



Artificial Intelligence for EHS Compliance and Sustainability Management

April 16, 2020



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Today's Speakers



Neno Duplan
Founder & CEO
Locus Technologies



Robert Pierce
Machine Learning
Engineer
Locus Technologies



Dr. Todd Pierce
Director of EIM & GIS
Development
Locus Technologies



Artificial Intelligence for EHS Compliance and Sustainability Management

Locus Technologies

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Agenda

- ◇ Overview of AI and Machine Learning
- ◇ Data requirements
- ◇ Case Study: Forest Disturbance Monitoring
- ◇ EHS&S examples
- ◇ Takeaways

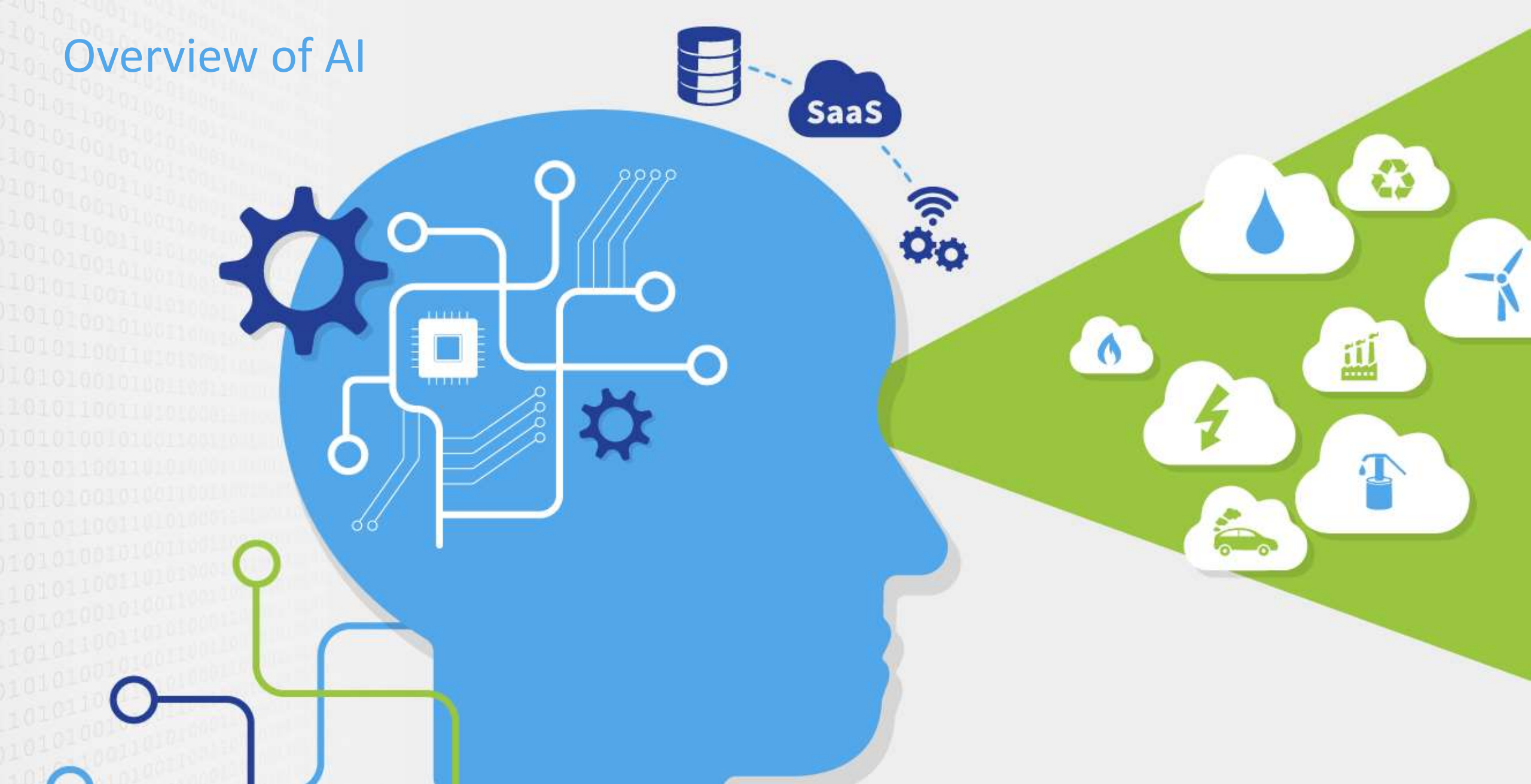


Poll Question #1

- ◇ How familiar are you with AI?
 - ◇ Very familiar
 - ◇ Somewhat familiar
 - ◇ Not familiar



Overview of AI

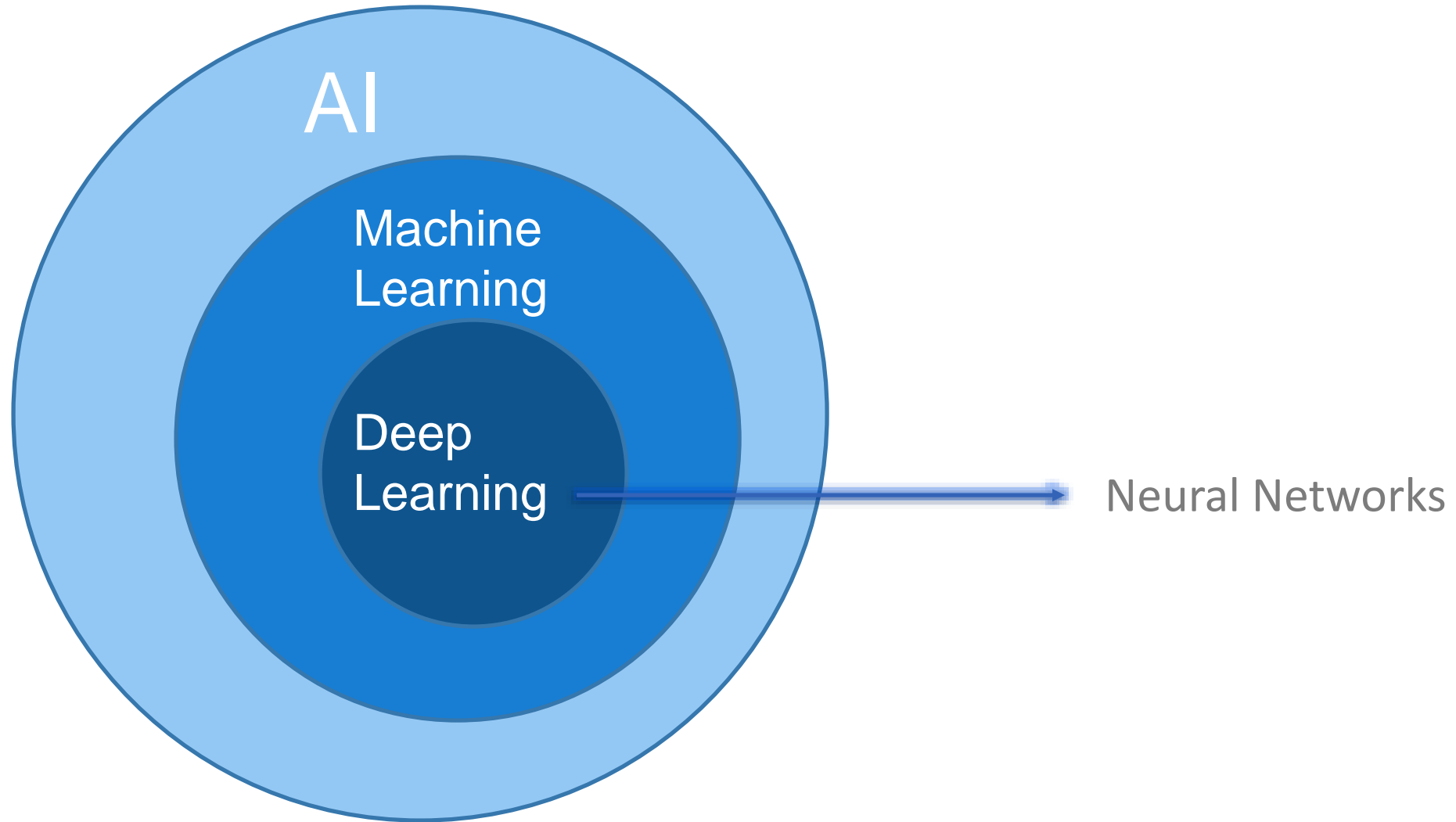


Overview of AI

- ◇ AI is the ability of a computer to perform tasks that require human-level intelligence
- ◇ Used alongside big data to draw inferences and conclusions about many aspects of life
- ◇ Must be adaptable for many different data types and situations



Overview of AI



Machine Learning

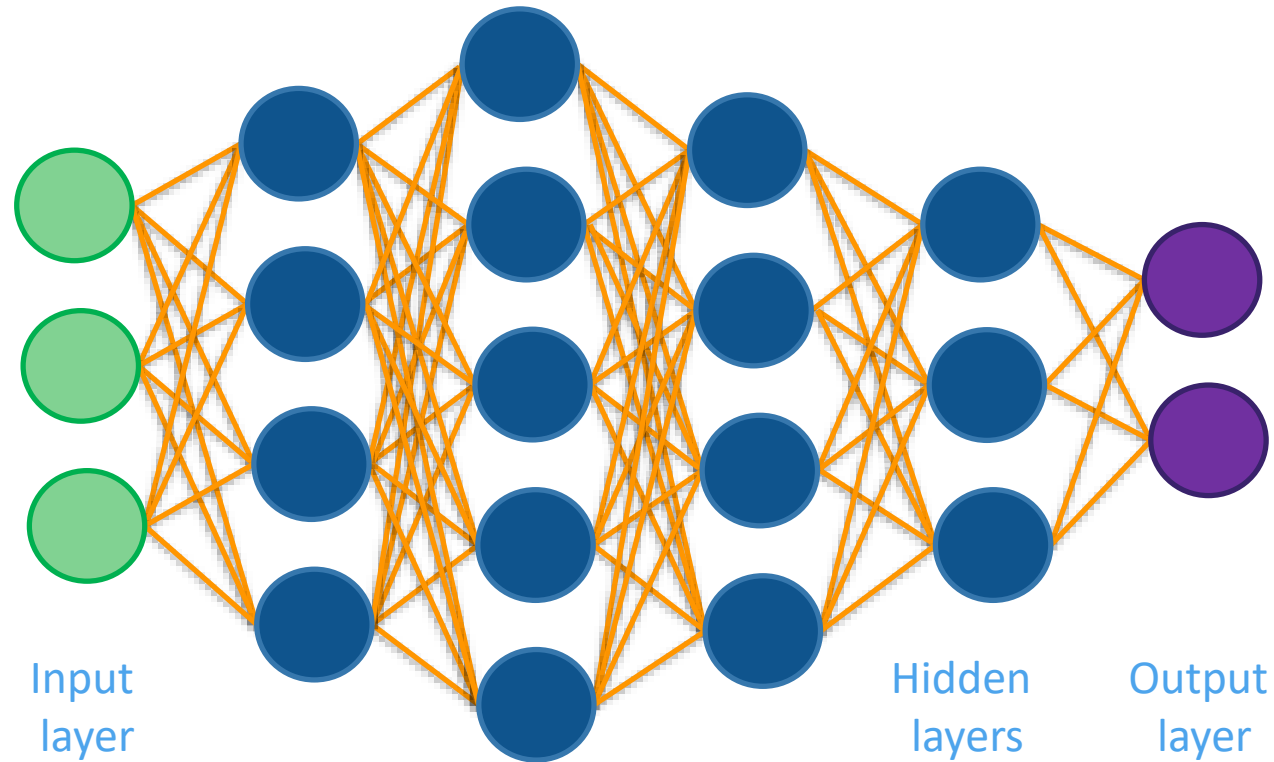
- ◇ Algorithms used by computer systems to perform a task when explicit instructions are not available
- ◇ Can improve performance with training
 - ◇ Training is based on a model of a real-world process
 - ◇ "All models are wrong, but some are useful."
(attributed to George Box, statistician)
- ◇ Many everyday applications such as streaming recommendations

A correlation matrix heatmap showing the relationships between eight variables: Years, Dissolved Oxygen, Flow (in gpm), Oxidation-Reduction Potential, pH, Specific Conductance, Temperature, and Turbidity. The diagonal elements are all 1.0, indicating perfect self-correlation. The off-diagonal elements represent the Pearson correlation coefficients between pairs of variables. The color scale ranges from dark purple (negative correlation) to yellow (positive correlation).

