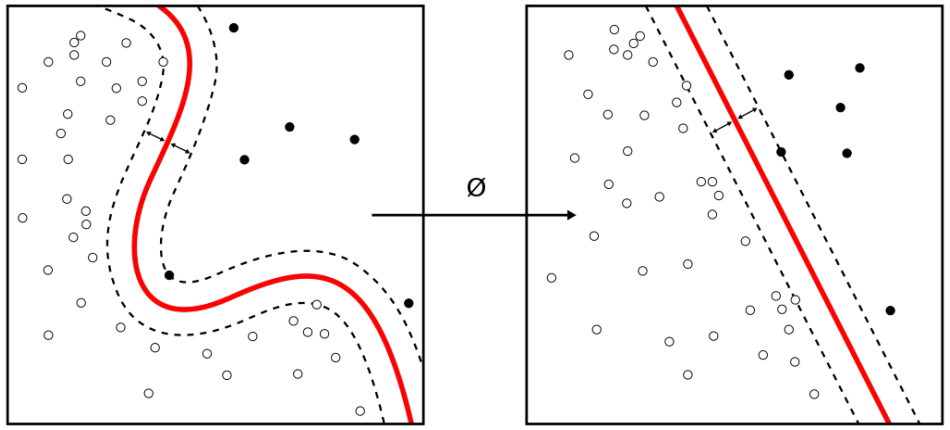
Section	Domain	DT	GA	DL	RF	BRT	SVM	BN	KM	KNN	MAXENT	NB	NFM	ANN	Other
1.1	Fuels characterization	1	-	-	4	1	2	-	-	1	-	-	-	1	-
1.2	Fire detection	-	1	18	-	-	2	1	1	-	-	-	2	11	3
1.3	Fire perimeter and severity mapping	1	2	-	4	1	12	-	1	2	1	-	1	6	6
2.1	Fire weather prediction	-	-	-	1	-	-	-	1	-	-	-	-	-	3
2.2	Lightning prediction	1	-	-	2	-	-	-	-	-	-	-	-	-	-
2.3	Climate change	2	-	-	5	6	1	-	-	-	7	-	-	2	-
3.1	Fire occurrence prediction	1	-	-	5	-	3	1	-	1	2	1	-	7	4
3.2	Landscape-scale Burned area prediction	1	1	1	2	-	1	-	1	-	1	-	-	1	1
3.3	Fire Susceptibility Mapping	9	3	1	26	8	12	2	1	-	27	2	2	16	3
3.4	Landscape controls on fire	15	3	1	40	19	10	2	1	1	30	1	2	11	2
4.1	Fire Spread and Growth	-	13	3	1	-	-	2	-	1	-	-	-	4	2
4.2	Burned area and fire severity prediction	7	1	2	6	3	7	1	-	3	-	1	-	10	5
5.1	Soil erosion and deposits	1	-	-	-	-	-	-	1	-	1	-	-	1	-
5.2	Smoke and particulate levels	-	-	-	4	2	1	-	-	1	-	-	-	2	2
5.3	Post-fire regeneration and ecology	2	1	-	10	6	1	1	-	-	2	1	-	1	-
5.4	Socioeconomic effects	-	-	-	-	-	-	1	-	-	-	-	-	-	-
6.1	Planning and policy	-	1	-	2	-	-	1	-	-	-	-	-	-	2
6.2	Fuel treatment	-	1	-	-	-	-	1	-	-	-	-	-	-	1
6.3	Wildfire preparedness and response	-	1	1	-	1	-	2	-	-	1	-	-	1	1
6.4	Social factors	-	-	-	-	-	-	1	-	-	-	-	-	-	-

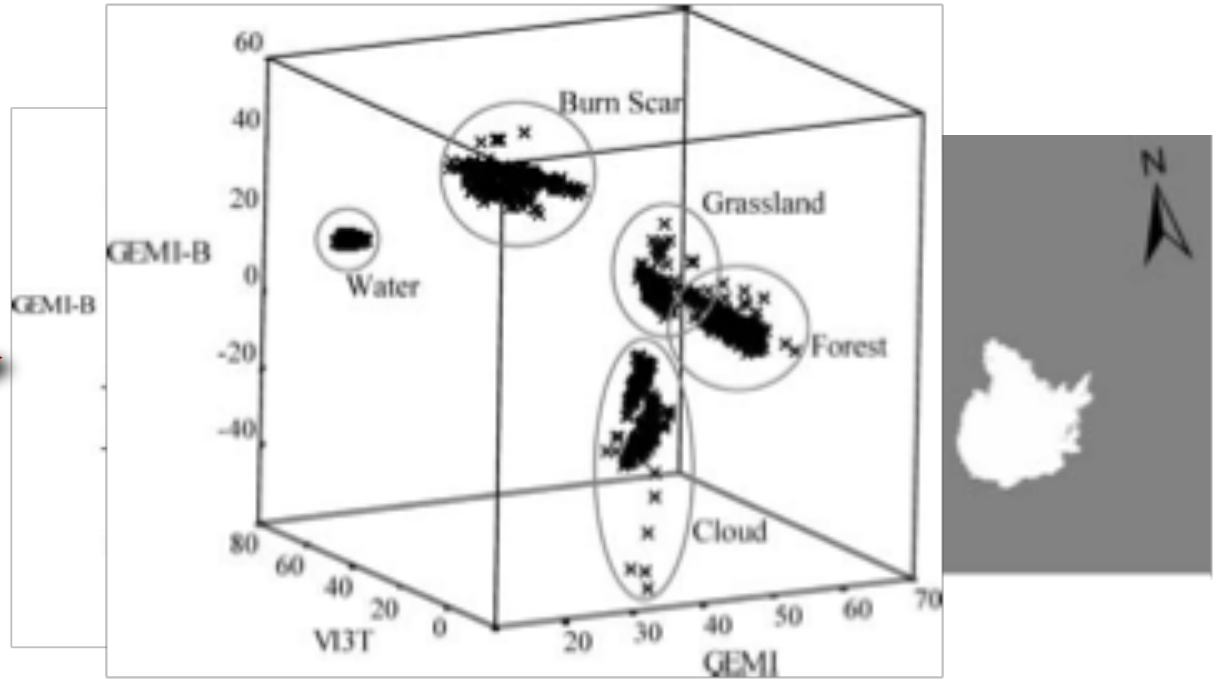
Summary of application of ML methods applied to different problem domains in wildfire science and management.

