Kettle Re

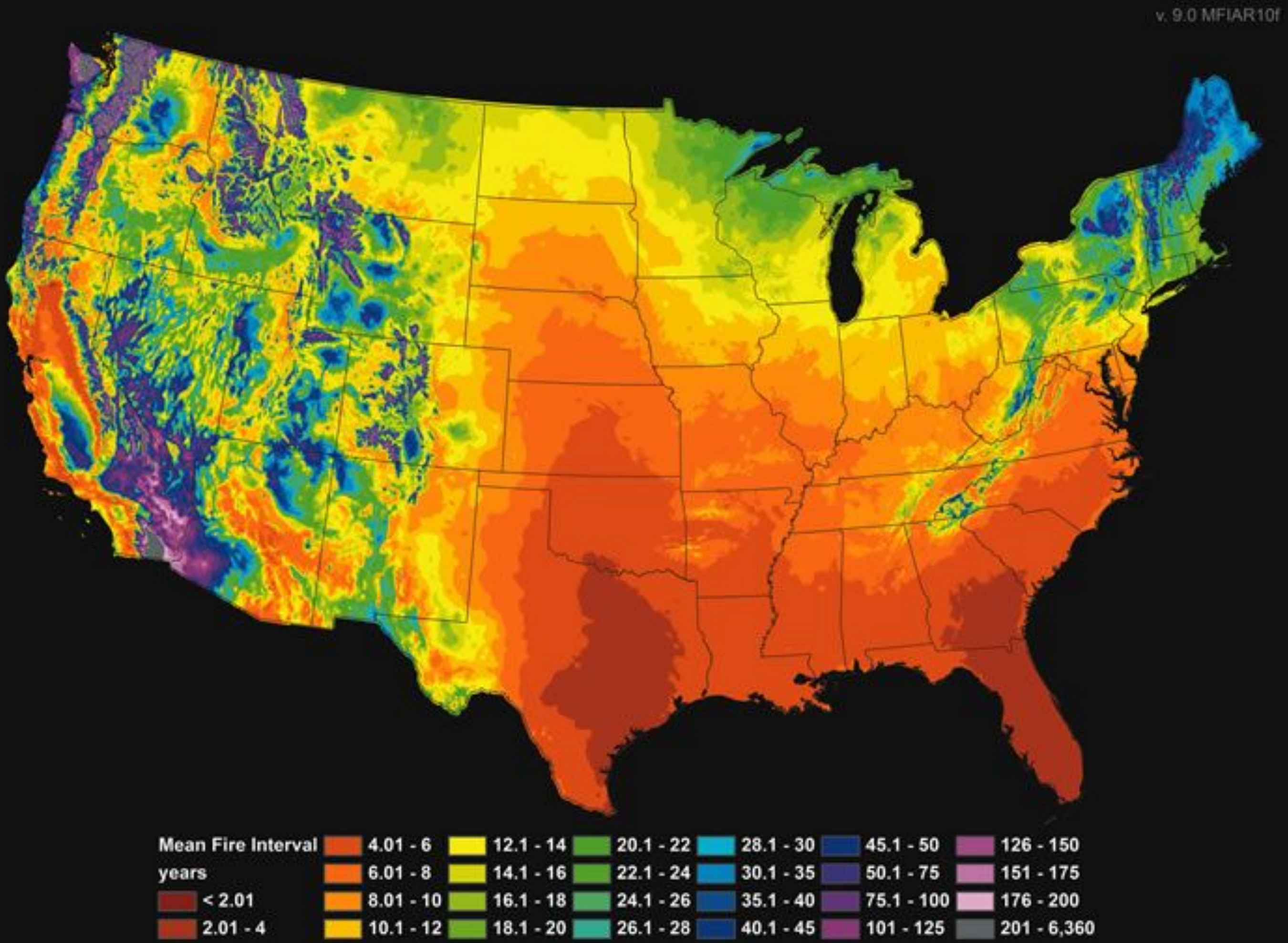
RISK IS CHAOS

A history of risk and future innovation





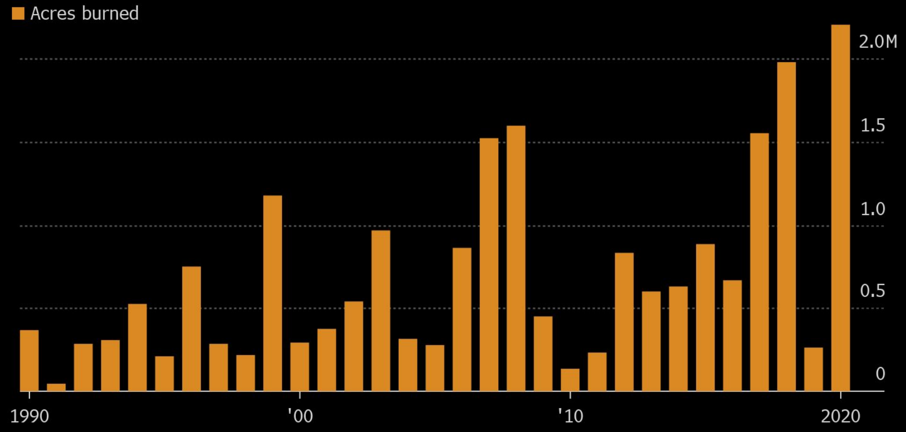



v. 9.0 MFIAR10f
Mean Fire Interval years
< 2.01
2.01 - 4
4.01 - 6
6.01 - 8
8.01 - 10
10.1 - 12
12.1 - 14
14.1 - 16
16.1 - 18
18.1 - 20
20.1 - 22
22.1 - 24
24.1 - 26
26.1 - 28
28.1 - 30
30.1 - 35
35.1 - 40
40.1 - 45
45.1 - 50
50.1 - 75
75.1 - 100
101 - 125
126 - 150
151 - 175
176 - 200
201 - 6,360

We’re all gonna die?

California Inferno

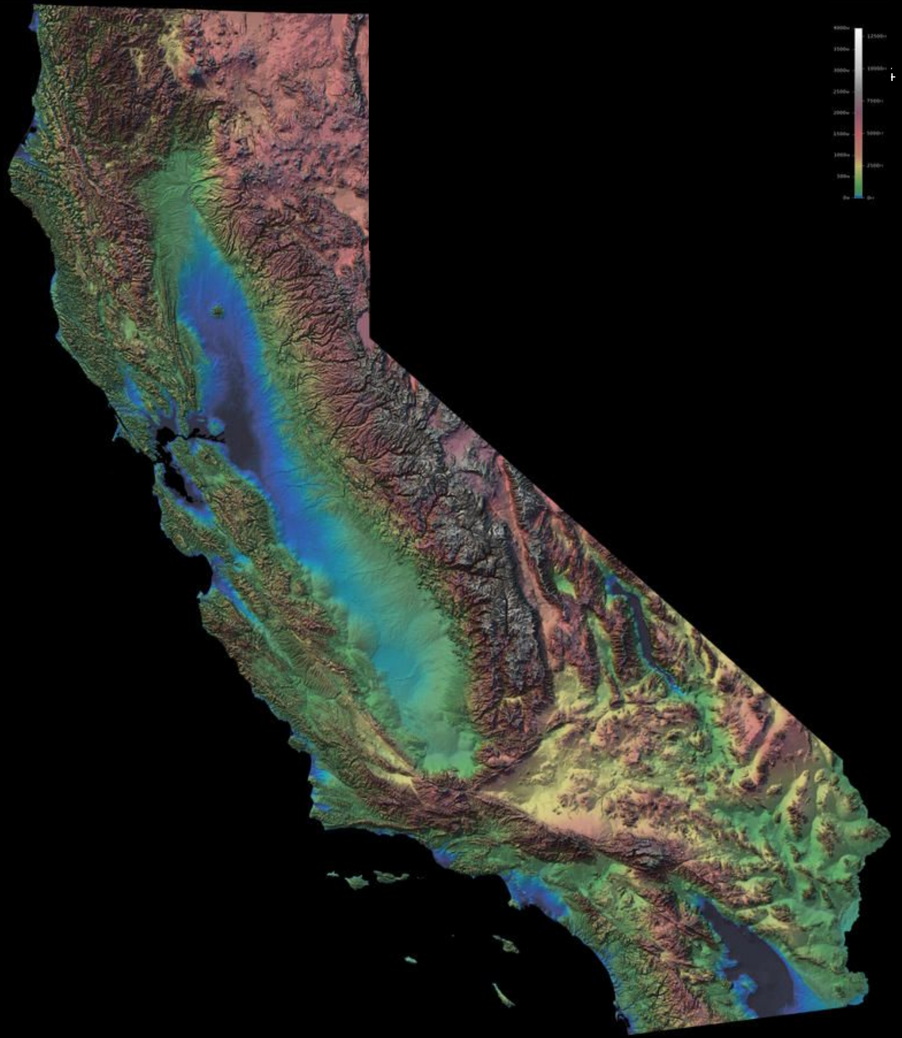
Wildfires have burned more state acres in 2020 than any other year on record