Years	1	-0.45	-0.81	-0.36	0.006	0.46	-0.37	-0.17
Dissolved Oxygen	-0.45	1	0.32	-0.2	-0.34	-0.47	0.055	-0.0068
Flow (in gpm)	-0.81	0.32	1	0.32	0.11	-0.23	0.46	0.17
Oxidation-Reduction Potential	-0.36	-0.2	0.32	1	-0.16	-0.18	-0.21	-0.34
pH	0.006	-0.34	0.11	-0.16	1	0.19	0.4	0.51
Specific Conductance	0.46	-0.47	-0.23	-0.18	0.19	1	-0.38	-0.17
Temperature	-0.37	0.055	0.46	-0.21	0.4	-0.38	1	0.75
Turbidity	-0.17	-0.0068	0.17	-0.34	0.51	-0.17	0.75	1

Deep Learning

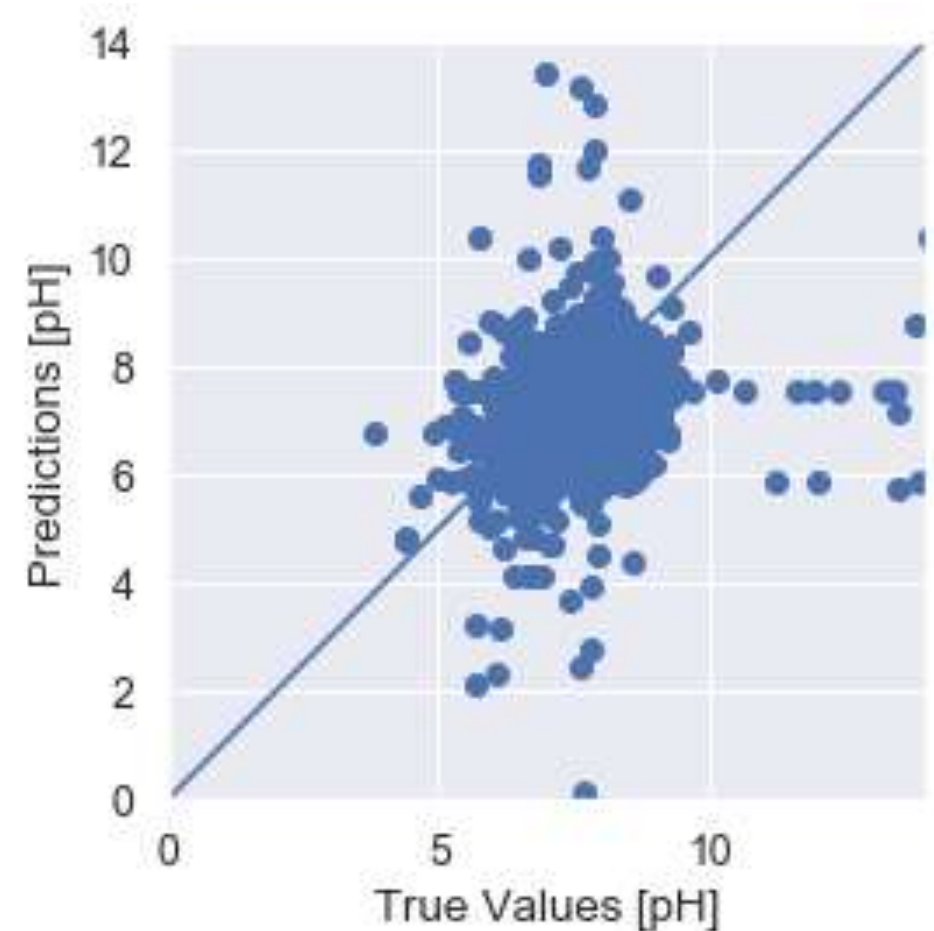
- ◇ Neural Networks – designed after human nervous system
- ◇ Independent logic inside each node



Predictive Analytics

- ◇ Use of statistical techniques to make predictions based on existing data
- ◇ In terms of safety, can help alleviate risk of human error
- ◇ Most likely will not provide the exact value of a parameter, but a well-designed system can be very accurate
- ◇ Amazon "anticipatory shipping"

"It's tough to make predictions, especially about the future."
— Yogi Berra



Poll Question #2

- ◇ Has your organization implemented AI?
 - ◇ Yes
 - ◇ No, but we are planning to soon
 - ◇ No, and we have no plans to do so



Data Requirements

- ◇ Accurate AI systems require aggregate data from many sources, especially for prediction
- ◇ The data obtained must come from accurate sources
- ◇ Collected data must be an appropriate input
- ◇ Need one system of record
- ◇ Turning data into information



Data Collecting

- ◇ Cloud systems
- ◇ Shared Platform
- ◇ Internet of Things
- ◇ Big Data



Current Centralized Model is Unsustainable

THE WALL STREET JOURNAL

A2 | Saturday/Sunday, March 9 - 10, 2019

U.S. NEWS

THE NUMBERS | By Jo Craven McGinty

Forget Gigabyte, Even a Yottabyte Won't Do

2022, then in 2026." Even then, the proposal could be rejected.

Counting Up
The largest named prefix for a number is yotta, or 1 followed by 24 zeros, also known as septillion. A British metrologist proposes adding prefixes for even larger numbers.

VALUE	SI PREFIX
Thousand	kilo
Million	mega
Billion	giga
Trillion	tera
Quadrillion	peta
Quintillion	exa
Sextillion	zetta
Septillion	yotta

Source: National Institute of Standards and Technology

Richard J.C. Brown, a British chemist who studies weights and measures, has a big idea: He wants to name the next set of prefixes used to identify gargantuan numbers.

To facilitate international trade, manufacturing and scientific communication, most countries use a standard system of units sanctioned by the International Bureau of Weights and Measures. The seven base units include the

without expanding the list of prefixes, there will be no way to talk about the next great chunk of numbers.

Even worse, dilettantes could fill the void by popularizing glib prefixes such as bronto or hella—terms that have already won fans.

Without professional intervention, Dr. Brown fears, the next numerical prefix could become the Boaty McBoatface of weights and measures.

"The most dangerous thing for people who set rules is that these prefixes get so widely adopted, they become de facto the names,"

more than a century has been tied to the mass of a metal cylinder sanctioned in 1889 and stored in France. The new definition, based on a fixed

executive secretary, Estefania de Mirandes, declined to speculate, and even if the committee likes the idea, final approval would take years.

The group, which meets on

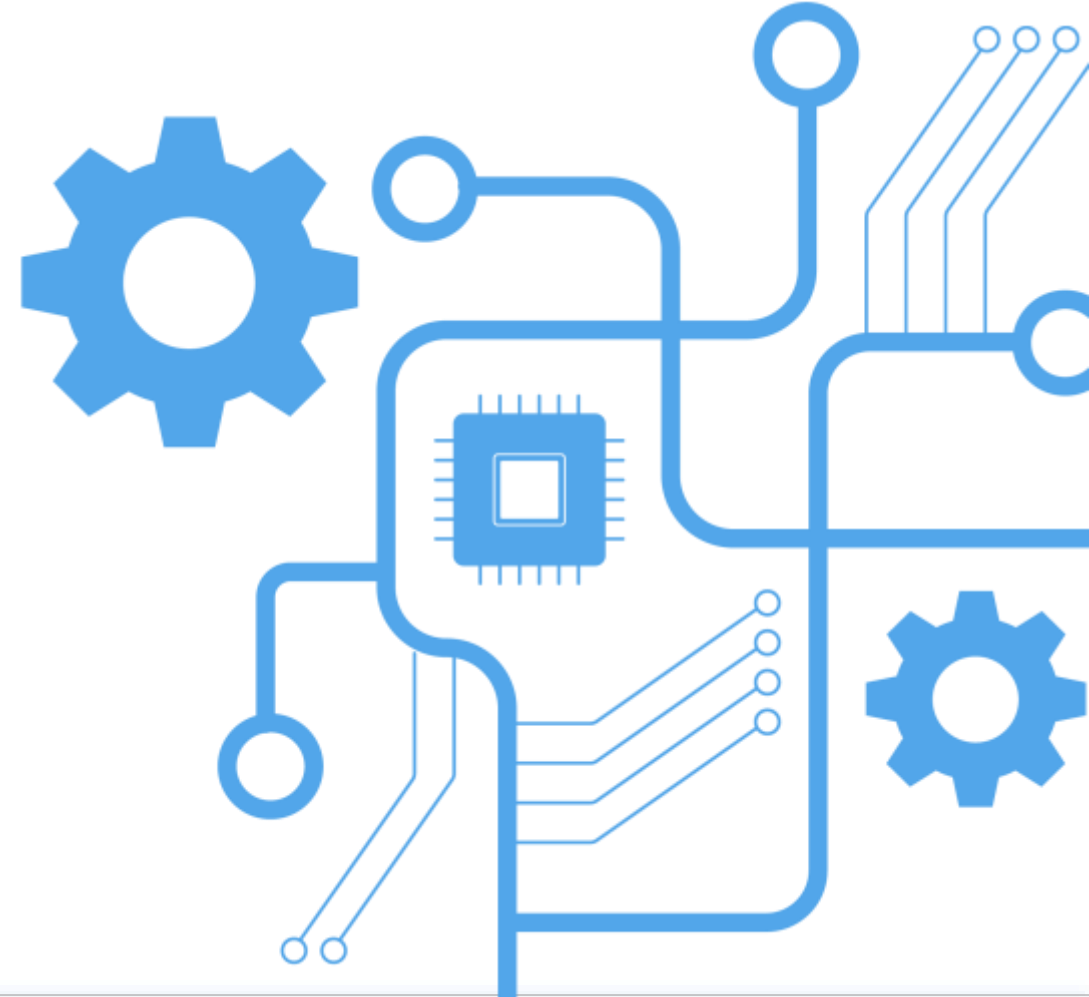
A potential sticking point is that Dr. Brown's primary reason for coining the terms is to ensure that big data can grow even bigger with a vocabulary to match.

Computer scientists and engineers, borrowing official prefixes, already use megabyte, gigabyte and terabyte to describe the capacity of a computer hard drive. But "byte" isn't a unit under the control of the Bureau of Weights and Measures, and serving the data community isn't traditionally a concern of the bureau.

