

Inferknow

**Better Response to
Wildfires**



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Mission

**Provide California's Emergency Coordinators with the
Best Information to Quickly Save Lives and Property**

Problem

1. Wildfires are highly destructive and disruptive
 - a. 2018 California wildfires caused \$400 billion in damages
2. Becoming more frequent and severe, to date in 2020:
 - a. ~35% more than the 5-year average, 7,786 reported fires
 - b. 5x more severe than 5-year average, with ~2.2m acres burned
3. Emergency Response Coordinators have to be well informed to combat these natural disasters

Target Customer and Proposed Solution

- **Customer:** *California Geographic Area Coordination Center (GACC)* whose principal mission is to provide cost-effective and timely coordination for the response for wildfires.
- **Our Product:**
 - An integrated solution that will conduct the following after a reported fire:
 - Model fire propensity (size)
 - Scan satellite imagery for Areas of Interest (Buildings, important infrastructure etc.)
 - Indicate areas of most urgent action (most populated or most critical infrastructure etc.)

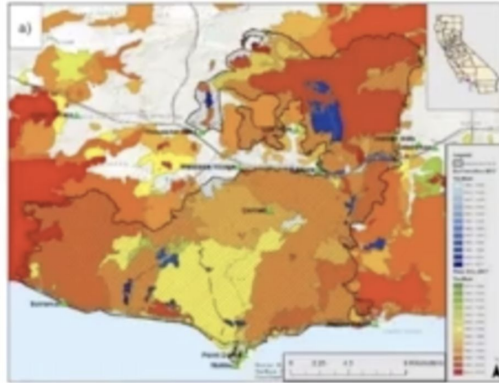
Focus on SoCal Fires

Wind-Dominated Fires

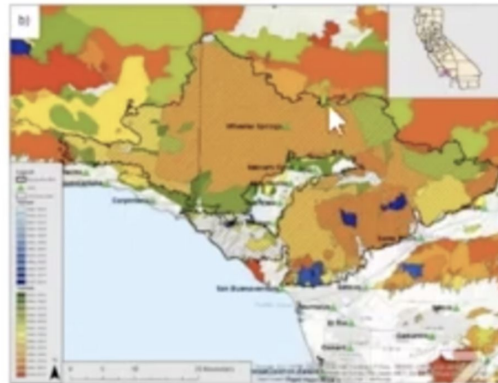
Typically coastal, and although managed by the same fire-suppression policy, the nature of these fires has not resulted in fire exclusion.

'All' are direct/indirect result of human activities and with 40 million people in the state such fires are frequent and thus nearly always burn over landscapes of young fuels, ie, not controlled by anomalously high fuel loads.

2018 Woolsey Fire



2017 Thomas Fire



SoCal has the unique aspect of a drought season, wind-dominant fires, and always burn over landscapes.

NorCal you can explain ~ 50% of the fire size variation with just temperature, while prior year precipitation and high winds have more of an effect in SoCal

Solution Deep Dive

Data Sources

Fire Propensity:

- 1998 - 2015 California Wildfire Occurrences (Kaggle)
- 1998 - 2015 Hourly weather data (NOAA)

Computer vision:

- Satellite images, labelled for buildings and roads (Spacenet)
- Raw satellite footage (Planet Labs)

Baseline Fire Propensity Model Features

Hourly Weather Data

- Temperatures
- Relative Humidity
- Wind Speed

Rolling Average/Sum of Weather Data

- Rolling 7, 30, 60, 90 Day Average Temperatures
- Rolling 7, 30, 60, 90 Day Average Relative Humidity
- Rolling 7, 30, 60, 90 Day Sum Average Relative Humidity
- Average 2 Day Wind Speed Average

Fire Cause Description

Discovery Month/ Hour

Propensity Model Initial Findings

Total Records: 36K

Split: 80% Train, 20% Test

7-Class (A-G) Fire Propensity Model Performance

| Model | F1-Score Macro | F1-Score Micro (Accuracy) | F1-Score Weighted |
|-----------------------------|-------------------|------------------------------|----------------------|
| GBT Classifier | .13 | .5937 | .4949 |
| Random Forest Classifier | .107 | .606 | .457 |
| XGBoost | .1707 | .59315 | .5507 |

Takeaways:

- Data is imbalanced with small fires (ABC) accounting for 95%
- Multi-class classifiers shows poor performance

Additional Features to Propensity Model

Count the number of acres burned nearby a location of interest for the past 3 and 12 months

- 0.01, 0.07, 0.22, 0.38, 0.7, 1.6, 3 miles.
- These miles match the the size of the each fire class (A,B,C,D,E,F,G).
- **Rationale:** more fires occurred in the past nearby, less fuels to burn and less likely to have large fires
- These features are proxies for how much fuels left to burn nearby

Fire Propensity Iterations (2-Class)

| Category | Metrics | Baseline Model | Baseline Model (Oversampling) | Latest Model |
|----------|-----------|----------------|----------------------------------|--------------|
| ABC | Precision | .97 | .98 | .98 |
| | Recall | 1 | .56 | .71 |
| | F1 Score | .99 | .71 | .83 |
| DEFG | Precision | .10 | .05 | .06 |
| | Recall | .01 | .69 | .63 |
| | F1 Score | .01 | .09 | .12 |

Computer Vision Modeling

- Retrained a pre-trained ensemble model from SpaceNet
- Scoring metric IOU
- SP2 models (1-3) did not extend well to Planet Data

| | Cloud Training | | Testing | | | Extending to Planet Data | | | |
|--------------|--------------------|-----------------------|-----------|--------|-----------|--------------------------|-----------|--------|-----------|
| Model name | Dataset (# images) | Training Time | Precision | Recall | F-1 score | True Positives | Precision | Recall | F-1 score |
| inferknow_v1 | SP2 Vegas (3,100) | 10 epochs 3 hours | 0.90 | 0.82 | 0.86 | 0 | 0.00 | 0.00 | 0.00 |
| inferknow_v2 | SP2 Vegas (3,100) | 20 epochs 6 hours | 0.90 | 0.85 | 0.87 | 0 | 0.00 | 0.00 | 0.00 |
| inferknow_v3 | SP2 All (7,500) | 25 epochs 16 hours | 0.86 | 0.75 | 0.80 | 1 | 0.33 | 0.00 | 0.00 |
| inferknow_v4 | SP7 (1,100) | 30 epochs 4 hours | 0.11 | 0.05 | 0.07 | 253 | 0.11 | 0.02 | 0.00 |
| inferknow_v5 | SP7 (1,200) | 50 epochs 7 hours | 0.12 | 0.04 | 0.08 | 225 | 0.12 | 0.02 | 0.03 |