Fire mapping with SVM (11 papers)

https://commons.wikimedia.org/wiki/File:Kernel_Machine.svg



eg. Bioinformatics,
face detection



Cao et al. (2009). An automatic method for burn scar mapping using support vector machines. International Journal of Remote Sensing, 30(3), 577–594

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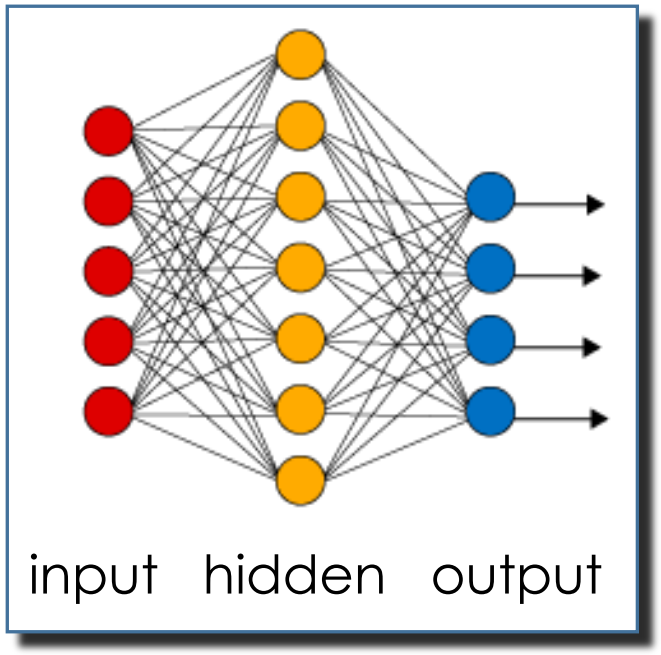
Fire occurrence prediction with ANN (7 papers)



eg. Handwriting recognition, Medical diagnosis

Alonso-Betanzos et al.. (2002). A Neural Network Approach for Forestal Fire Risk Estimation.

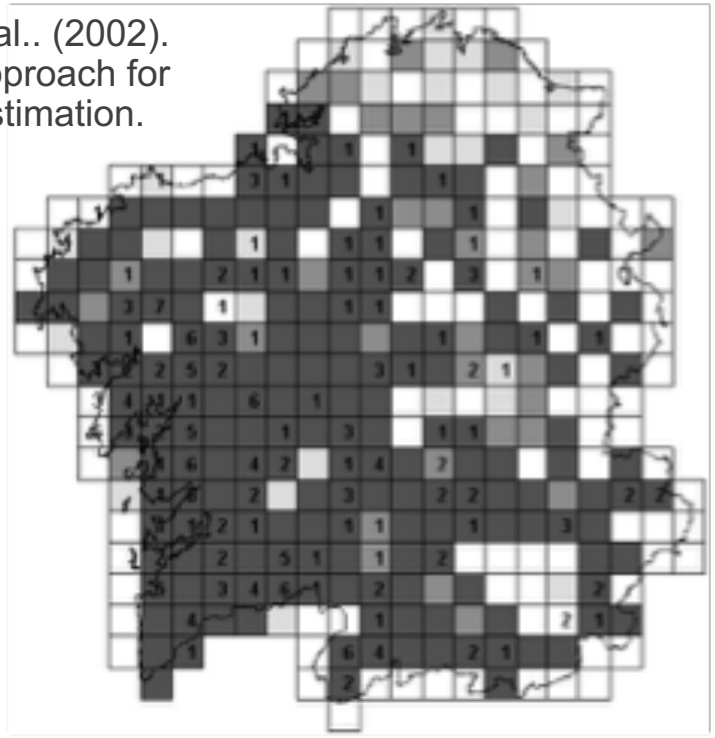
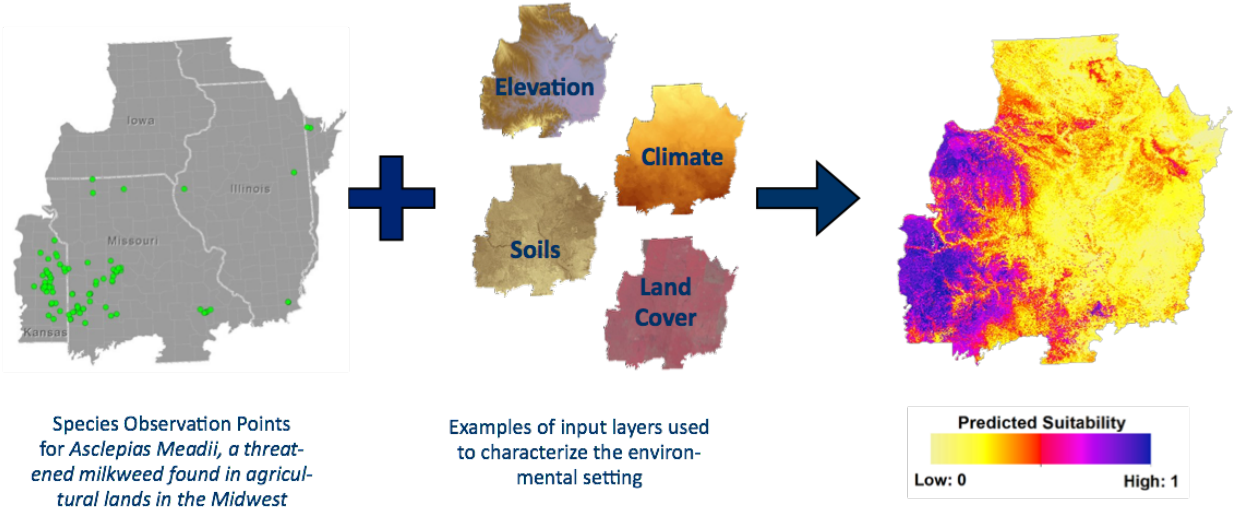