In addition, since the last revision, the Consultative

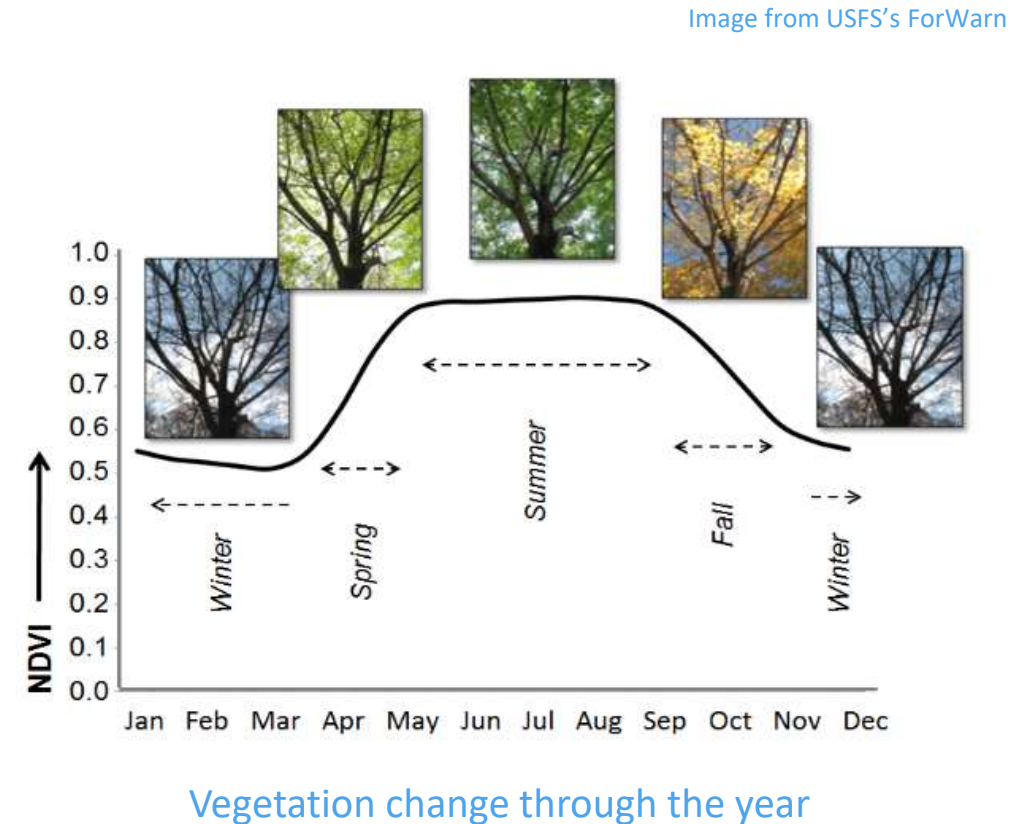
Big Data

- ◇ Extremely large data sets and the field involved with analyzing them
- ◇ Too large for human analysis
- ◇ Can provide insights into many aspects of life and society



Case Study: Forest Disturbance Monitoring

- ◇ Forests change naturally through the year as trees green up in the summer and then brown down in the winter
- ◇ This cyclical pattern can be disturbed by many things:
 - ◇ Diseases
 - ◇ Pests
 - ◇ Weather
 - ◇ Climate change



Case Study: Forest Disturbance Monitoring

- ◇ Early identification of these disturbances is critical for natural resource managers to understand and respond to these threats
- ◇ Aerial and ground surveys can find disturbances
- ◇ In the United States, there are just too many acres of managed forests and crops for regular visual inspection

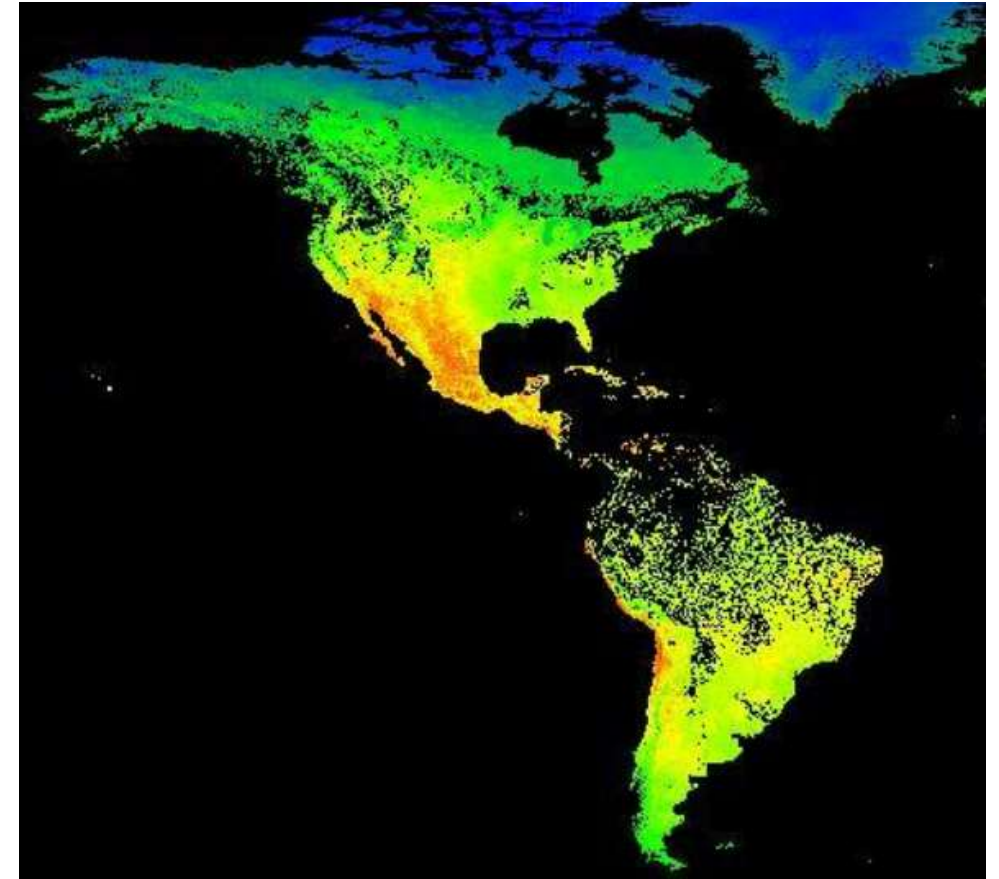
Images from USFS



Case Study: Forest Disturbance Monitoring

- ◇ Daily satellite images can be used to identify regions affected by disturbances
- ◇ The imagery is processed to show change in vegetation from the normal level
- ◇ <https://forwarn.forestthreats.org/>

Image from USGS EROS

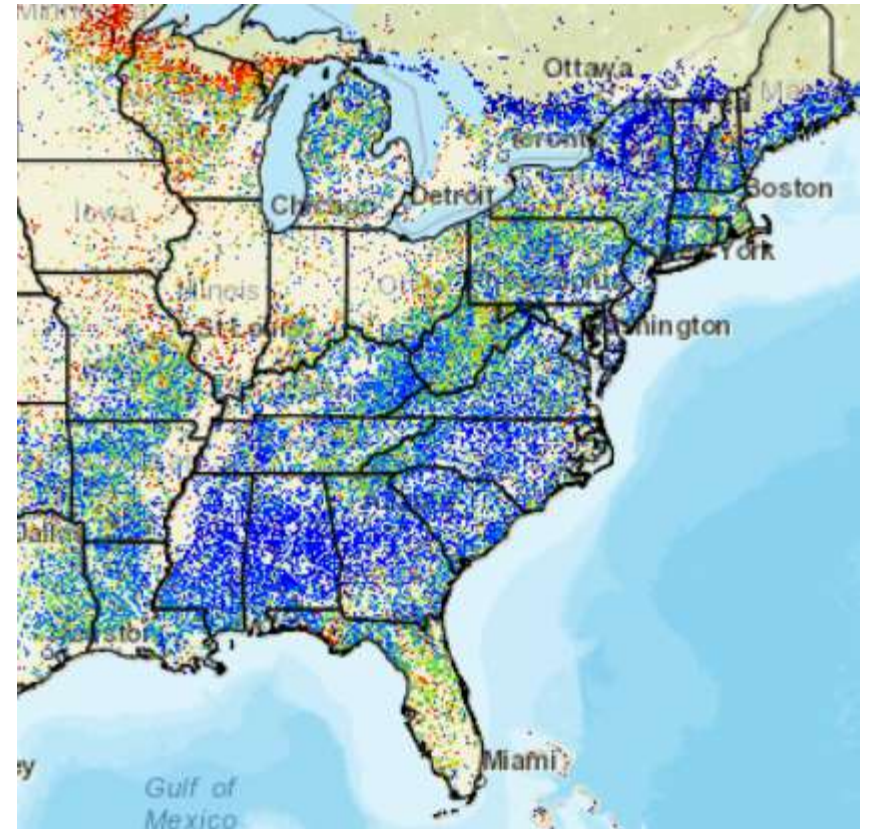


Example of daily satellite image from NASA

Case Study: Forest Disturbance Monitoring

- ◇ Again, though, there are too many images to manually inspect them
- ◇ Neural networks (deep learning) can be used to automatically identify disturbances and alert managers

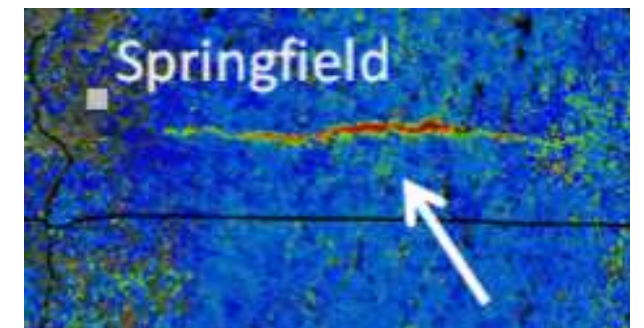
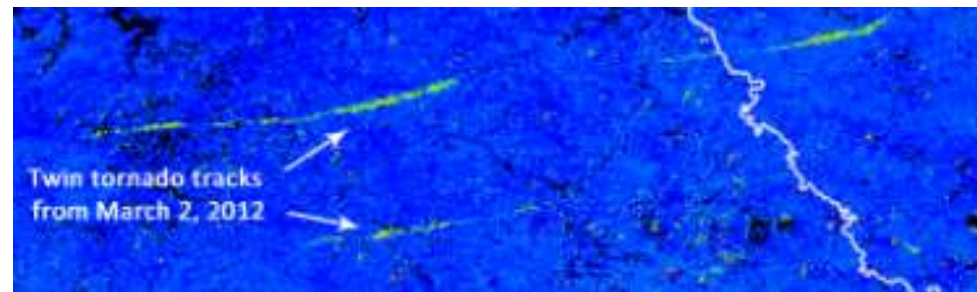
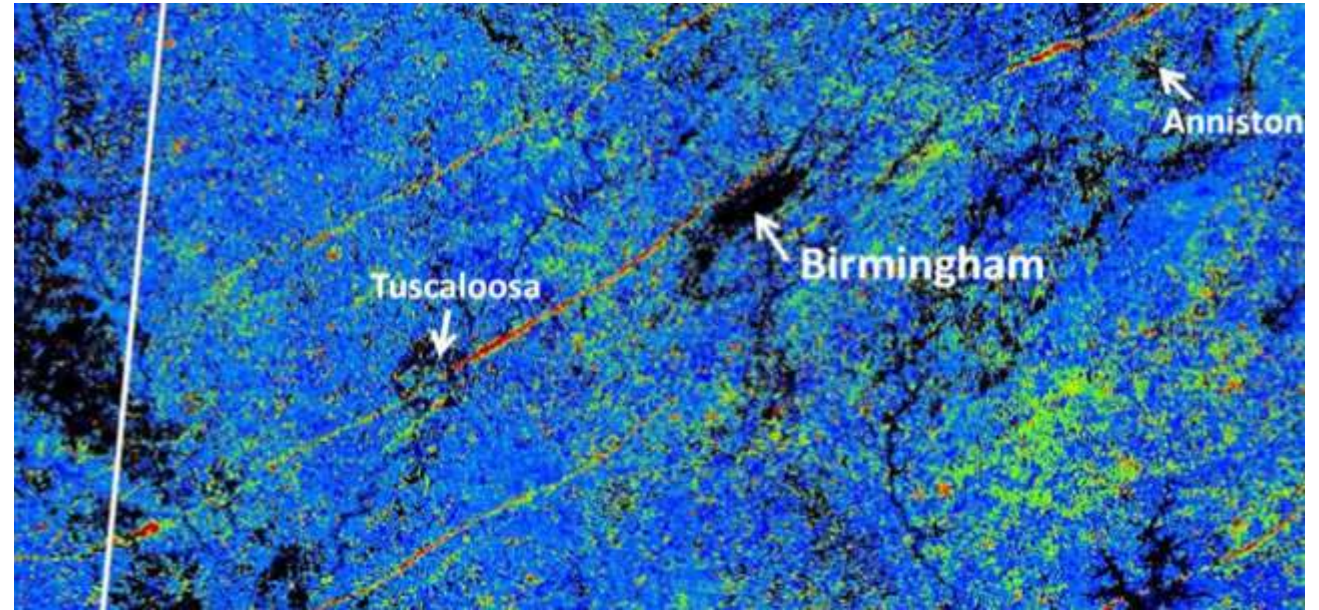
Image from USFS ForWarn