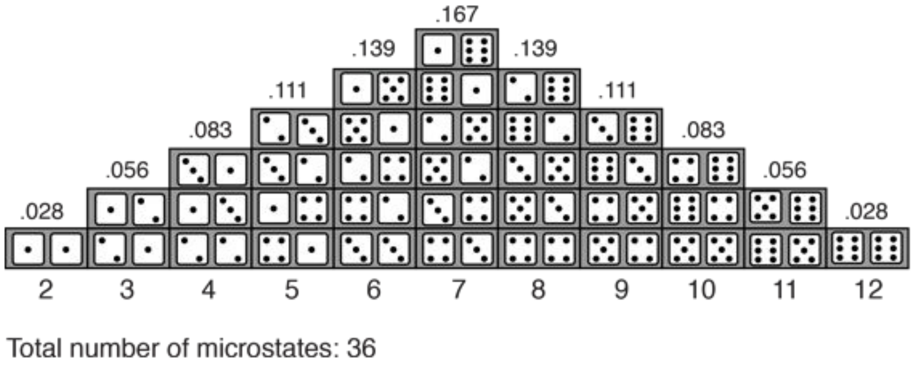
Source: CalFire

Note: Figure for 2020 is through Sept. 8. Figures for 2019 and 2020 exclude some fires in small jurisdictions.

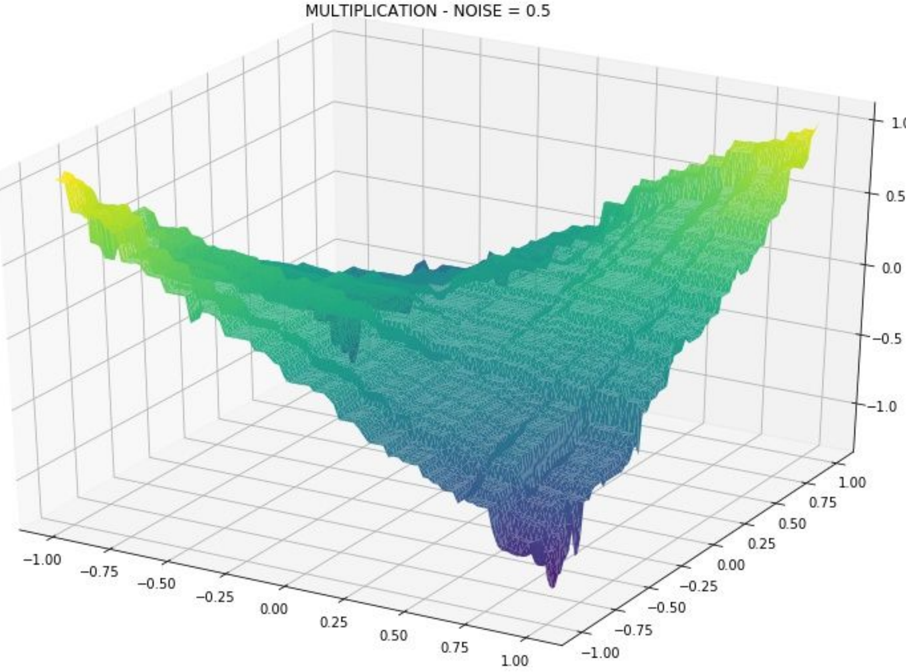
Bloomberg



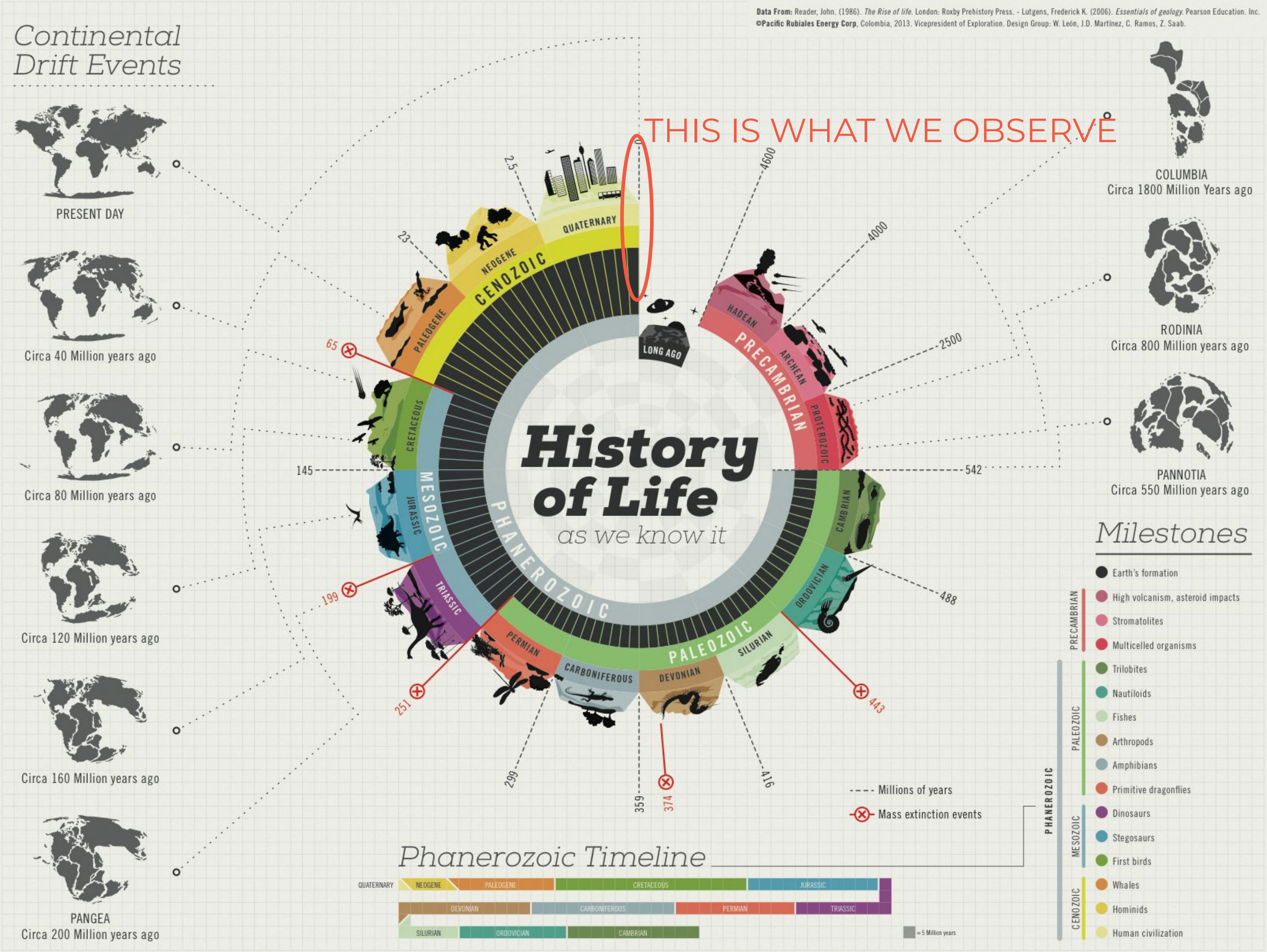
Probability works beautifully with set number of outcomes....