Figure 6. System prediction for Galicia, 20 August 1998. The level of risk is indicated by a colour code and the number in each square represents the number of recorded fires

Fire susceptibility mapping with Maximum Entropy (27 papers)

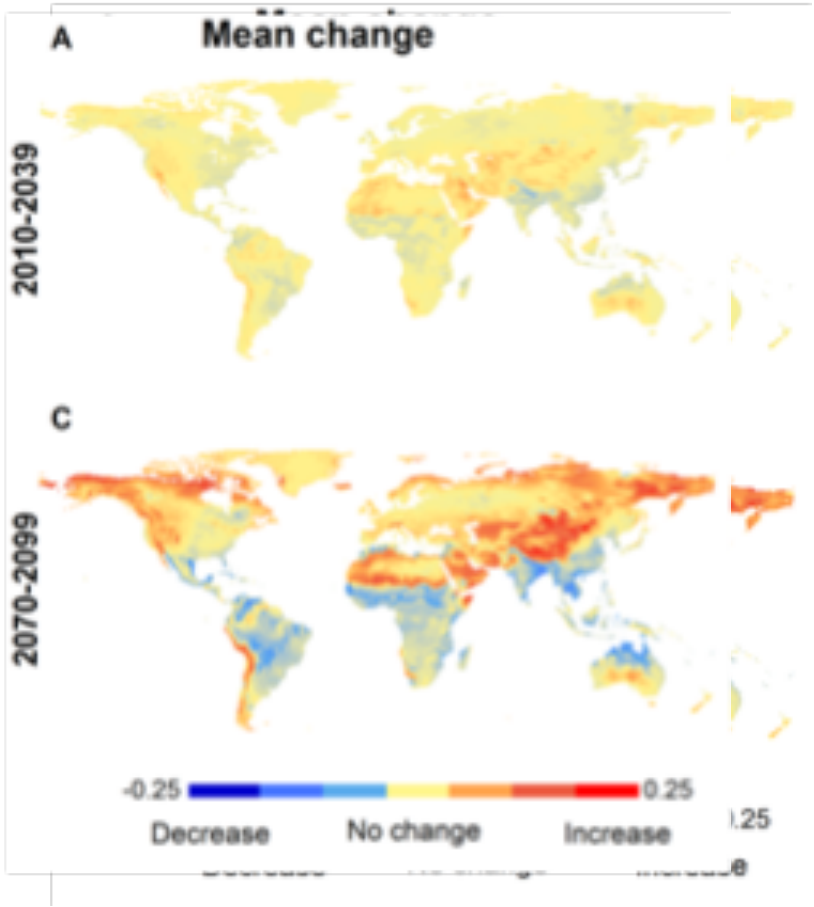


Species Observation Points for *Asclepias Meadii, a threatened milkweed found in agricultural lands in the Midwest*

Examples of input layers used to characterize the environmental setting

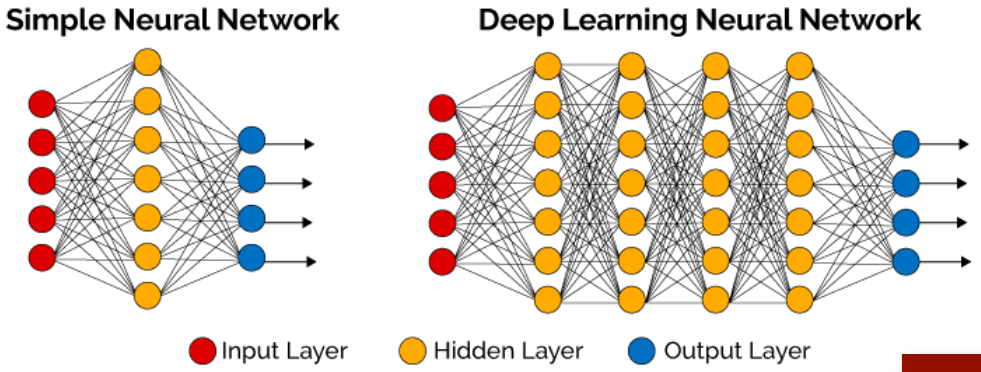
https://www.natureserve.org/conservation-tools/species-distribution-modeling

eg. Used in species distribution modelling, statistical mechanics (physics)