Example of vegetation change
(red below normal, blue above normal)

Case Study: Forest Disturbance Monitoring

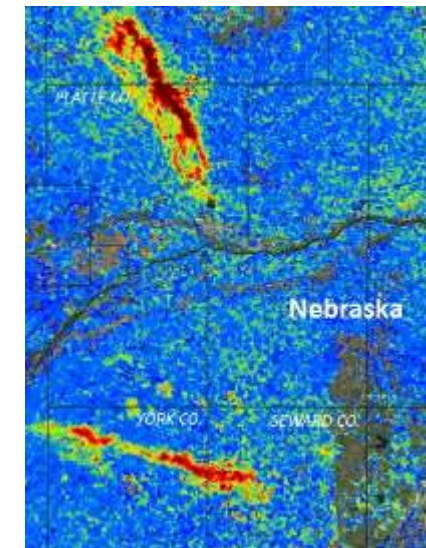
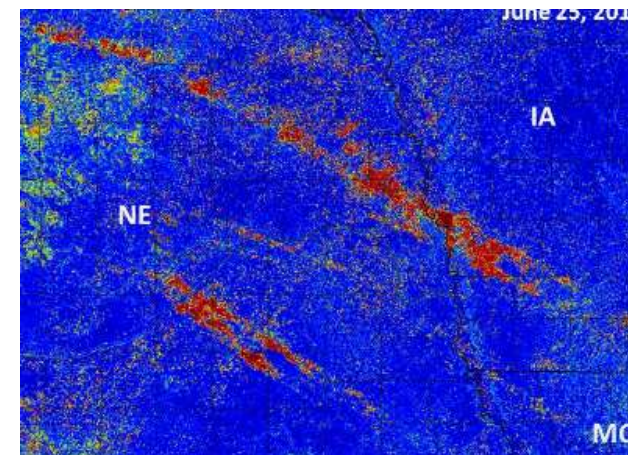
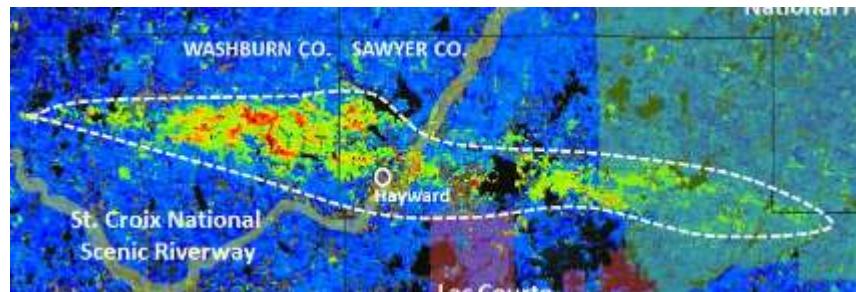
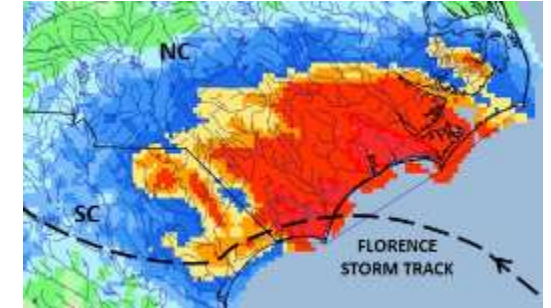
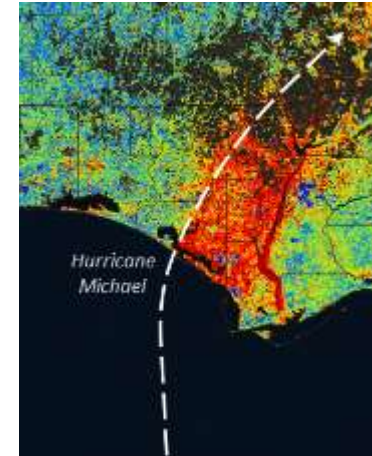
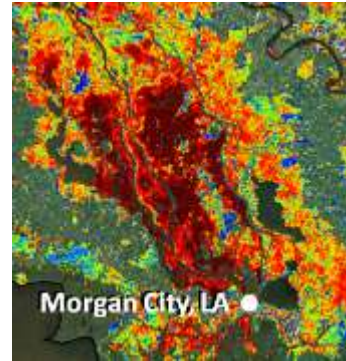
- ◇ To train the network, known disturbance patterns must be fed into the system
- ◇ Here are examples of vegetation differences due to tornadoes



Images from USFS's ForWarn

Case Study: Forest Disturbance Monitoring

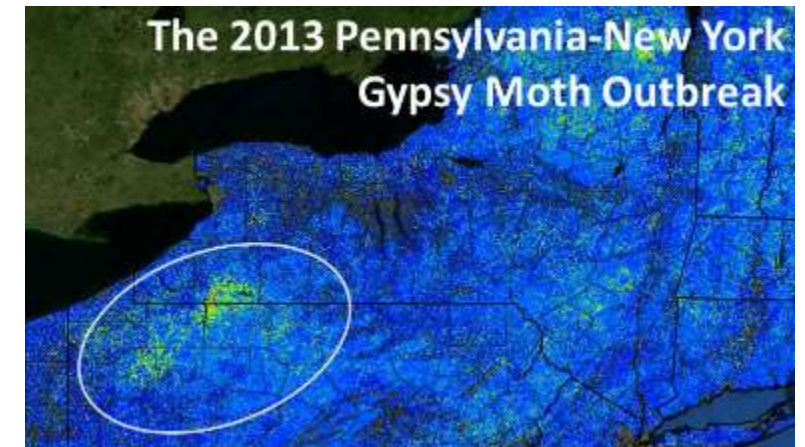
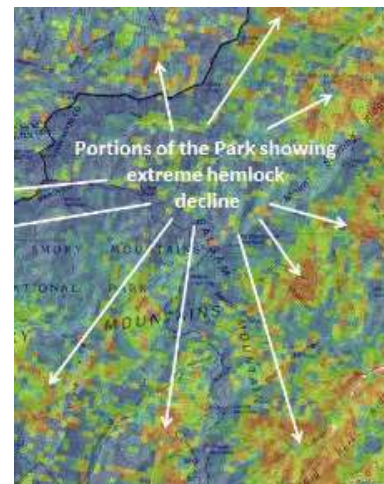
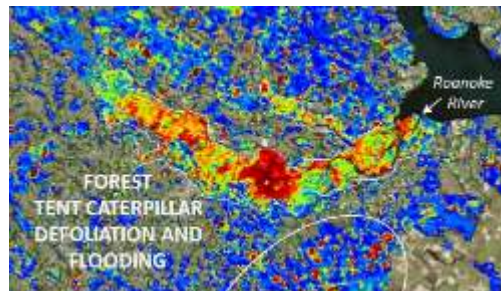
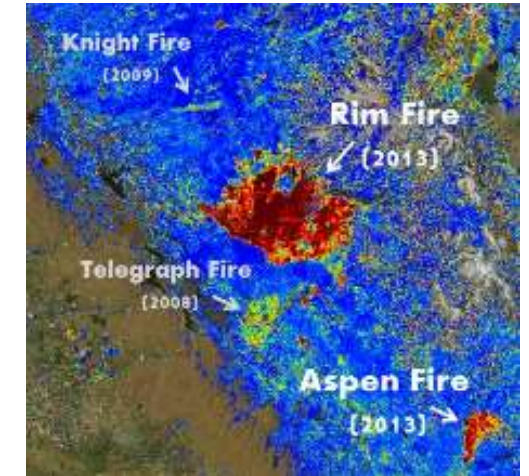
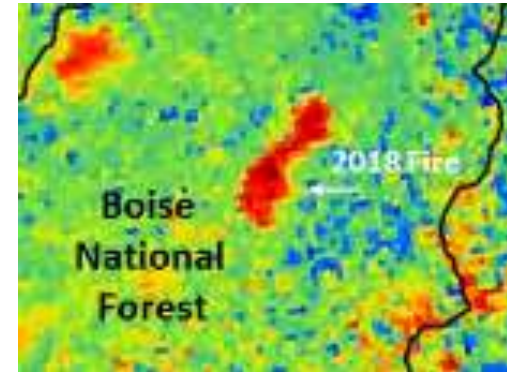
- ◇ Different disturbances show different patterns
- ◇ The first row here shows flooding and hurricanes; the bottom row shows hailstorms



Images from USFS's ForWarn

Case Study: Forest Disturbance Monitoring

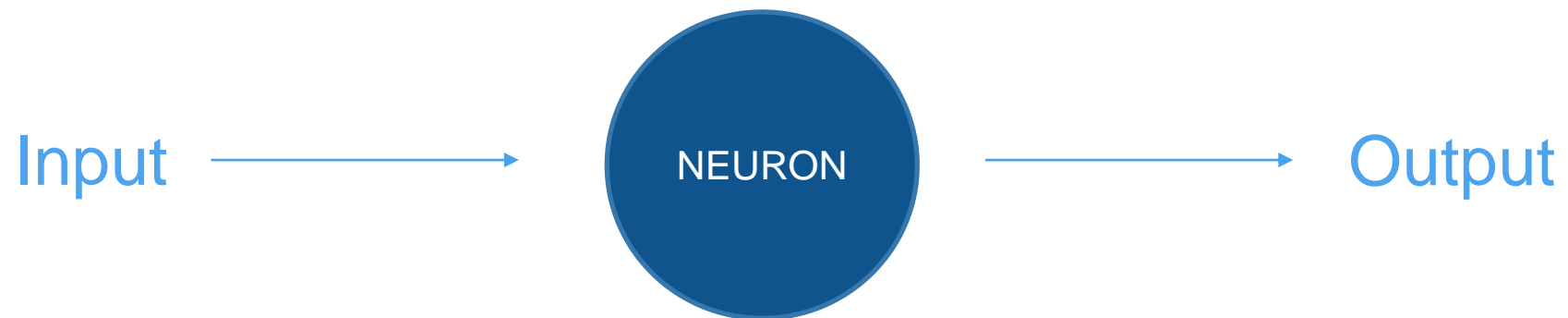
- ◇ Here are vegetation patterns from other disturbances including wildfires and various insects