But what about in chaos?



THIS IS WHAT WE OBSERVE



Kettle Team

Andrew Engler - CEO
Founder/VP of Digital at Argo
Field Director - Allstate Com, AZ

Amit Shah - President
Head of Speciality, Ariel Re
Argo Re, Swiss RE, Guy Carp,

Brian Espie - CUO
Fidelis - Head of Property Cat NA
TMK - VP analytics

Nat Manning - COO
CEO, Ushahidi
First Chief Data Officer, USAID

Son Le - CTO
Head Quant Engineer, Argo
Mathematics w/ AI specialty, NYU

Kevin Copeland - CFO
CFO/CIO James River
COO Tokio Marine

Nigel Mortimer - EC
President, Exec VP at Argo
EVP of Product at XL Catlin

Dr. Yaling Liu - Head of DS
Lead Research Scientist, Columbia
Phd Earth Sciences and CS (focus in ML)

Dr. Ichihan Tai - Head of Risk
Cnsmr Trader, Point72; DS, Goldman Sachs
Fund Mgr/Head of DS, Tokio Marine AM

Dr. Max Dion - Sr. Quant Engineer
Quant Dev, Team lead, Akuna Capital
PhD Nuclear Eng., University of Montreal

Faran Sikandar - Sr. ML Engineer
Data Scientist, Revolut
Master in Economics + ML, Harvard

Dr. Yufei Zou - Sr. Climate Sci
Research Scientist, PNNL
PhD Earth Science, Georgia Tech

Jeremy Oustrich - Sr. Engineer
10 years software dev experience
7 years cloud infrastructure experience

Kate Cowen - Head of Product
Business Analyst, Momentive.AI
Product Manager, Momentiv.AI

Dr. Sean Choi - Sr. ML Infra Sci
Research Scientist, Facebook, VMWare
PhD/MS Electrical Eng / CS, Stanford

Matt Lindeboom - Lead Engineer
5 years SurveyMonkey
2 years LearnVest

Dr. Zhiyue Ding - Sr. Quant Eng
Insight Data - ML/AI focus
Phd Physics, Baylor University

Adrian Bauer - Sr. ML Engineer
5 years ML engineering at startups
Software engineer at Google

Dr. Andrew Pessi - Sr. Data Sci
Research Scientist, Vaisala, SiteZeus
PhD, Meteorology, University of Hawaii

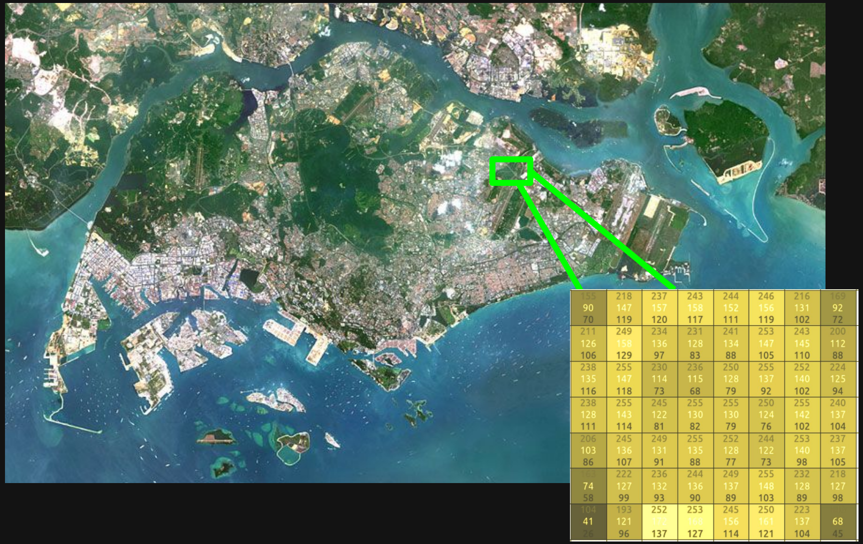
Santhosh Subramanian - Data Eng
CTO, diascan
Mathematics, Berkeley

Noam Rosenthal - Data Scientist
PhD student, UCLA
Earth Systems, Stanford

Prof. Pierre Gentine - Sci Advisor
Professor, Columbia
PhD, MIT

Dr. Niels Andela - Sci Advisor
Lecturer, Cardiff
PhD, Amsterdam

A PICTURE IS WORTH A THOUSAND WORDS?



90% of the world's data was created in the past 2 yrs

81% of all data is unstructured

The most important data for underwriting **is unreadable** by computers (satellite images, weather maps, etc.)

Every image, video, document, or file is a soup of data points.

All of this unstructured data could lead

THE DATA

AN OCEAN

1.2 terabytes of local data

3 petabytes of total available data

1. 1.88 million wildfires in the U.S. - National Fire Program Analysis System
2. All us Weather data since 1980 - Arcgis
3. 26,000 weather stations with daily data feed - Arcgis
4. U.S. Landsat 4-8 Analysis Ready Data (ARD) Level-2 Tiles (Albers projection)
5. ASTER Global Emissivity Dataset 100-meter V003 - AG100
6. ASTER Global Emissivity Dataset 1-kilometer V003 - AG1KM
7. Global Food Security-support Analysis Data (GFSAD) Cropland Extent 2010 North America 30 m V001
8. Global Land Cover Characterization: 1992-1993
9. Global Multi-Resolution Terrain Elevation Data
10. Global Topographic 30 Arc-Second Digital Elevation Model: Released 1996
11. Landsat 7 Enhanced Thematic Mapper Plus Collection 1 Level-1
12. Landsat 7 Collection 1 Level-2 Scene Products (Surface Reflectance)
13. MODIS/Terra and Aqua MAIAC Land Surface BRF Daily L2G Global 500 m and 1 km SIN Grid Version 6
14. MODIS/Terra and Aqua MAIAC Land Aerosol Optical Depth Daily L2G 1 km SIN Grid Version 6
15. MODIS/Terra and Aqua MAIAC BRDF Model Parameters 8-Day L3 1 km SIN Grid Version 6
16. MCD43A1: MODIS/Terra and Aqua BRDF/Albedo Model Parameters Daily L3 Global 500 m SIN Grid Version 6
17. MCD43A2: MODIS/Terra and Aqua BRDF/Albedo Quality Daily L3 Global 500 m SIN Grid Version 6
18. MCD43A3: MODIS/Terra and Aqua Albedo Daily L3 Global 500 m SIN Grid Version 6
19. MCD43A4: MODIS/Terra and Aqua Nadir BRDF-Adjusted Reflectance Daily L3 Global 500 m SIN Grid Version 6
20. MODIS/TERRA MOD09A1 Surface Reflectance 8-Day L3 Global 500m Version 6
21. MODIS/TERRA MOD09GA Surface Reflectance Daily L2G Global 1km and 500m Version 6
22. MODIS/TERRA MOD09GQ Surface Reflectance Daily L2G Global 250m Version 6
23. MODIS/TERRA MOD09Q1 Surface Reflectance 8-Day L3 Global 250m Version 6
24. MODIS/COMBINED MOD11A1 Land Surface Temperature and Emissivity Daily L3 Global 1 km Grid SIN Version 6
25. MODIS/TERRA MOD11A2 Land Surface Temperature & Emissivity 8-Day L3 Global 1km Version 6
26. MODIS/TERRA MOD11B1 Land Surface Temperature and Emissivity Daily L3 Global 5 km Grid SIN Version 6
27. MODIS/TERRA MOD11B2 Land Surface Temperature and Emissivity Daily L3 Global 5 km Grid SIN Version 6
28. MODIS/TERRA MOD11_L2 Land Surface Temperature and Emissivity 5-Minute L2 Swath 1 km Version 6
29. MODIS/TERRA MOD13A1 Vegetation Indices 16-Day L3 Global 500m Version 6
30. MODIS/TERRA MOD13A2 Vegetation Indices 16-Day L3 Global 1km Version 6
31. MODIS/TERRA MOD13Q1 Vegetation Indices 16-Day L3 Global 250m Version 6
32. MODIS/TERRA MOD14A1 Thermal Anomalies & Fire Daily L3 Global 1km Version 6
33. MODIS/TERRA MOD14A2 Thermal Anomalies & Fire 8-Day L3 Global 1km Version 6
34. MODIS/TERRA MOD14 Thermal Anomalies & Fire 5-Min L2 Swath 1km Version 6
35. MODIS/TERRA MOD15A2H Leaf Area Index - Fraction of Photosynthetically Active Radiation 8-Day L4 Global 500 m Version 6
36. MODIS/Terra Net Evapotranspiration 8-Day L4 Global 500 m SIN Grid Version 6
37. MODOIS/TERRA MOD17A2H Gross Primary Productivity 8-Day L4 Global 500m SIN Grid Version 6
38. MODOCGA: MODIS/Terra Ocean Reflectance Daily L2G-Lite Global 1 km SIN Grid Version 6
39. U.S. Landsat 4-8 Burned Area (BA) Landsat Science Product Tiles (Albers projection)
40. U.S. Landsat 4-8 Dynamic Surface Water Extent (DSWE) Landsat Science Product Tiles (Albers projection)
41. Shuttle Radar Topography Mission 1 Arc and 3 Arc Second Digital Terrain Elevation Data
42. Shuttle Radar Topography Mission 1 Arc and 3 Arc Second Digital Terrain Elevation Data - Void Filled
43. Shuttle Radar Topography Mission 1 Arc-Second Digital Terrain Elevation Data - Global
44. NASA Shuttle Radar Topography Mission (SRTM3) Global 1 arc-second
45. NASA Shuttle Radar Topography Mission (SRTM3) Global 3 arc-second
46. NASA Shuttle Radar Topography Mission (SRTM3) Global 30 arc-second
47. NASA Shuttle Radar Topography Mission (SRTM3) Global 3 arc-second sub-sampled