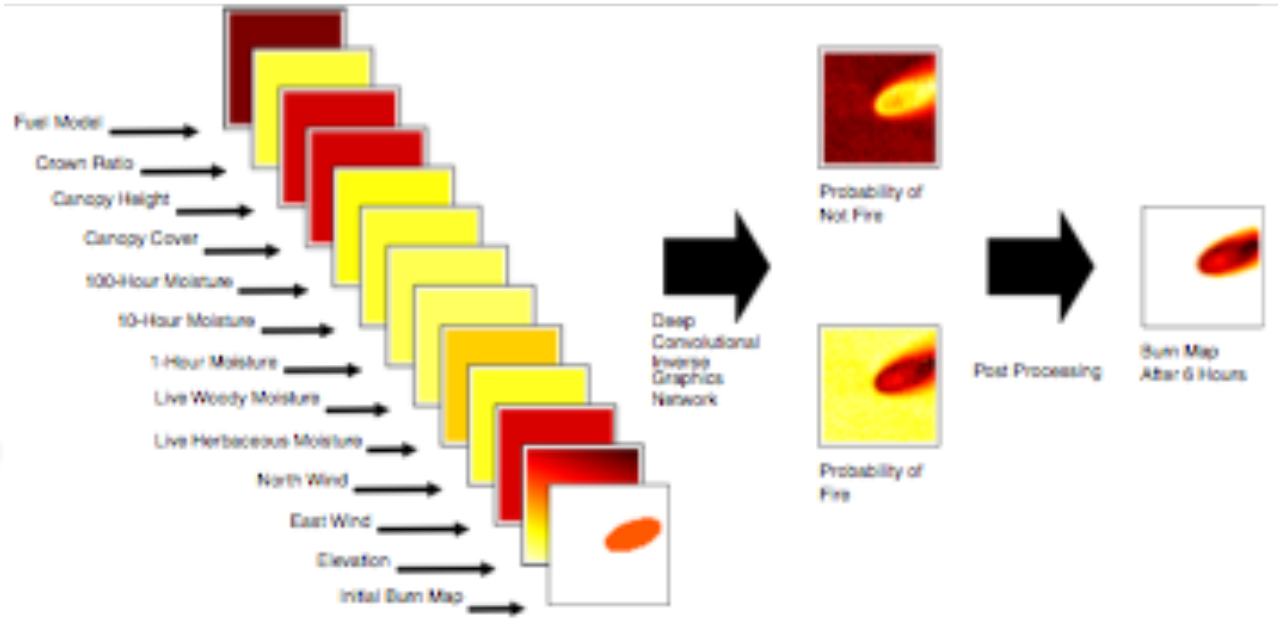


Moritz et al, (2012). Climate change and disruptions to global fire activity. Ecosphere, 3(6)

Fire spread with Deep Learning (2 papers)