Images from USFS's ForWarn

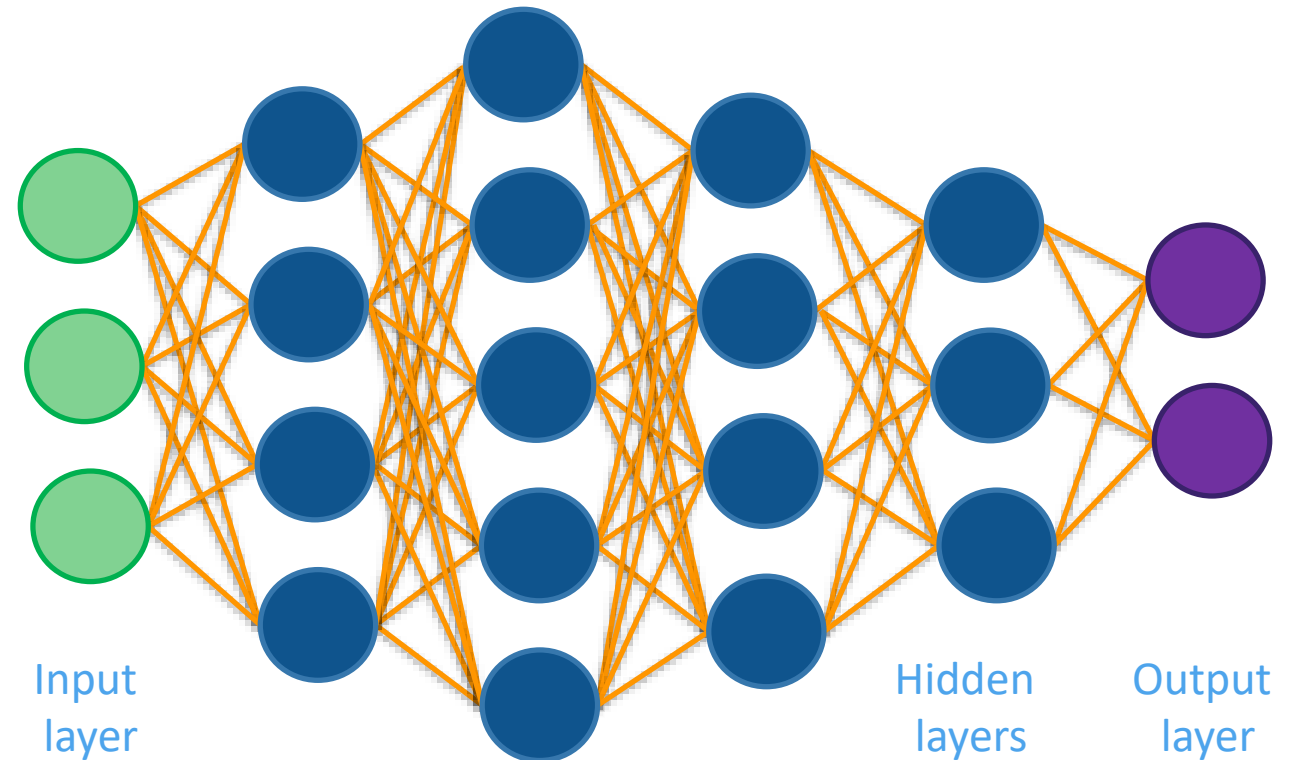
Case Study: Forest Disturbance Monitoring

- ◇ A neural network consists of multiple units called neurons
- ◇ Each neuron is a distinct model that takes some input, processes it, and returns some output
- ◇ A neuron by itself is not powerful; multiple neurons working together can do much more



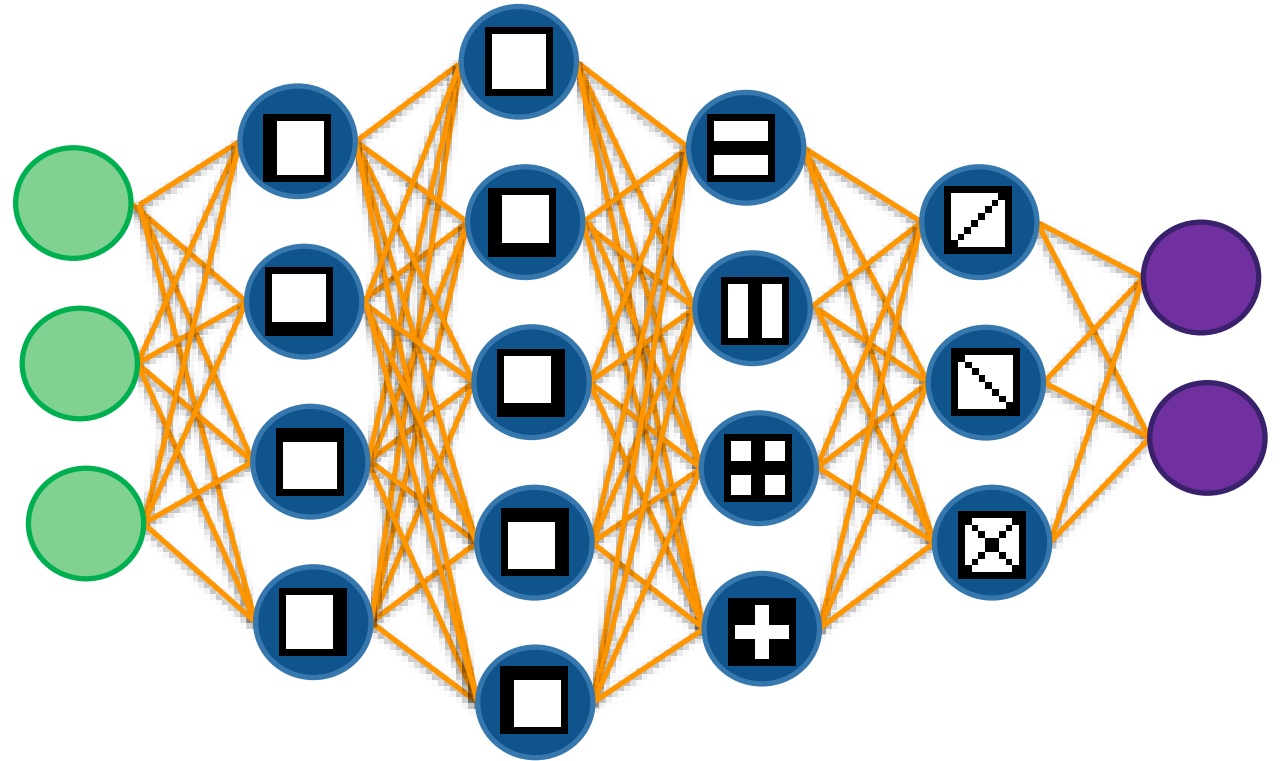
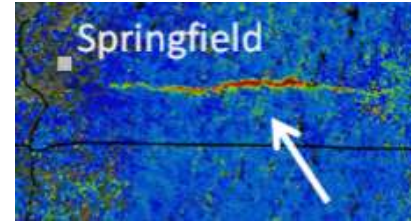
Case Study: Forest Disturbance Monitoring

- ◇ Neurons are organized into layers of increasing complexity
- ◇ Each layer feeds into the next layer
- ◇ The layers between the Input and Output layers are “hidden” and are what makes deep learning “deep”



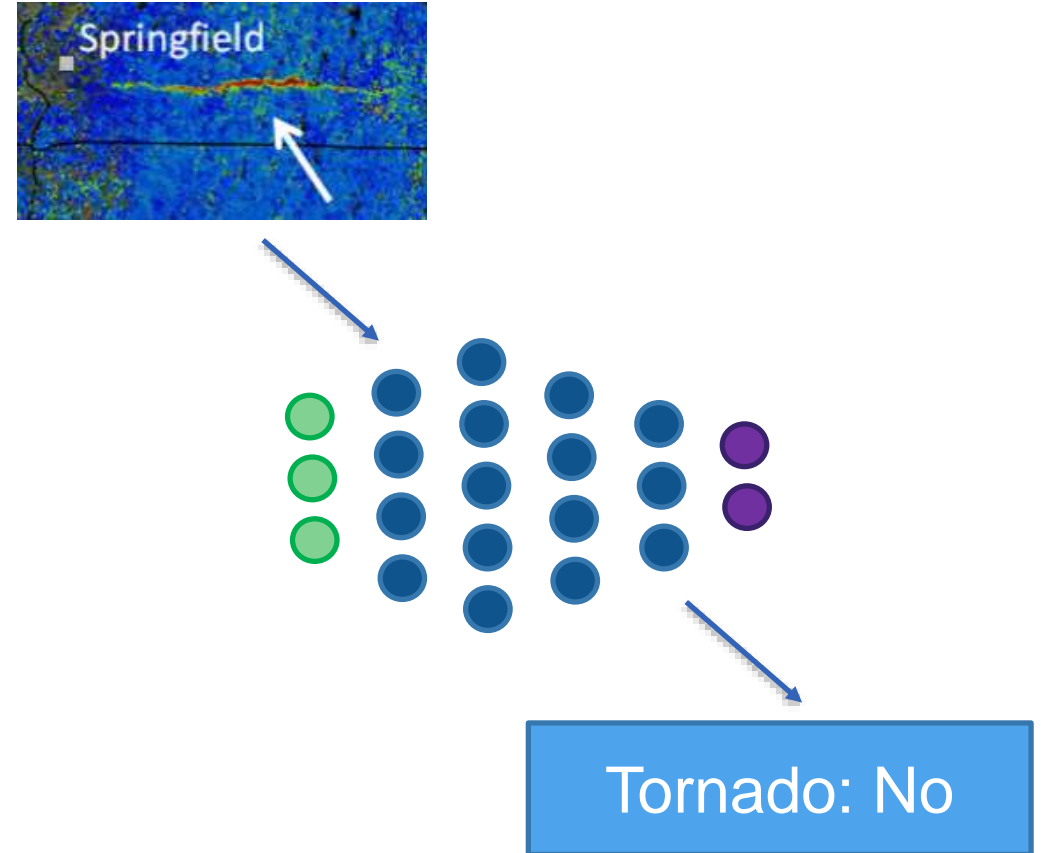
Case Study: Forest Disturbance Monitoring

- ◇ For our forest disturbance model, each neuron recognizes a specific pattern of pixels in an image
- ◇ These patterns are very low level
- ◇ Combined, the neurons can recognize high level patterns that point to a specific forest disturbance