THE ISSUE

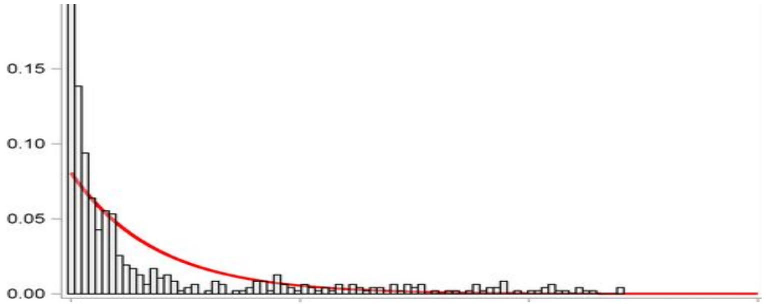
RISK REIMAGINED

Climate change has altered the fundamentals of insurance risk. Using historical data that no longer pertains to the current paradigm is insufficient in pricing risk

Risk assessment must therefore **shift from historical-static, to real time-fundamental based**.

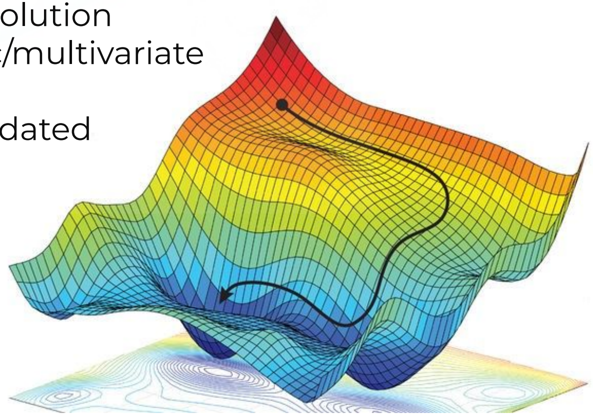
PRESENT -
Technical

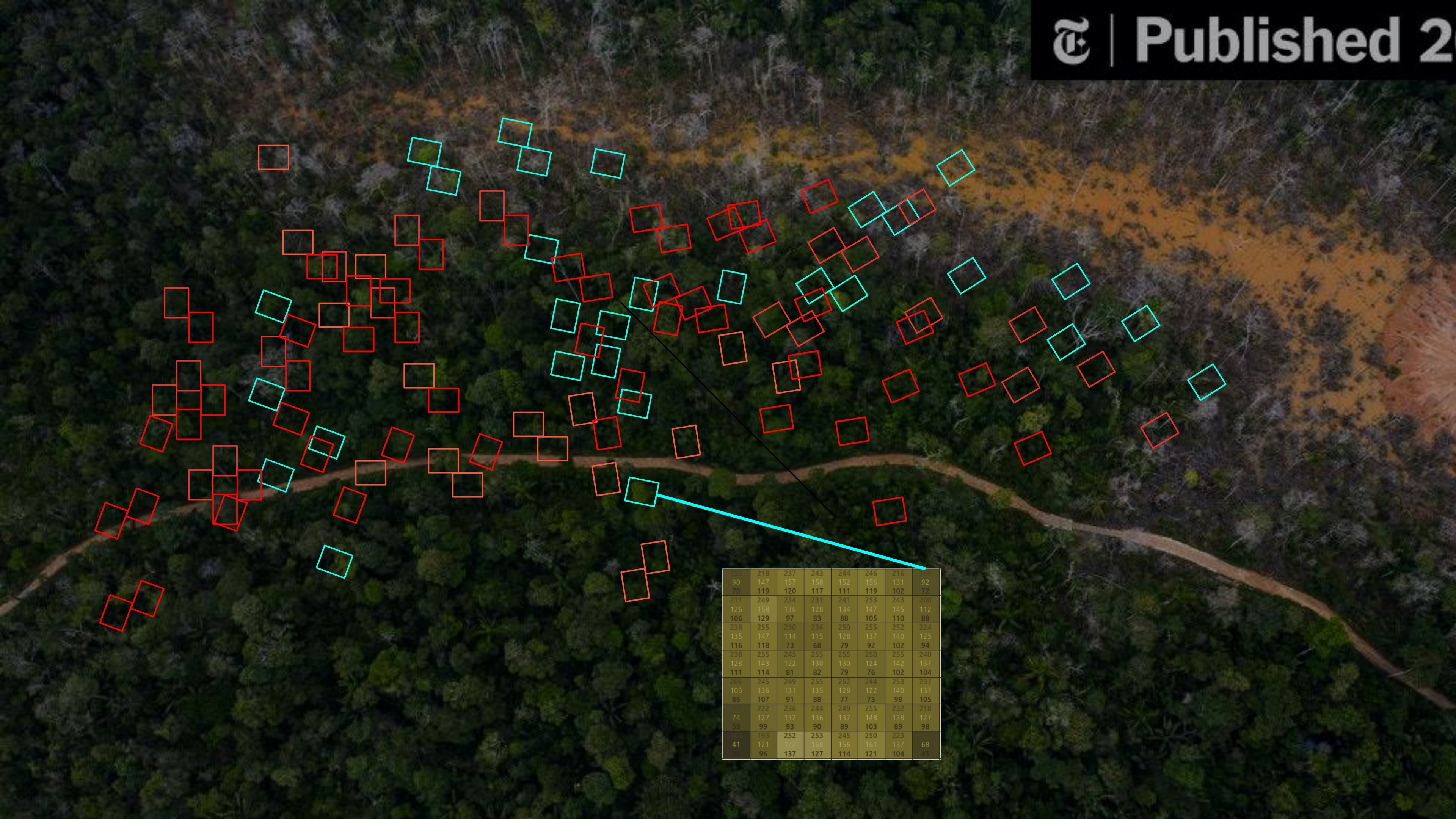
- Historical Based Pricing (backwards looking)
- Static/Non-Dynamic
- Low level resolution (zip code)
- Stochasticly driven
- Local Server Based
- Opaque/incorrect data



FUTURE -
Fundamental Based

- Real time pricing based on current fundamentals
- Dynamic and always changing
- Improved Transparency
- High level resolution
- Deterministic/multivariate
- Cloud Based
- Real Time Updated
- Instant alerts