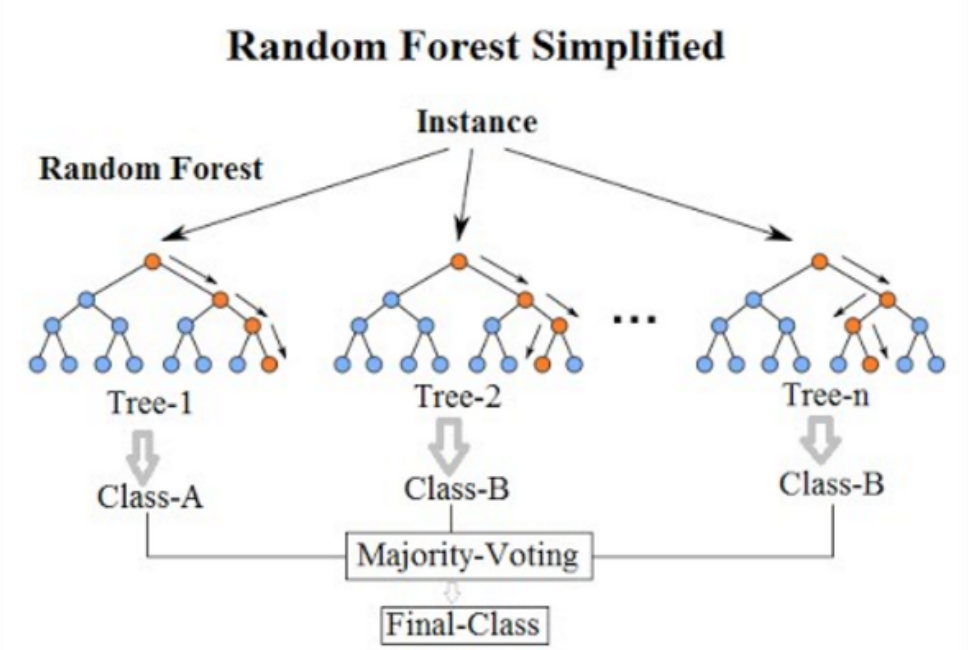


eg. Object detection and classification,
Super-frame and super-resolution video

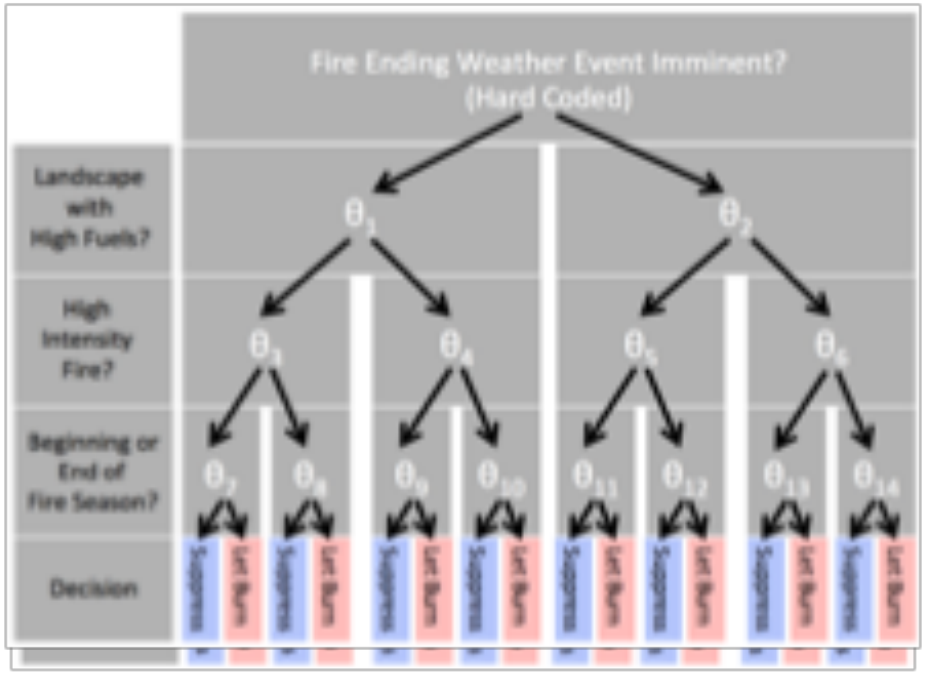


Hodges & Lattimer. (2019). Wildland Fire Spread Modeling Using Convolutional Neural Networks. Fire Technology, 55, 2115–2142

Fire Management with Random Forests (2 papers)