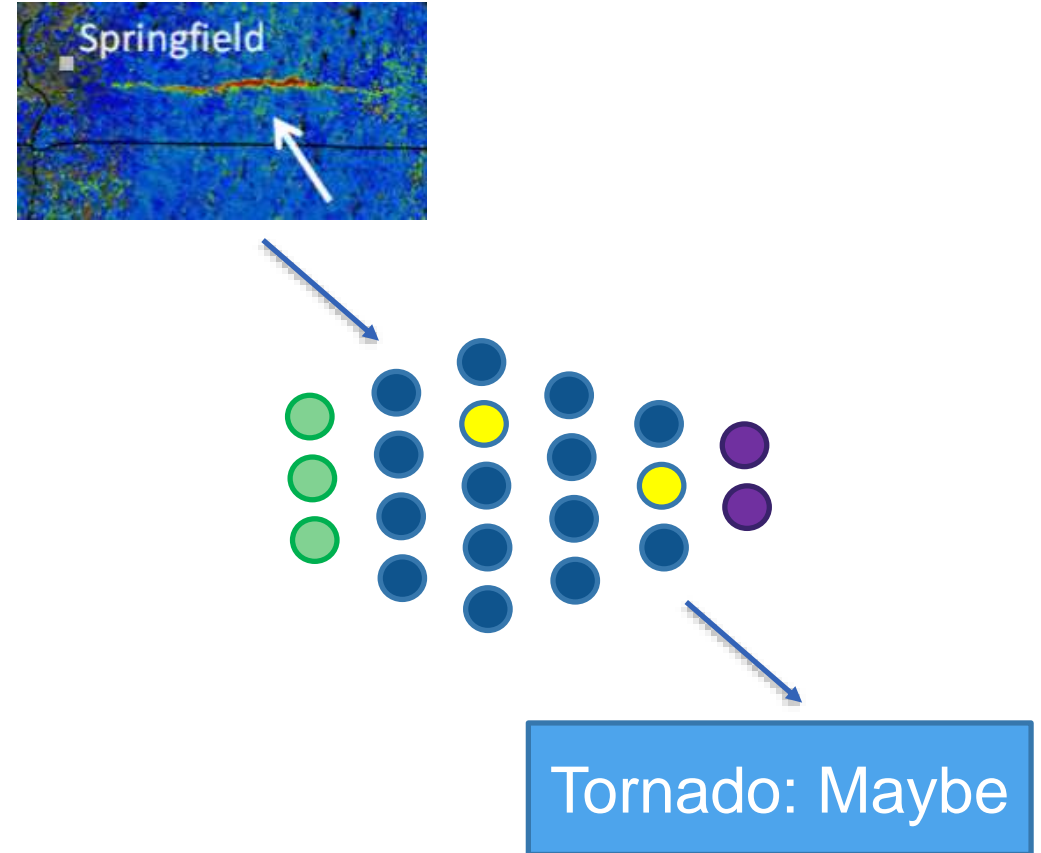
Case Study: Forest Disturbance Monitoring

- ◇ For training, known disturbances are fed into the network and compared to the output
 - ◇ If the output is not correct, the neurons' models are tweaked and the network run again
 - ◇ Only adjustments that improve the output accuracy are kept
- ◇ The training stops when the output matches the expected results
- ◇ In this way the model trains itself by evaluating its own performance



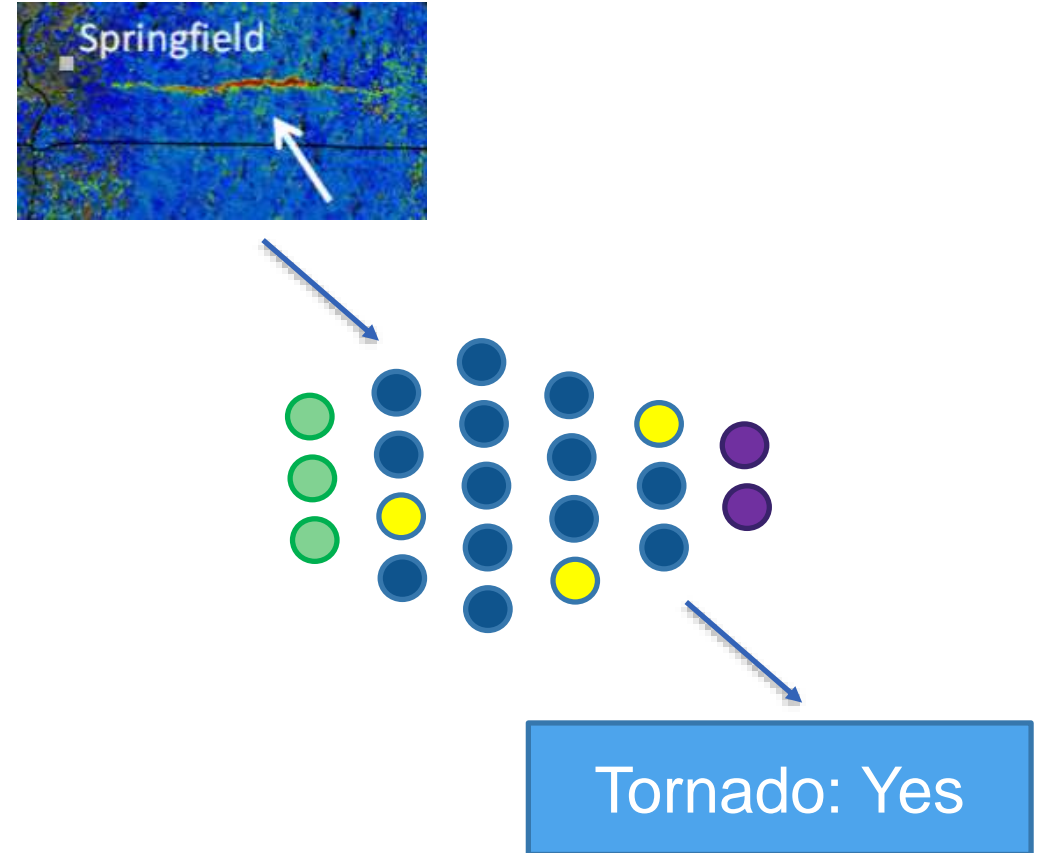
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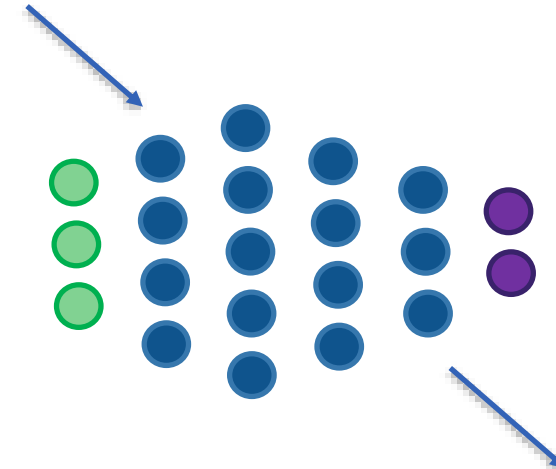
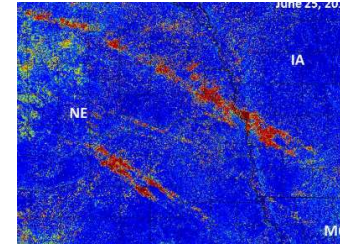
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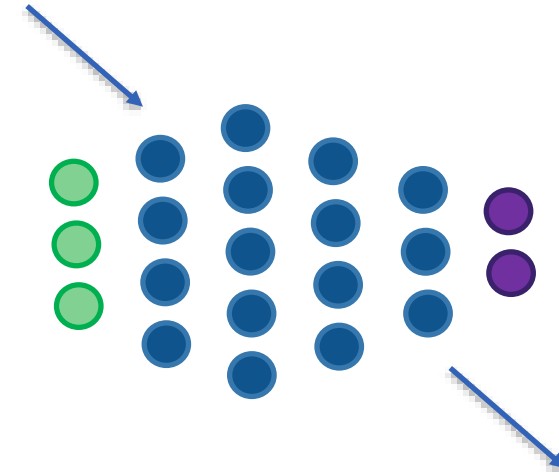
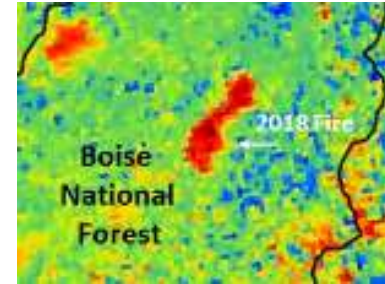
- ◇ The network must be trained for different disturbances
- ◇ Multiple examples of each disturbance are needed
- ◇ Disturbances not considered will not be recognized



Tornado: No
Hail: Yes

Case Study: Forest Disturbance Monitoring

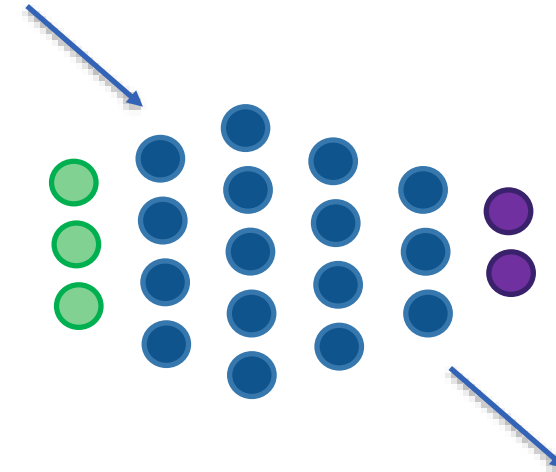
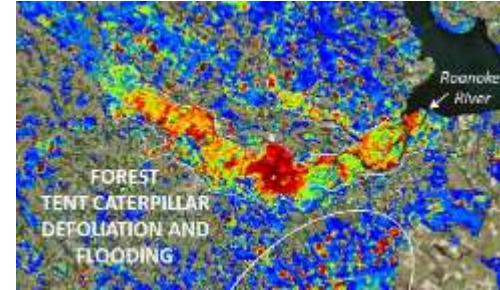
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Tornado: No
Hail: No
Fire: Yes

Case Study: Forest Disturbance Monitoring

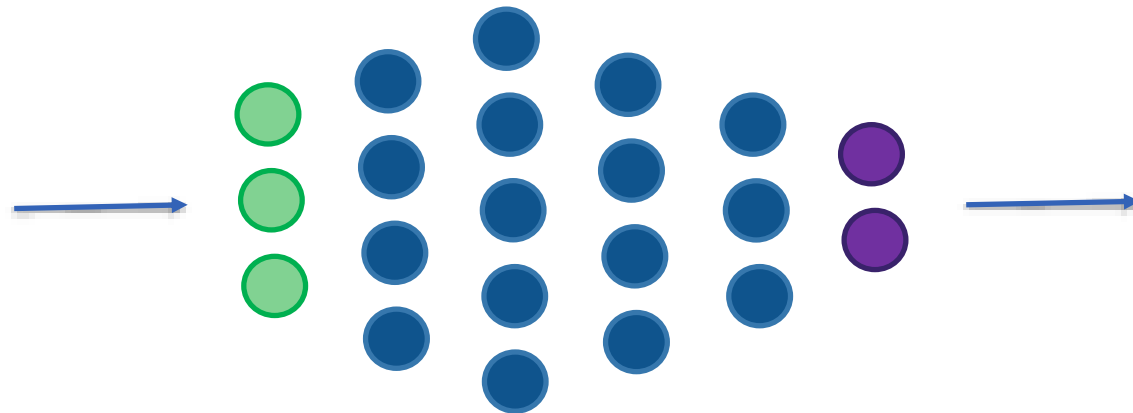
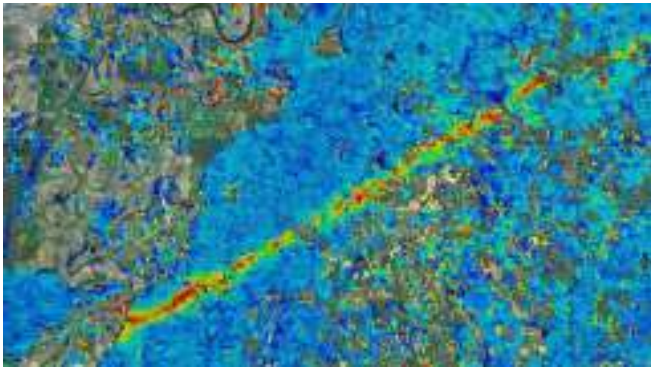
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Tornado: No
Hail: No
Fire: No
Insects: Yes