Published 2
155 90 70 | 218 147 119 | 237 157 120 | 243 158 117 | 244 152 111 | 246 156 119 | 216 131 102 | 169 92 72
211 126 106 | 249 158 129 | 234 136 97 | 231 128 83 | 241 134 88 | 253 147 105 | 243 145 110 | 200 112 88
238 135 116 | 255 147 118 | 230 114 73 | 236 115 68 | 250 128 79 | 255 137 92 | 252 140 102 | 224 125 94
238 128 111 | 255 143 114 | 245 122 81 | 255 130 82 | 255 130 79 | 250 124 76 | 255 142 102 | 240 137 104
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74 58 | 222 127 99 | 236 132 93 | 244 136 90 | 249 137 89 | 255 148 103 | 232 128 89 | 218 127 98
104 41 26 | 193 121 96 | 252 172 137 | 253 168 127 | 245 156 114 | 250 161 121 | 223 137 104 | 68 45

DigitalGlobe
A MAXAR COMPANY

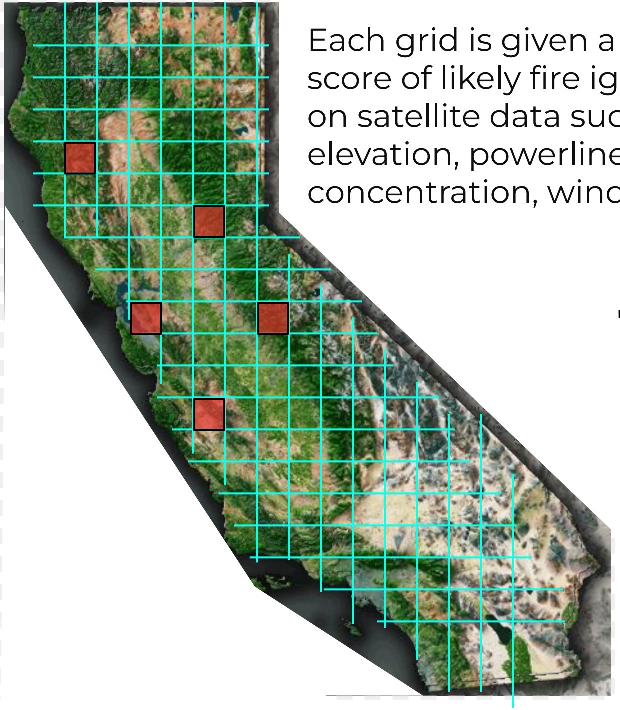
Complexity Theory

SELF ORGANIZING CRITICALITY IN A FAT TAILED WORLD

THE SCIENCE

RISK REIMAGINED

The **Genesis Model** splits CA up into 320,280 separate .5 square mile grids.



Each grid is given a probability score of likely fire ignition based on satellite data such as elevation, powerline concentration, wind speed, etc.

The **Contagion Model** uses genesis points, or current fires, and predicts their spread/path using variables such as wind direction/speed, elevation, brush patterns, etc

Our Moat

Asynchronous Data
(satellite imagery)

+

Swarm Neural Networks
(derived from robotics)

=

22%+ Higher
Precision
/Recall

We divide CA into
320,000 micro grids
each 0.5 square miles

Get 320m satellite images
in unstructured data

Translate into computer
readable format through
CV

Run a swarm of 115,456
separate neural network
nodes

$3x10^{42}$

This equates to **42.3mm**
simulations and gives us...

=

84.7% Precision/recall

Compared to 62% industry standard

Overview of the Kettle modeling pipeline

Simulate scenarios

Time-varying:
- Climate
- Vegetation
- Drought
- Socioeconomics
- 100k sims per grid
- 4,410 grid cells

Predict ignition probability

- Based on fire ignition model
- Trained & tested on 25.5 yrs train, test 6.5 historical data
- 0.1-degree resolution

Predict number of wildfires

- Ada boost eco zone level - monthly
- Nat. & anthro factors
- Trained & tested on historical data
- Ecological div level

Simulate ignitions

- Based on ignition probability (p) & number of fires

Simulate fire spread

- Based on ignition source & satellite imagery
- CNN
- Transient as fire goes

Dynamic pricing

- Pricing based on Dutch auction algorithm
- Geographic separation discount

Portfolio optimization

- Based on clients' risk and return appetite
- Minimizes risk
- Constraints on total limit and/or transferred risk

Validation Models

Information Coefficient Analysis	Data Validation	Advanced Logging
Quintile Portfolio Backtesting	Natural Distribution	ML Metrics
Event Studies Analysis	Unit Testing	Sensitivity Analysis
Model Assumptions Testing	Model Selection Validation	Uncertainty Analysis
Usability	Maintainability	Statistical Metrics

Main Models

1. Swarm ignition model v3 (prod)
2. Rothermel adapted model v1 (prod)
3. UNet spread model
4. Residual-convolutional spread model
5. YL ignition model (prod)
6. Home total loss prediction CNN (prod)
7. Convolutional neural network model for vegetation and building classification (prod)
8. XGBoost loss estimation model (prod)
9. Mixture Density Network loss estimation model (prod)
10. Wildfire number prediction model (prod)
11. Ecozone-level wildfire number prediction model
12. Lightning frequency prediction model
13. Exchange-traded Instrument Hedging Model
14. Multi-Factor Risk Model (prod)
15. Buffered Premium Pricing Model (prod)
16. Geographic Separation Premium Discount Model (prod)
17. Dutch Auction Dynamic Pricing Model (prod)
18. Demand-driven Surging Dynamic Pricing Model (prod)
19. Composite Dynamic Pricing Model (prod)

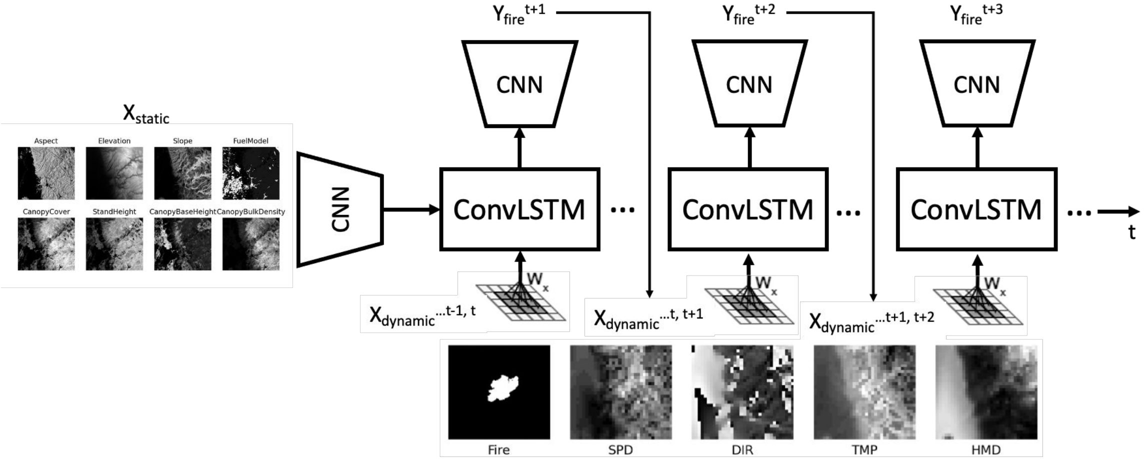
Validation Models

20. Information Coefficient Analysis Model (prod)
21. Quintile Portfolio Backtesting Model (prod)
22. Event Studies Analysis Model (prod)
23. Data Validation Model
24. Natural Distribution Model
25. Unit Testing Model
26. Advanced Logging Model
27. ML Metrics Model
28. Sensitivity Analysis Model
29. Uncertainty Analysis Model
30. Model Selection Validation Model
31. Model Assumptions Testing Model
32. Usability Testing Model
33. Maintainability Testing Model
34. Statistical Metrics Model

CONVOLUTIONAL-LSTM FIRE SPREAD MODEL

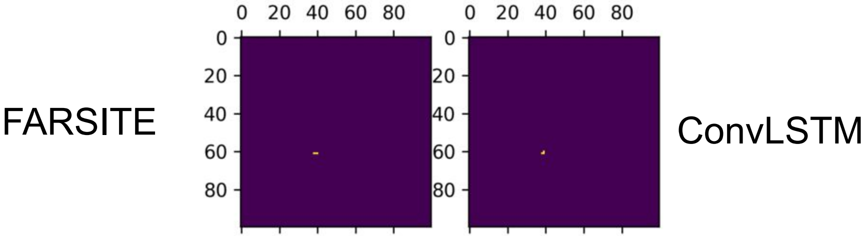
Fire dynamics learned from fire behavior models, then fine tuned with real observations