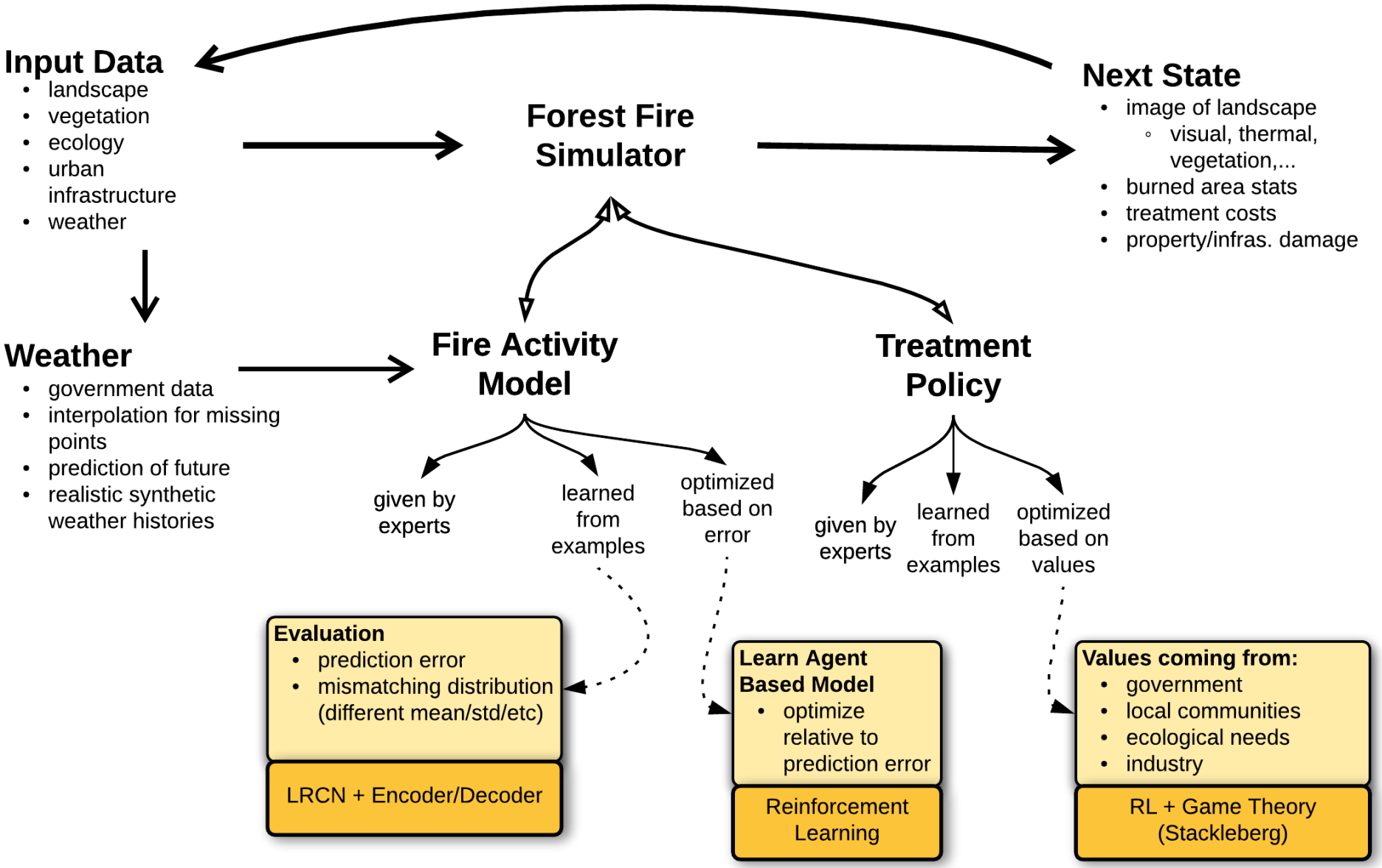


eg. Fraud detection, drug development, recommender systems

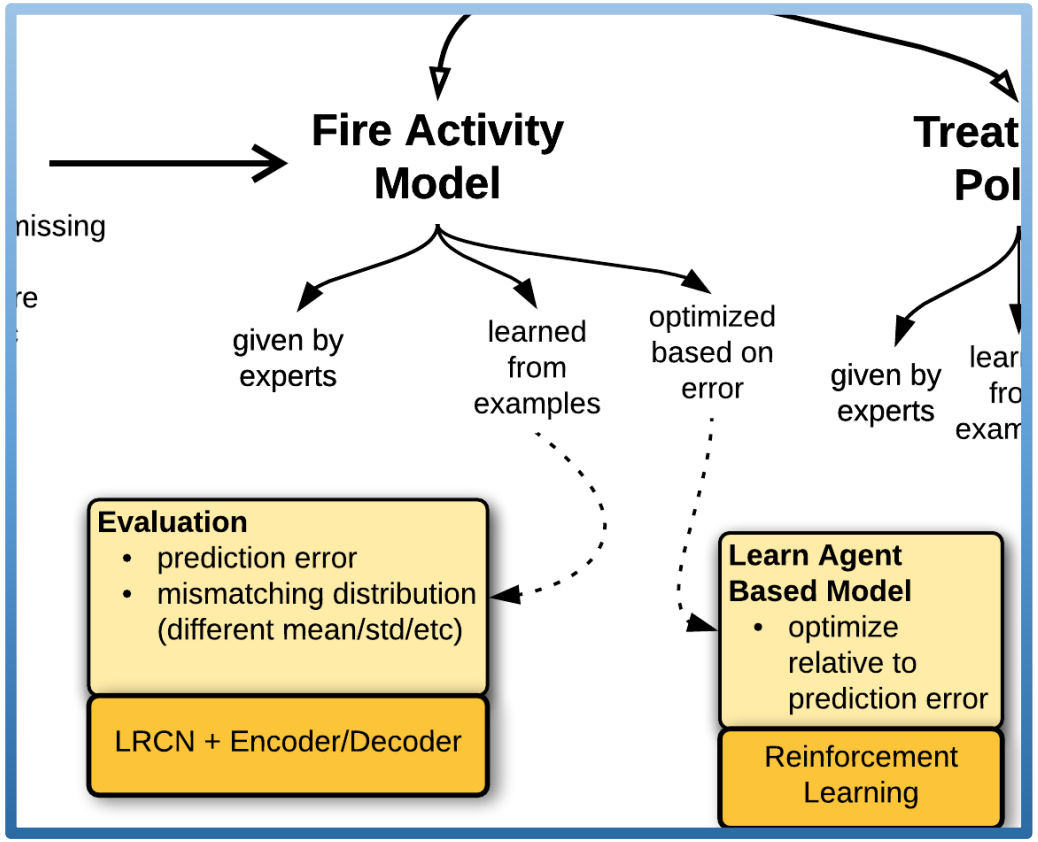


McGregor et al. (2017). Fast Optimization of Wildfire Suppression Policies with SMAC. http://arxiv.org/abs/1703.09391

Prediction and Decision Making for FFM



Learning Fire Activity Models from Examples



Students

Pardis Zohouri Sriram Ganapathi Subramanian

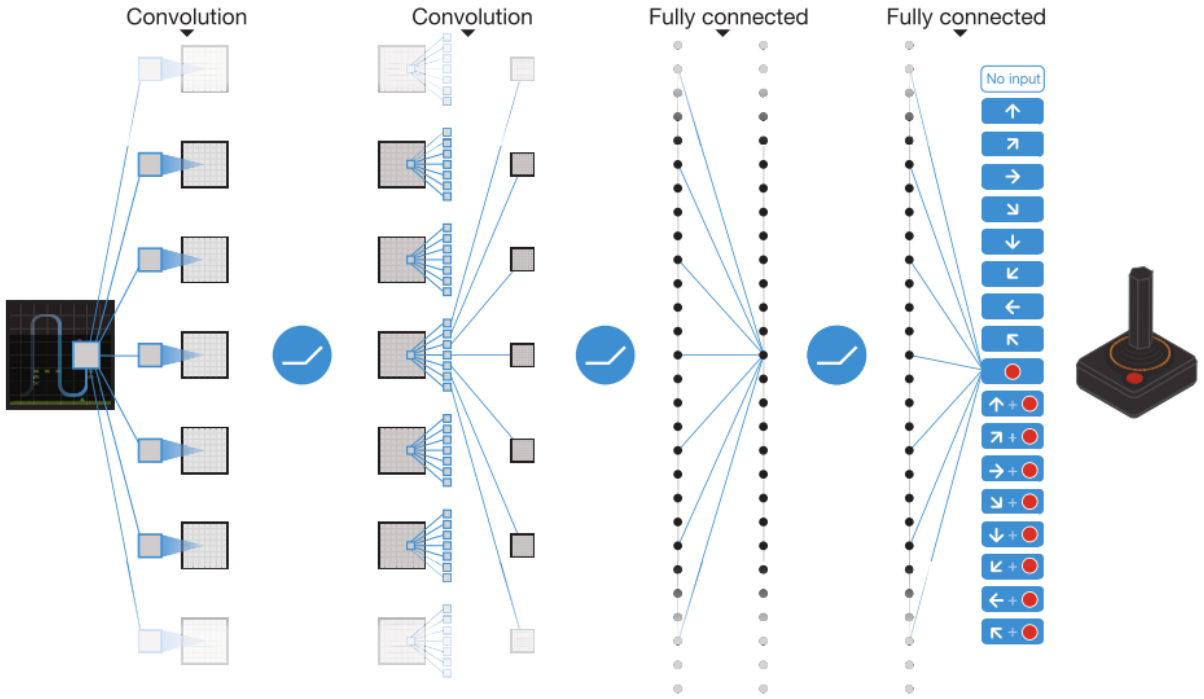
- Examples could come from
  - Simulations used by experts, educators, scientists
  - Satellite/Aerial data collected over time

We have tried two approaches:

- Supervised Approach
  - Learn a direct prediction function from a series of existing images using a Recurrent Neural Network
- **Semi-supervised Approach**
  - Learn an Agent Based Model using data, reasonable assumptions and Reinforcement Learning