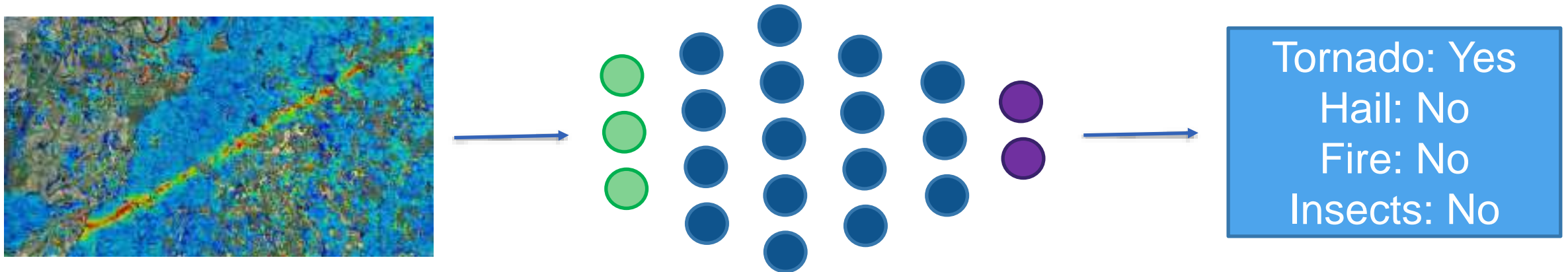
Case Study: Forest Disturbance Monitoring

Once trained, the model can be used to analyze images and identify disturbances



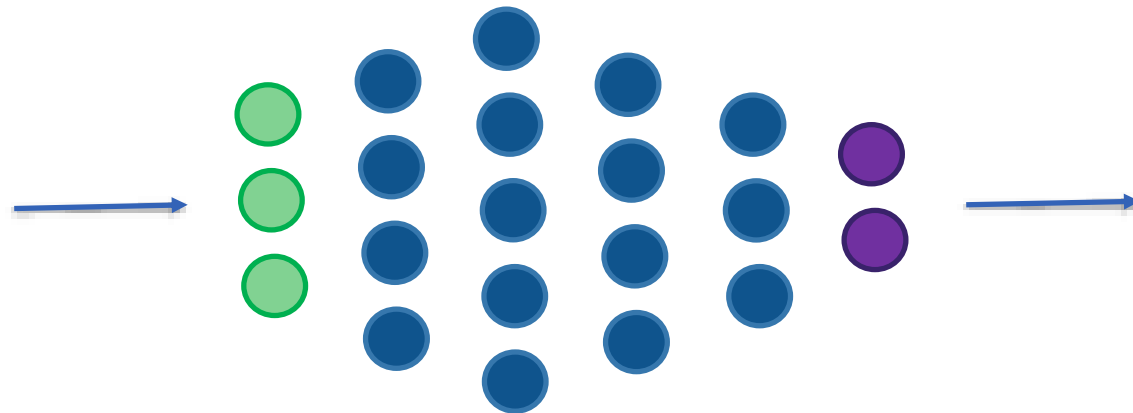
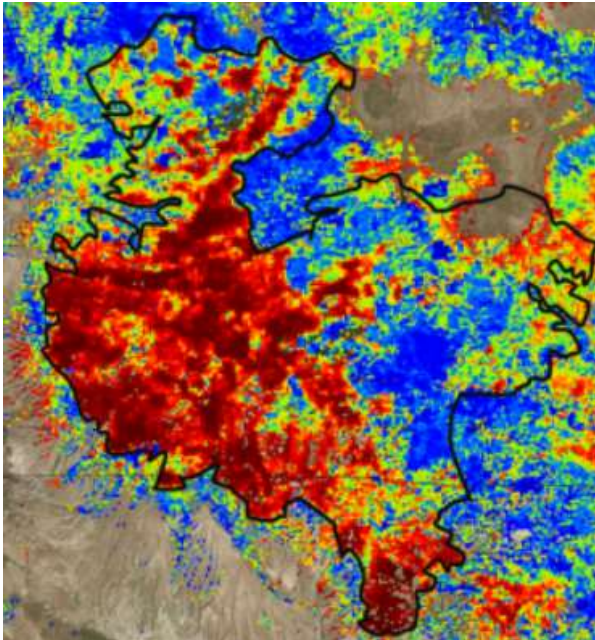
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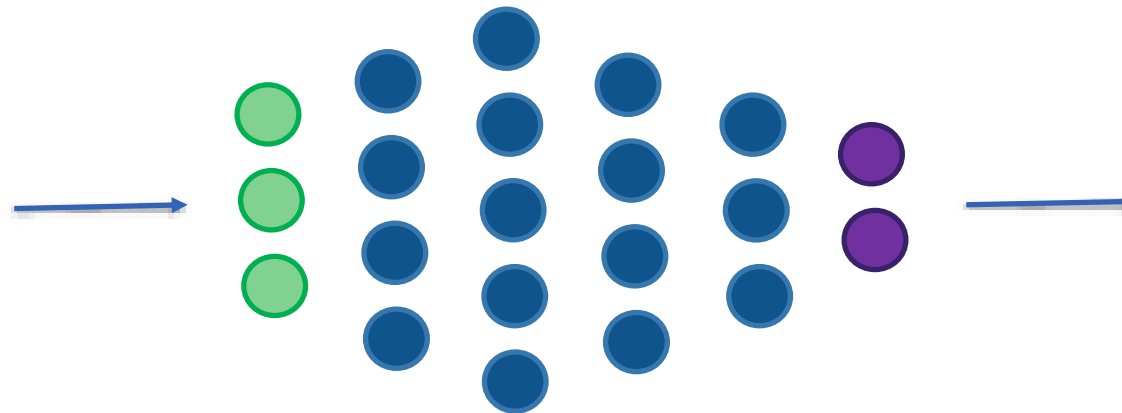
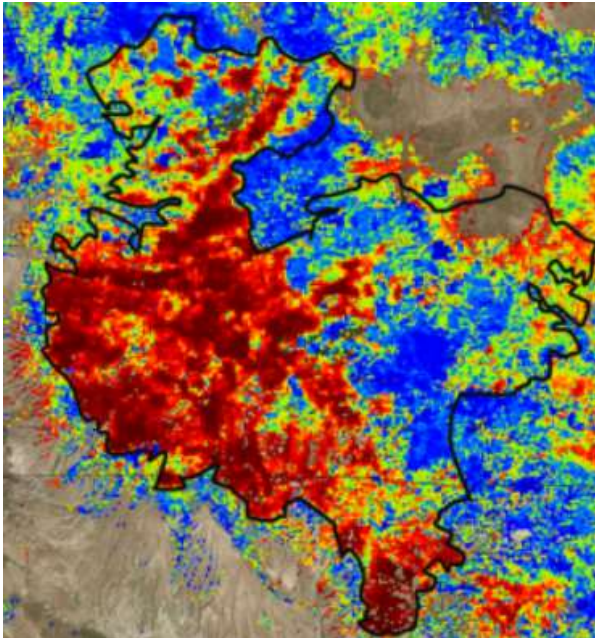
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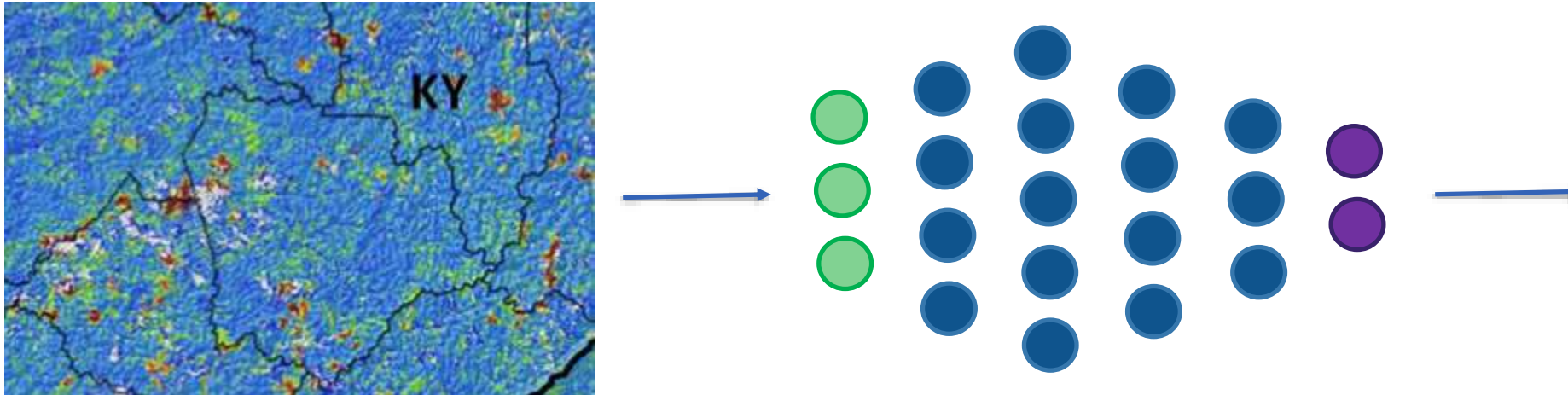
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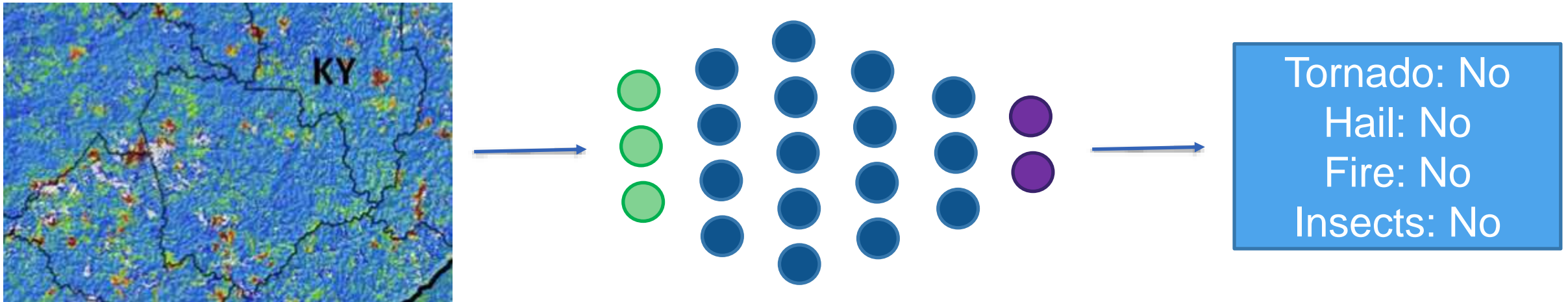
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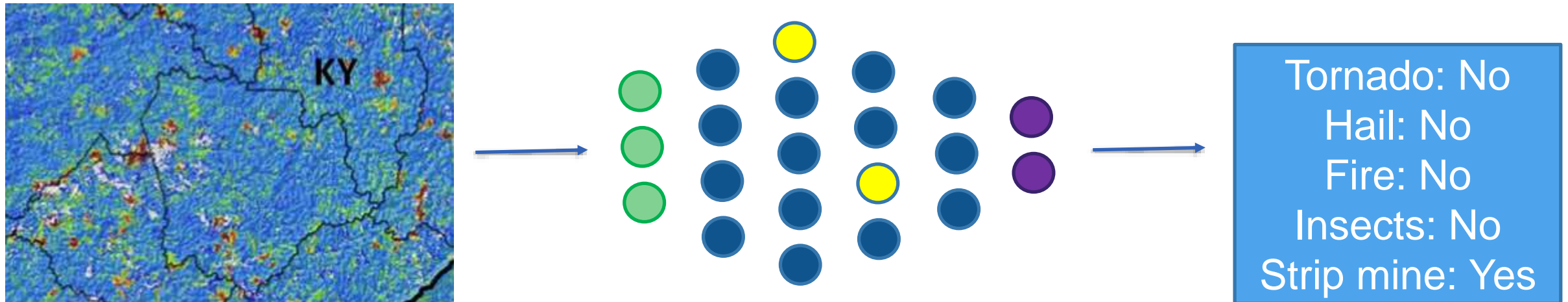
Case Study: Forest Disturbance Monitoring