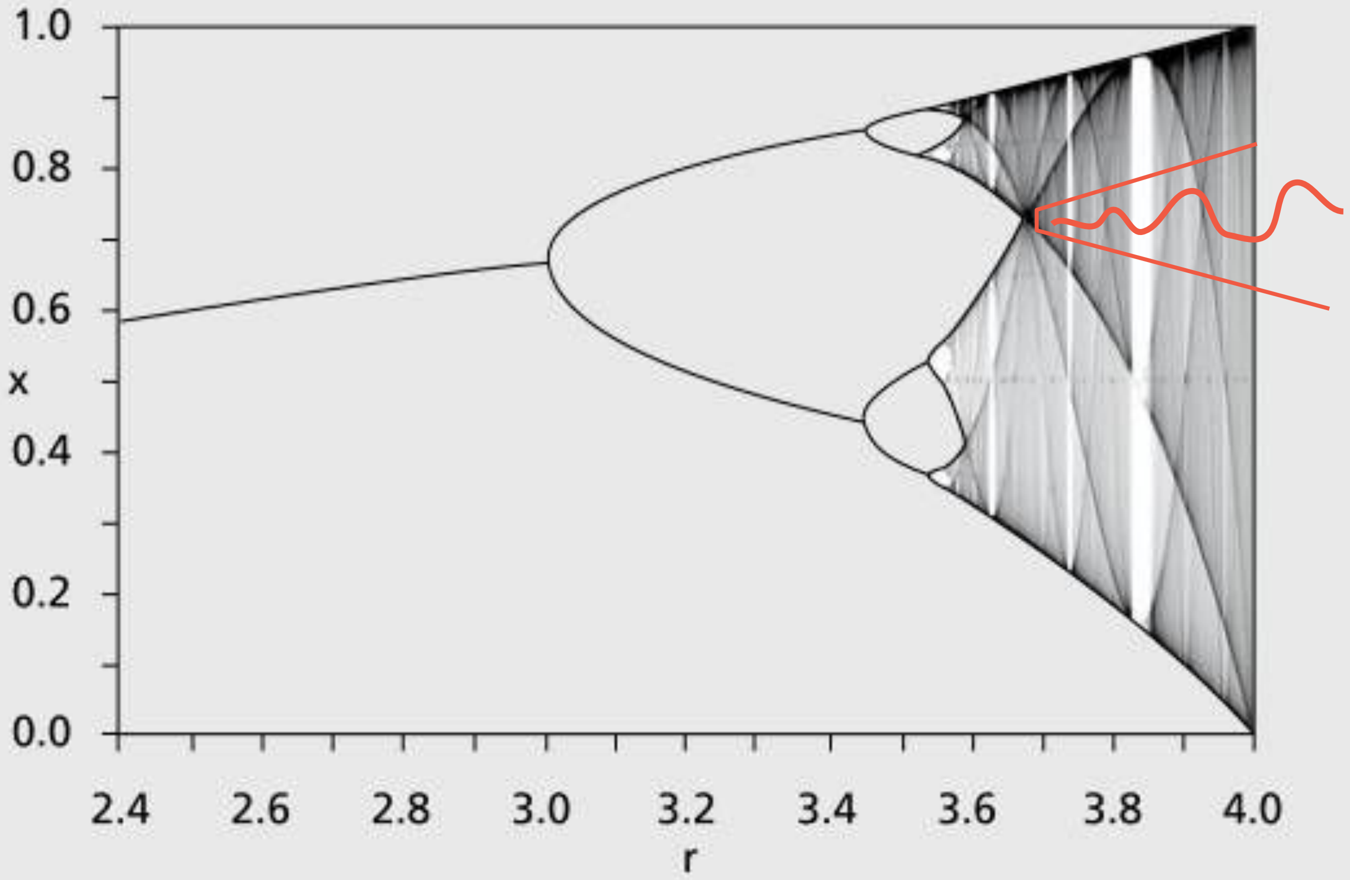
- Consider both dynamic and static environmental constraints
- Implicitly incorporate human impacts

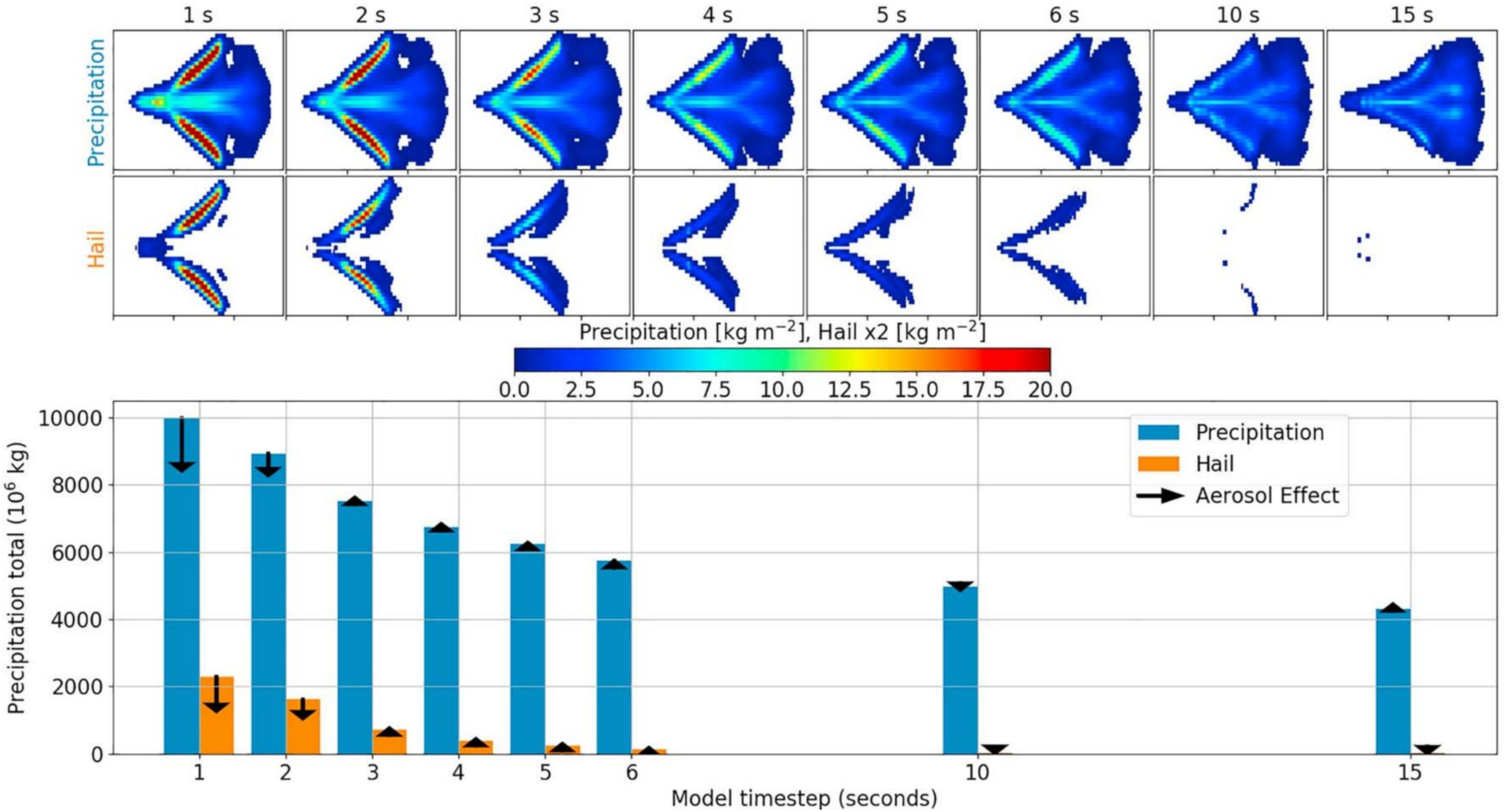


Other advantages

- Much faster computing speed with improved modeling performance
- Easy implementation within the current modeling pipeline for large-ensemble fire risk assessment