Deep Learning, Deep RL, DQN, A3C, etc…

- Can also use **CNNs + Fully Connected Deep Network** for learning a representation of a policy
- Flurry of advances since 2014 made famous by Google DeepMind and others creating Deep RL algorithms
- Deep Q-Learning – **DQN**
- Asynchronous Advantage Actor-Critic - **A3C**
- Many algorithms trying to provide a better way to learn the value function with DNNs
  - Alpha Go – RL + human training
  - Alpha Zero – RL + MCTS search + playing itself (Go, Chess)
  - TRPO, PPO, A2C,…



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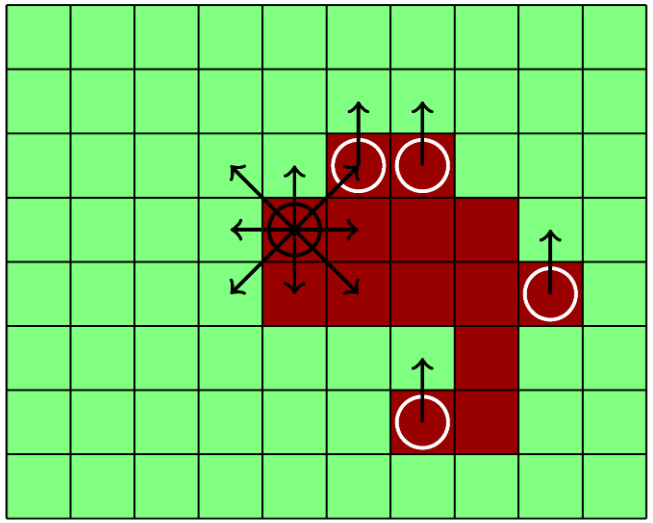
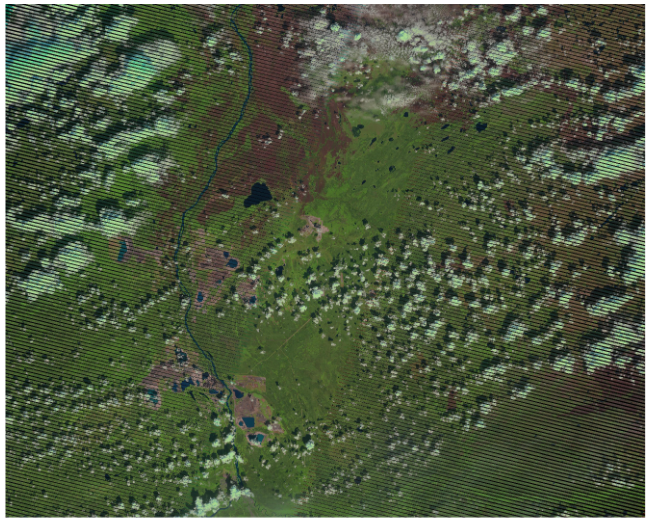
Agent Based Model Learning via Deep RL

Using satellite images from two large forest wildfires in Northern Alberta : Richardson 2011, For McMurray 2016.



(a) Schematic of the state and actions



(b) Raw Color Image

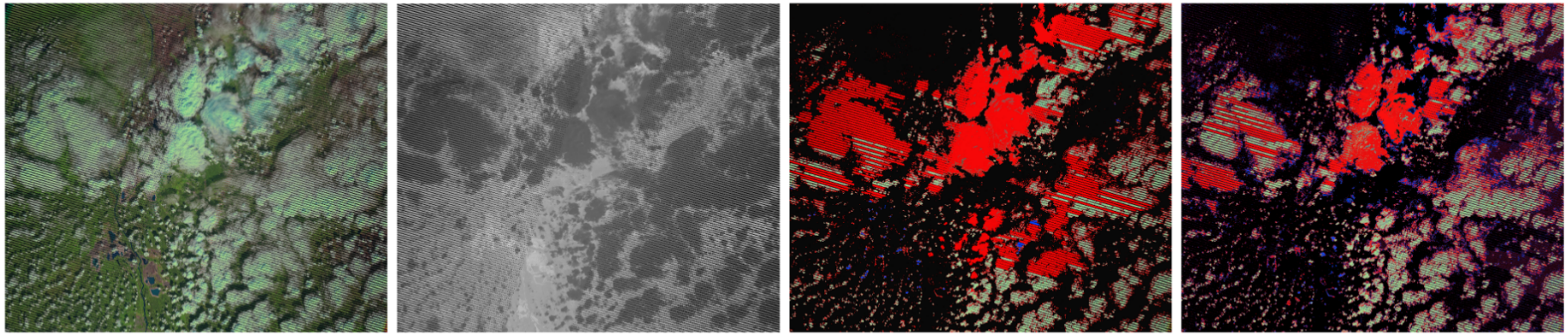
(c) Thermal Image

Prediction of Spatially Spreading Processes

Using Forest Wildfires as a demonstration domain:

- **Basic Idea** - The idea of using RL for learning dynamics from image data, comparison of classical RL algorithms with DQN
  [Ganapathi Subramanian, Crowley, RLDM, 2018]
- **Compared to Standard ML and RL methods:** beat most, but noticed a tradeoff with between tree search and A3C approaches.
  [Frontiers in ICT, 2018]
- **New Algorithm** - proposed a new algorithm MCTS-A3C to take advantage of strengths of both.
  [Ganapathi Subramanian, Crowley, Can AI Conf. 2017]