Disturbances not considered will not be recognized; the model must be trained for them



Case Study: Forest Disturbance Monitoring

Disturbances not considered will not be recognized; the model must be trained for them



Case Study: Forest Disturbance Monitoring

◇ Positives:

- ◇ Disturbances can be identified automatically and in real-time without manual surveys or analysis of images
- ◇ Disturbance identification is cheaper and faster
- ◇ Managers and landowners can get notices much quicker

◇ Caveats:

- ◇ Must spend time and effort training network on different disturbances
- ◇ Cannot handle previously unknown disturbances
- ◇ Should periodically 'ground truth' findings

Case Study: Forest Disturbance Monitoring

- ◇ A successful deep learning implementation requires good training, which requires good data
- ◇ For this case study, there are special considerations
 - ◇ The normal baseline can change, especially with climate change
 - ◇ Data must span different time scales
 - ◇ Data must span different spatial scales
- ◇ Bottom line: a significant investment may be needed for developing a well-trained network

EHS&S Examples

- ◆ Health
- ◆ Safety
- ◆ Compliance
- ◆ Sustainability
- ◆ Water Quality



Health

- ◇ Deep Genomics uses AI to develop new drugs
 - ◇ Helps find compounds to target specific diseases, and to predict effects on humans taking new drugs
 - ◇ Reduces time and cost to bring new drugs to market
 - ◇ A successful model would reduce the amount of clinical trials and human testing needed
 - ◇ The first of Deep Genomics compounds will be tested this year



Image from Getty Images

Health – Coronavirus

- ◇ AI speeds up genome sequencing
- ◇ AI can mine recent research, searching for patterns and common factors in outbreaks
- ◇ Potential problems:
 - ◇ Misleading and Insufficient data
 - ◇ Limitations
 - ◇ Difficulty of modeling

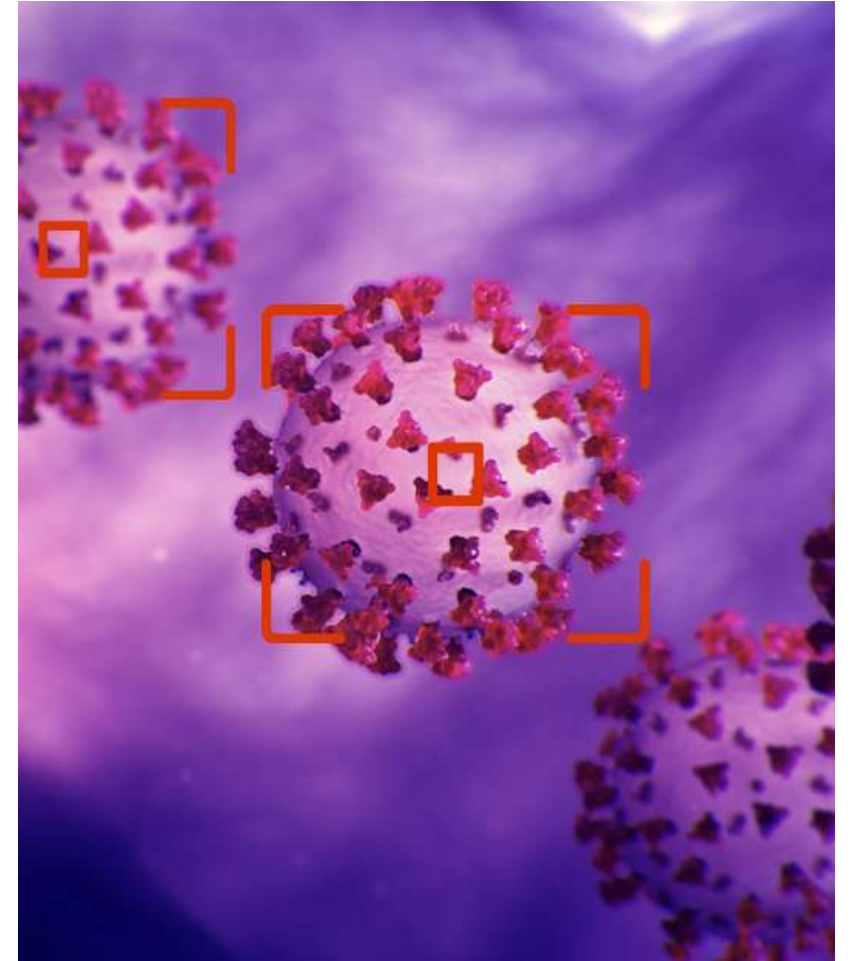


Image from Futurism.com

Safety

- ◇ Wearables
- ◇ Ability to predict proximity to equipment or in certain areas
- ◇ Given appropriate data, AI can monitor equipment and forecast failures or accidents
- ◇ AI-monitored safety gear in the workplace



Compliance

- ◇ AI systems can scan EHS permits and regulations in order to extract requirements, potentially eliminating weeks of work
- ◇ Pitfalls:
 - ◇ Effect of misinterpreting permits (they must be accurate)
 - ◇ Unlike with prediction, "good enough" is not sufficient



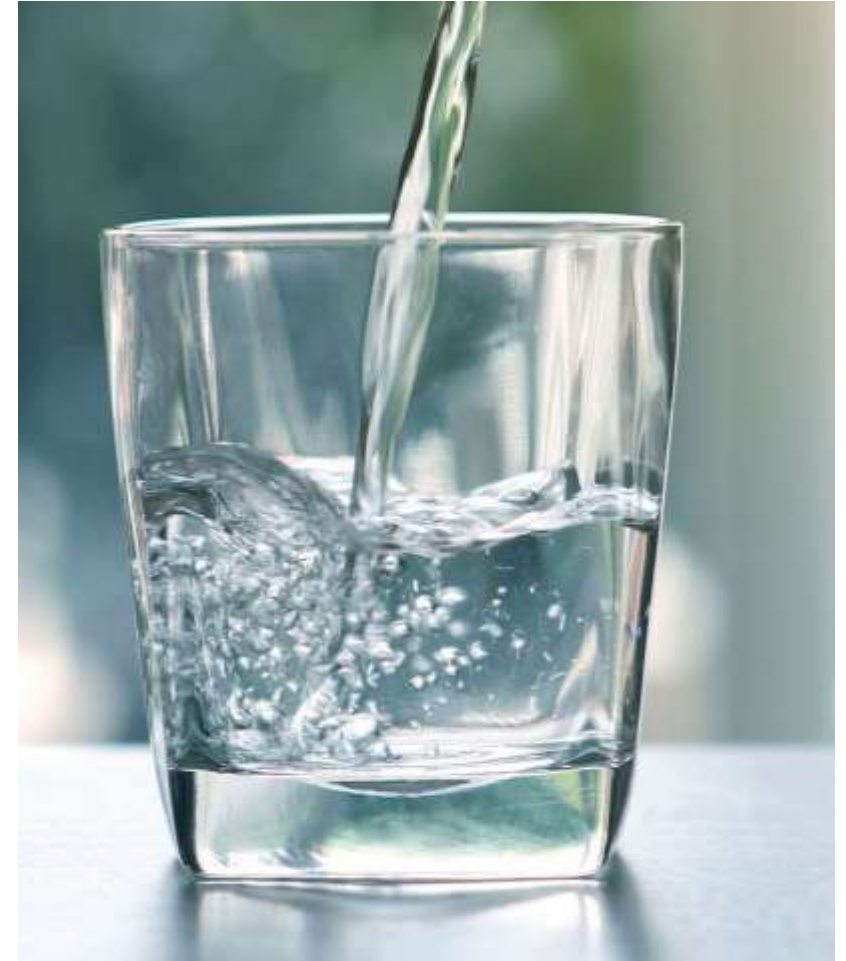
Sustainability

- ◇ Currently available AI technology could reduce US energy use by 12 to 22 percent
- ◇ Land: Erosion monitoring, migration tracking, poacher route prediction, effects of natural disasters
- ◇ Air: Air quality monitoring, reduction of traffic (dynamic routing, intelligent stoplights)
- ◇ Water: Tracking marine litter, improving water management systems



Water Quality

- ◇ Predictive AI systems can analyze the parameters of water sources and estimate a water quality index (WQI)
- ◇ A well-constructed system removes the need for extensive lab analysis
- ◇ Aids identification of poor quality water before it is released for use
- ◇ Alerts for bad conditions, certain bacteria/viruses
- ◇ Pitfalls: More parameters lead to a more complex system
- ◇ [Study: Predicting Water Quality with Machine Learning](#)



Poll Question #3

- ◇ If you're not using AI, what is stopping you?
 - ◇ Budget
 - ◇ Implementation
 - ◇ No need for it



Where to Start

- ◇ Identify needs for AI – where can it make a difference
- ◇ Identify appropriate data inputs for the model
- ◇ Collecting data – this is often the biggest cost and hurdle
- ◇ Standardization
- ◇ Shareability, industry groups
- ◇ Where can you improve productivity
- ◇ Uniform set of applications



Takeaways

- ◇ [Blog: Artificial Intelligence for Environmental Compliance](#)
- ◇ Why is AI coming up now
- ◇ Isolation as an environmental science dataset, reduction in traffic has led to marked improvements in air quality, how it will progress after things go back to normal



Thank you!

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Connecting On-Line and In-Person



EHS Operational Excellence Conference: Sustaining EHS During Times of Business Interruption

• May 21



Sustainability Impact Conference

• Aug 3-5



EHS&S Management Forum

• Oct. 20-23

***Check our website for registration
and additional information about our conferences!***

www.naem.org



New & Upcoming Reports from NAEM



- 2020 EHS & Sustainability Salaries
- 2020 Trends in Emerging Tech for EHS&S
- 2020 Staffing, Structure & Budgets
- Managing Covid-19 Challenges

All available @ [NAEM.org/research](https://naem.org/research)



NAEM's Excellence Awards

Opportunity to be recognized for outstanding achievement



- **Lifetime Achievement**

- Honoring one EHS&S visionary for driving positive impact over 20+ years.

- **Leadership in Action**

- Celebrating exceptional EHS&S leaders with 15+ years of proven success.

- **NexGen**

- Recognizing rising EHS&S managers with 5+ years of effectiveness.

Nominations due May 22nd!
<https://www.naem.org/awards>



Great Webinars!

April 23



Leveraging Remote Technologies for EHS Tasks

April 30



EHS & Sustainability Staffing, Structure & Budget

May 28



How to Build Corporate Social Responsibility in Your Supply Chain

FREE for NAEM members

Information & Registration on-line at www.naem.org



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Thank you for Attending!



**A recording will be
available in 3-4 days.
You will receive an
email once it's posted
to our site.**



Have a safe & healthy day!