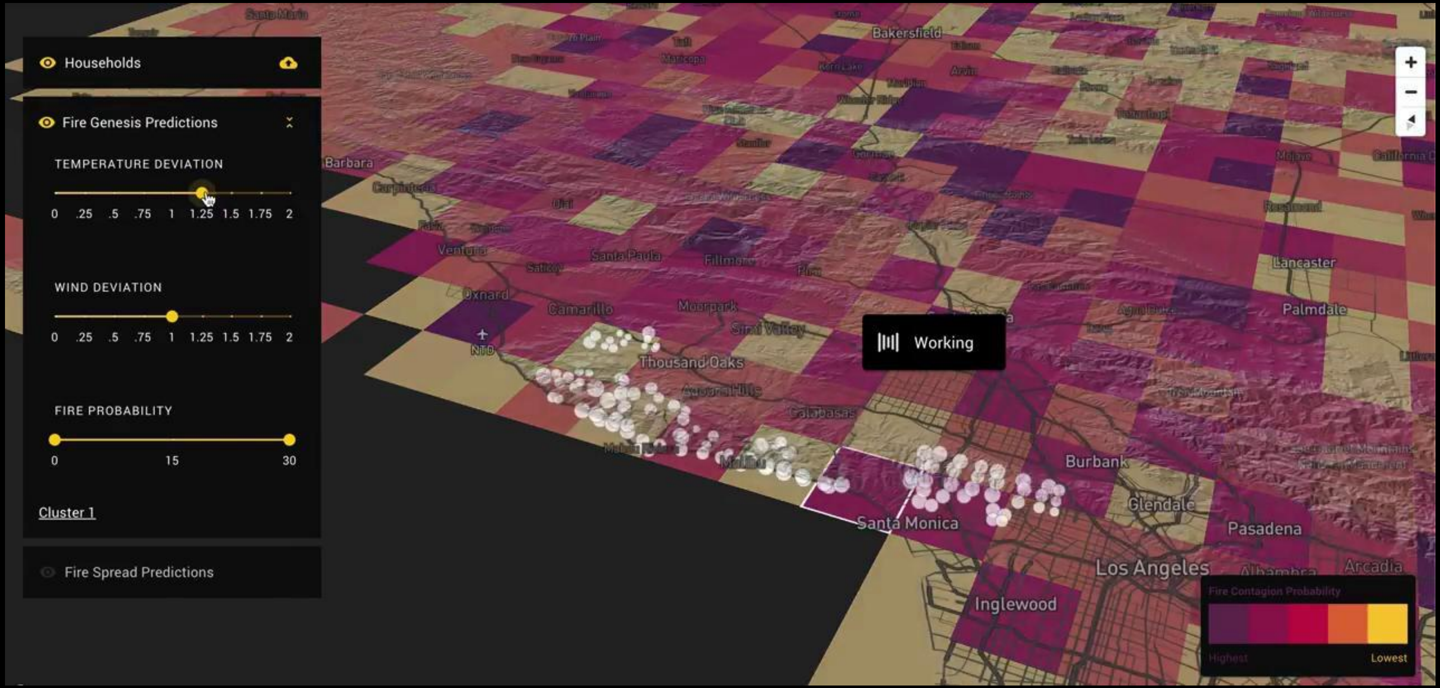



1.0
0.8
0.6
x
0.4
0.2
0.0
2.4
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0
r



1 s
2 s
3 s
4 s
5 s
6 s
10 s
15 s
Precipitation
Hail
Precipitation [kg m^{-2}], Hail x2 [kg m^{-2}]
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Precipitation total (10^6 kg)
10000
8000
6000
4000
2000
0
Precipitation
Hail
Aerosol Effect
1
2
3
4
5
6
10
15
Model timestep (seconds)

We Use Deep Learning
To Price Our Reinsurance Products with High Resolution



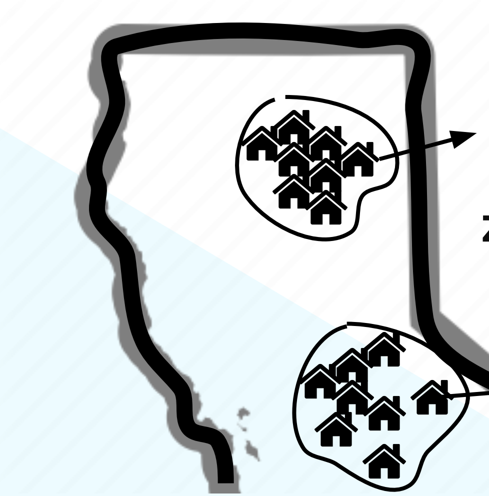
APPENDIX

CAT STRIP

THE PROCESS

Instead of pricing large areas using inaccurate historical data

Use real-time, hyper accurate Swarm NN to produce precision priced products



$25m xs $125m
4% ROL
1 year term
Low Level Risk

Zip 91024

$50m xs $75m
18% ROL
6 month term

Zip 91011

Create hyper specific returns and match them to markets with appetite

4-20% YoY ROI

3 Tredecillion ($3\text{x}10^{42}$)

CALCULATIONS PER RUN

529bn

SIMULATIONS

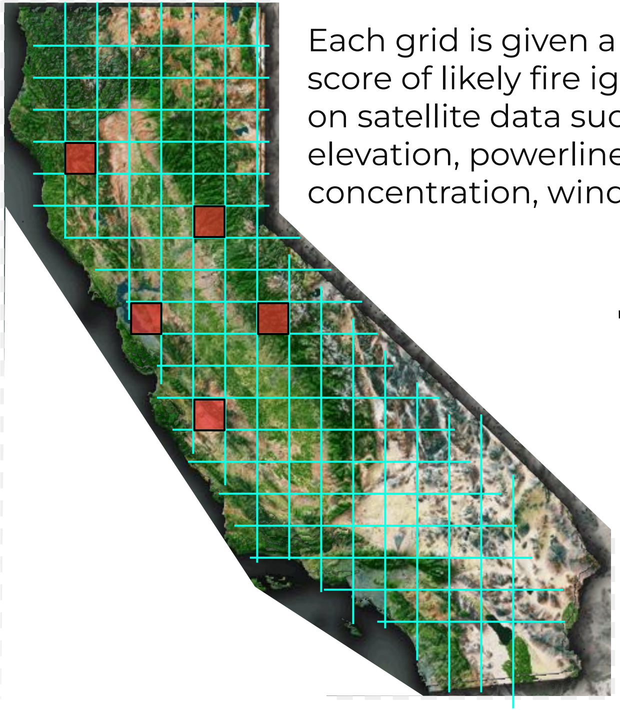
114m

NEURAL NETWORK NODES

THE SCIENCE

RISK REIMAGINED

The **Genesis Model** splits CA up into 320,280 separate .5 square mile grids.