Forest Fire Prediction – Results

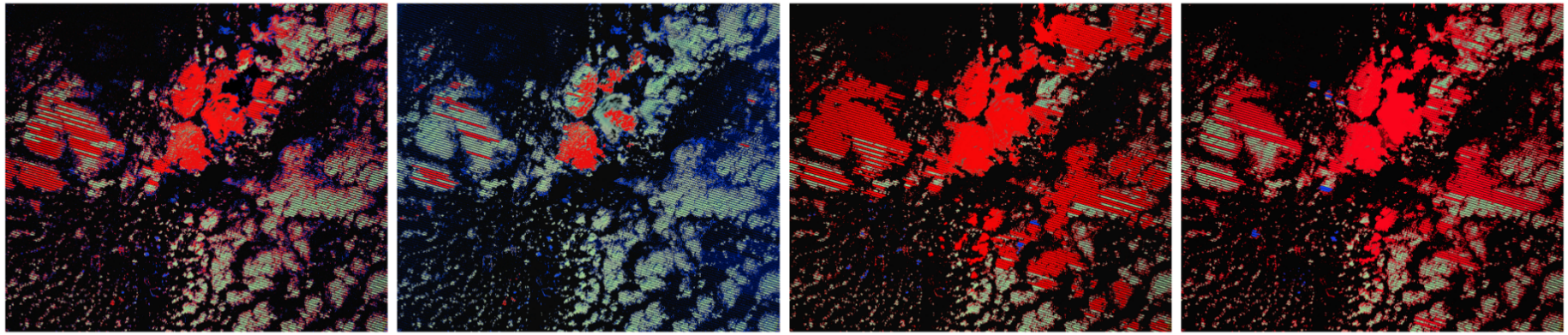


(a) Satellite Image of August 11

(b) Thermal Image of August 11

(c) Gaussian Process

(d) Value Iteration



(e) Policy Iteration

(f) Q Learning

(g) MCTS

(h) A3C

Adaptation : How can AI/ML Help?

- Reduce the frequency/size of fires
  - Prediction, planning, logistics
- Mitigate the effects and impacts of large fires
  - Fire smarting homes
  - Influencing human behavior (game theory?)
- Adapt our way of life to the increasingly challenging conditions, climate change means this isn't going away.
  - Reduce development in the Wildland-Urban Interface (WUI)
    - Urban planning, prediction of trends in weather, human and ecological growth patterns
  - Let more fires burn naturally
    - Prediction, planning, risk and confidence modelling, let-burn discussions

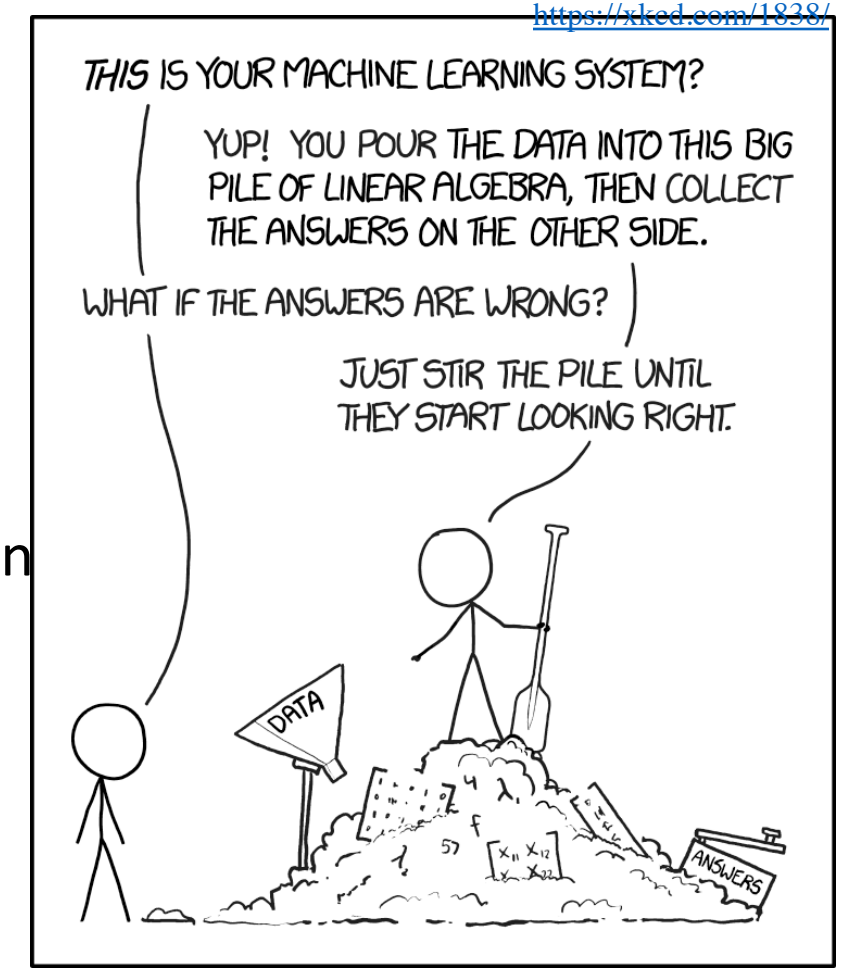
Machine Learning is just another tool

- **G-I-G-O** (Garbage in garbage out)
- **Overfitting** can be a problem
- **Validation and comparison** to traditional methods
- **Extrapolation** may be a problem

  - implications for predicting extremes and climate chan
- **Interpretation?**

  - Advancing science by seeing inside the “black box”

https://xkcd.com/1838/



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Challenges : Trust, Local Empowerment

- We can't assume the tool or method we develop will work in all scenarios or local situations → So tools needs to be open and well explained
- **Trust:** This can help build trust by the potential end users. They are right to be worried about
  - Oversimplification of the problem
  - Bias in the data or setup
  - Overconfidence in results arising from "error" metrics
- **Local:** Communities do so much of disaster response on their own
  - (see Quesnel, BC vs Paradise, CA)
  - They go to amazing lengths to prepare for climate disasters
  - but more and more work is downloaded to them, and without training or funding
  - **The Question:** How can *we* help them
    - Do more with less? Know when to ask for help vs when to deal with on their own?
    - Use existing expertise in the base way?

Thanks for Listening!

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