Computer Vision Model Output

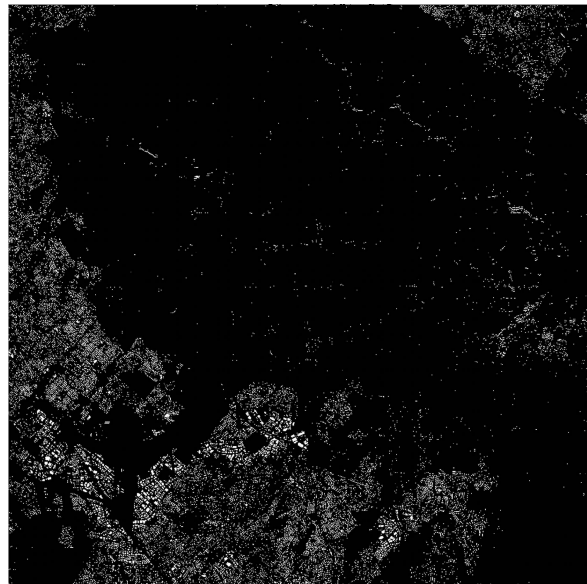
Original Image



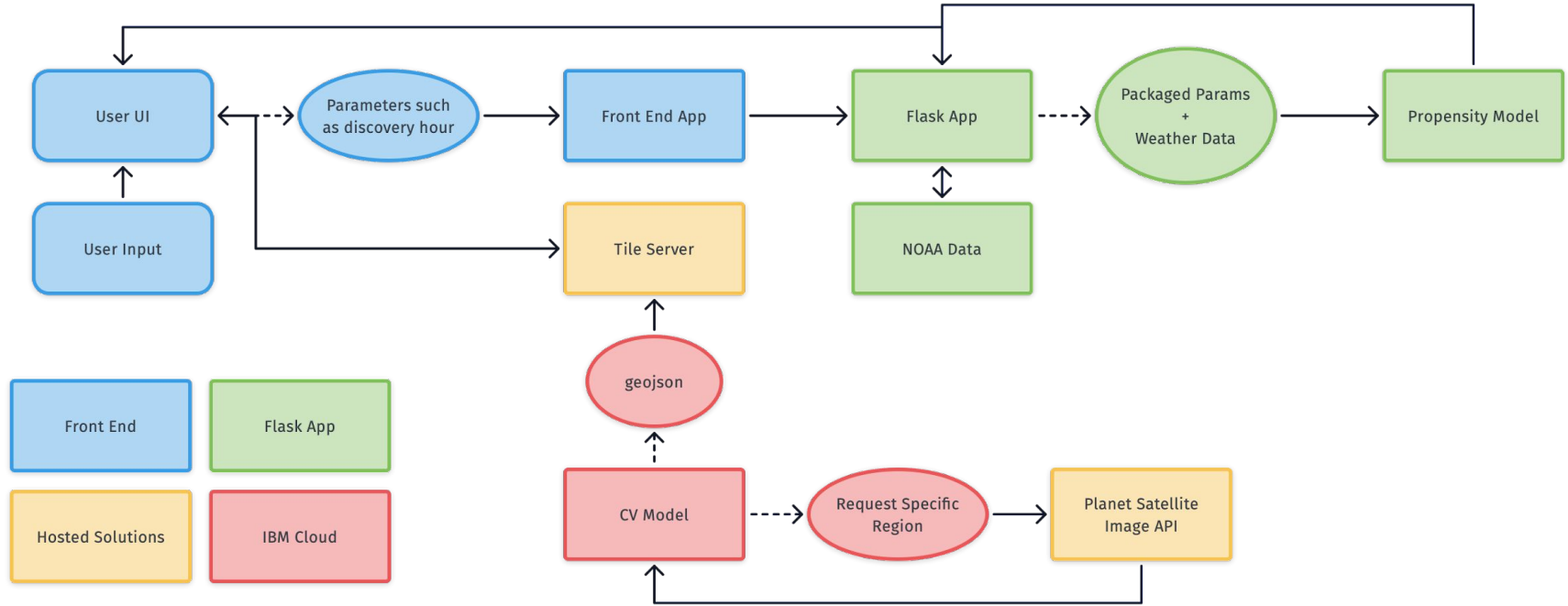
Inferknow_v3



Inferknow_v5
(final)



System Design and Infrastructure



Product Demo



References

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<https://www.fire.ca.gov/stats-events/>
- NOAA (2020). Land-Based Station Data. Asheville, NC.
<https://www.ncdc.noaa.gov/data-access/land-based-station-data>
- Planet Team (2017). Planet Application Program Interface: In Space for Life on Earth. San Francisco, CA. <https://api.planet.com>
- Short, Karen C. 2017. Spatial wildfire occurrence data for the United States, 1992-2015 [FPAFOD20170508]. 4th Edition. Fort Collins, CO: Forest Service Research Data Archive.
<https://doi.org/10.2737/RDS-2013-0009.4>

Appendix: Team Responsibilities

Bryan Morgan

- System design
- CV datasets + framework research
- Planet API EDA
- Infrastructure development
- Front-end development

Don Moon

- Fire propensity infrastructure
- Fire propensity data collection/engineering
- Fire propensity modeling

Francis Leung

- EDA: Computer vision (Spacenet Data)
- Literature review
- Integration with Planet API to pull new satellite images
- Developed computer vision model (acquiring training data, set up cloud training, testing and iterations, creating final geojson outputs)

Ray Xiao

- Wildfire research
- Fire propensity EDA
- Fire propensity modeling

Future Steps

- Propensity:
 - Improve model performance with more historical and topographical features
- Computer Vision:
 - Additional AOIs
 - Better performance (accuracy and time)
- Infrastructure
 - We would like to automate triggers
 - We would also like to pre-process building GeoJSON data to supply to tile server

Limitations of Existing Research

- Over 300 academic papers on fire prediction have been published
- Fire size prediction research is limited by sample data size and lack of California-specific focus
- No integrated solution