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The **Contagion Model** uses genesis points, or current fires, and predicts their spread/path using variables such as wind direction/speed, elevation, brush patterns, etc

WHAT KETTLE DOES

RISK REIMAGINED

Write with our Partner Carriers

Take the most uninsurable risk

Price it correctly using Deep Learning

OR

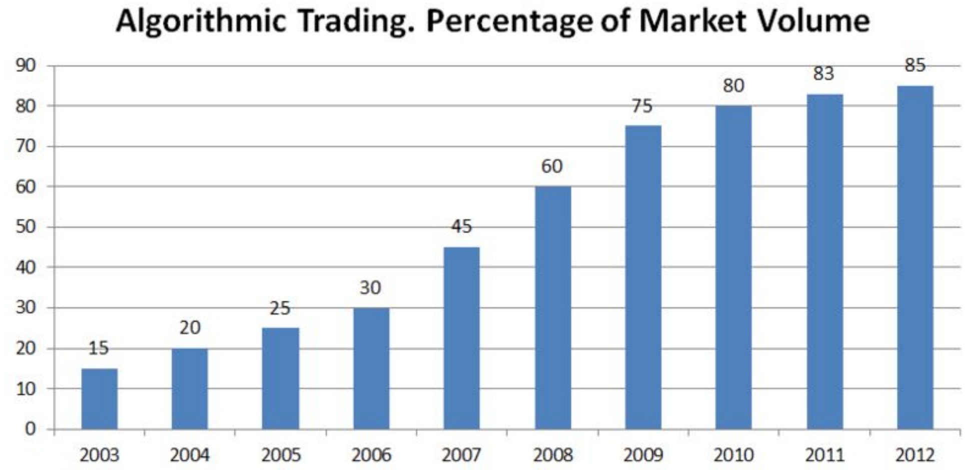
Transform/securitize it into a derivative

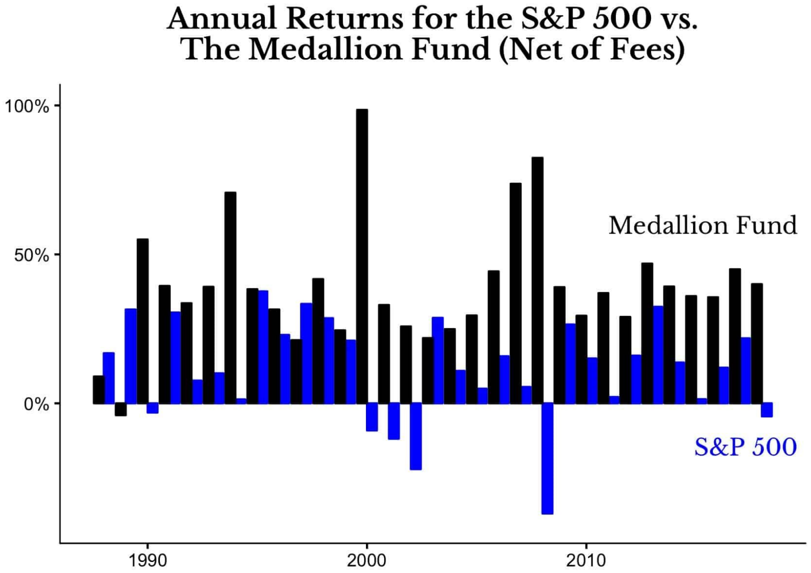
Sell as a micro-cat bond to the capital markets

Give all software/analytics back to Insurers, Policymakers, Frontline Responders, etc. for <u>FREE</u>

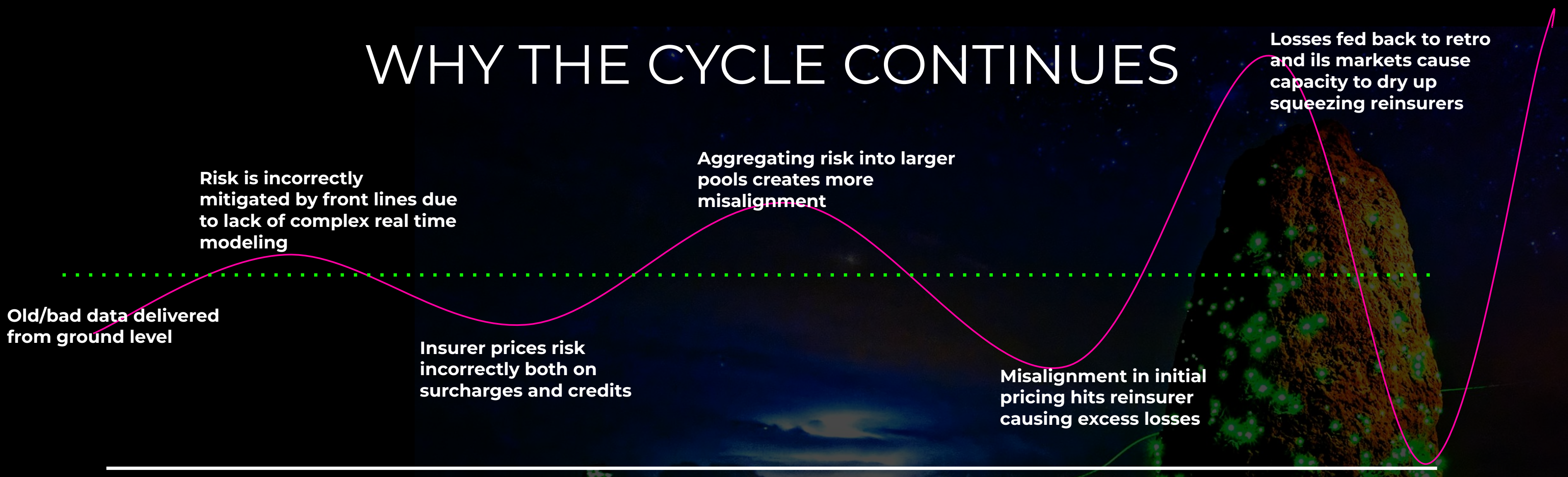
GREAT ARTISTS STEAL

COPYING CAPITAL MARKETS

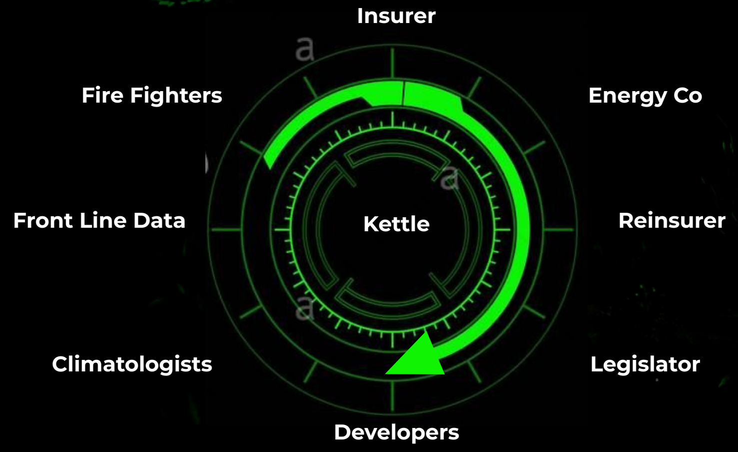




WHY THE CYCLE CONTINUES



SOCIAL PROFIT



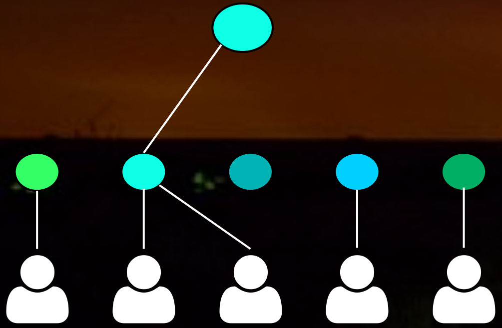
CORPORATE PROFIT

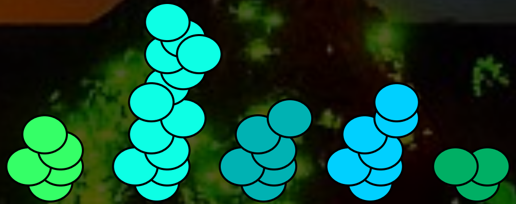
THE BIRDS AND THE BEES

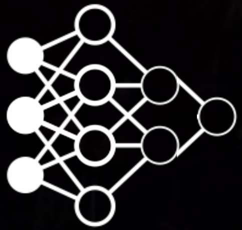
Nature contains the ultimate design and simplicity through evolution.

Humans are great abstractors and higher level thinkers, but complex predictive systems pale in comparison to Swarm Intelligence.

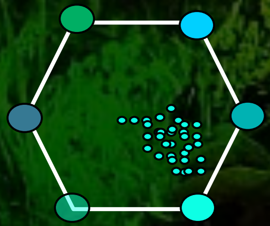
With this incredible ocean of data now structured, we need an intelligence system which can find trillions of patterns and signals while mathematically quantifying their relationship







The traditional voting system of a neural network creates rigid relationships between variables and weights



Swarm voting works like a hive of termites. Each little decision maker adjusts in real time to find the absolute optimum connection rather than a static fixed vote. Continuously updating, and becoming more intelligent

RISK IS EVOLVING

RE/INSURANCE EVOLVED