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Toward Autonomous Decision Making and Coordination in Intelligent UAVs' Operation in Dynamic Uncertain Remote Areas

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Autonomous UAV Systems in Disaster Management

Applications

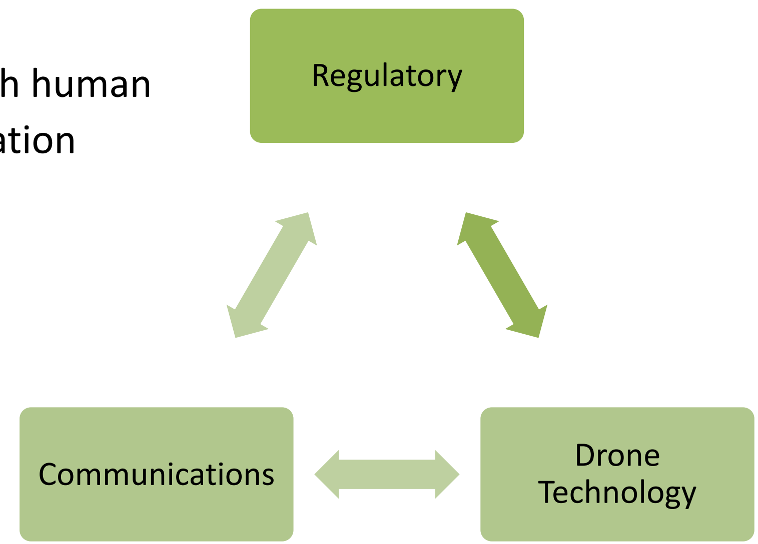
- Surveillance
- Search and Rescue
- Delivery of emergency supplies

Challenges

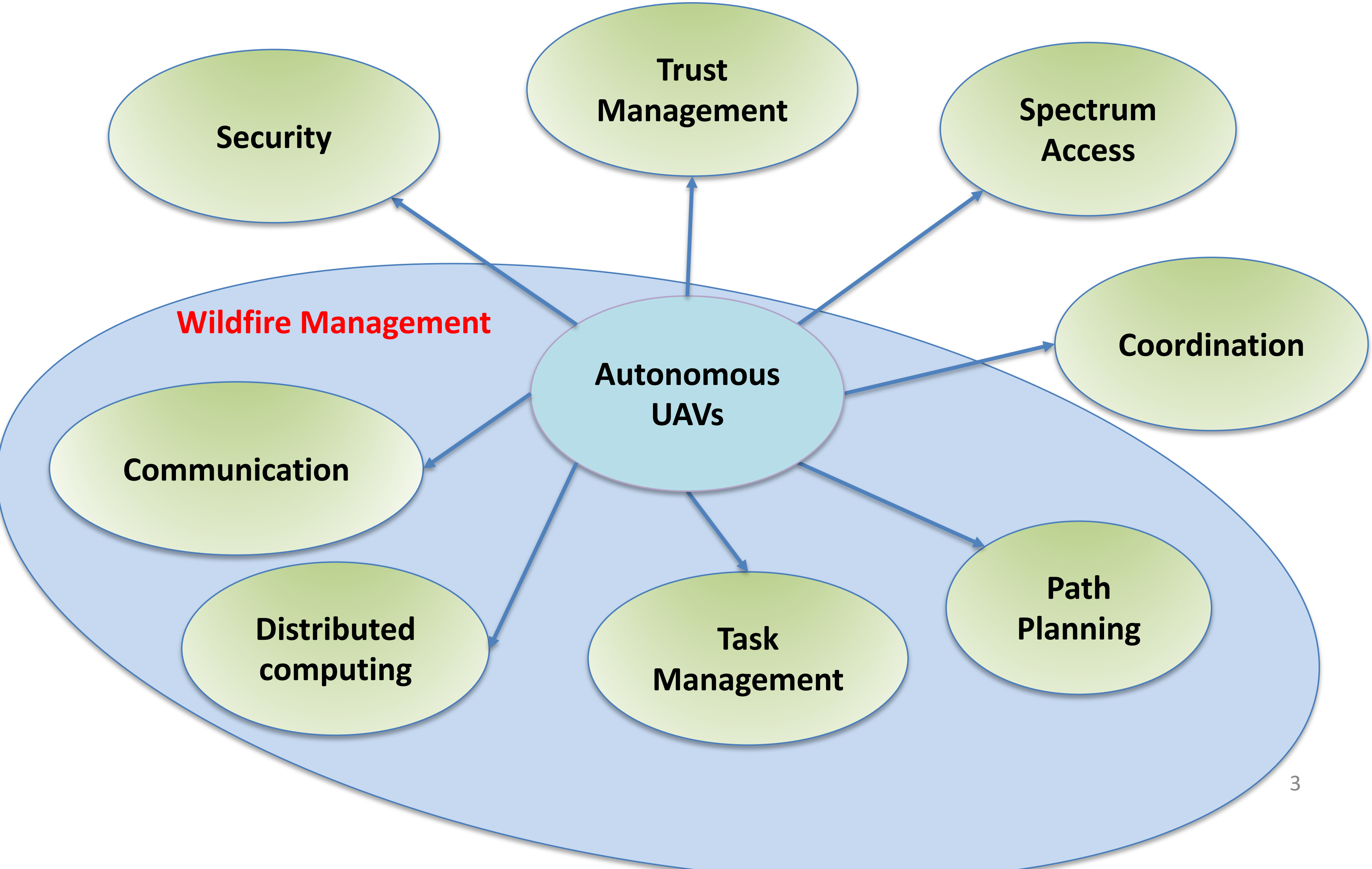
- Dynamic Environment
- Limited lifetime
- Communication constraints
- Interaction with human
- Partial Observation

Technologies

- Autonomy
- Navigation
- Communication
- Sensing
- Coordination



Our Research



Cellular-connected UAV Communications

Advantages

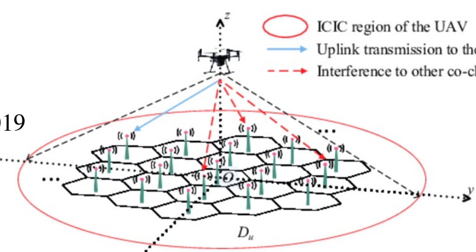
- Broadband coverage (BLoS)
- Secure communication
- SIM card identification
- LoS UAV-BS (reliable communication, high macro-diversity gain)

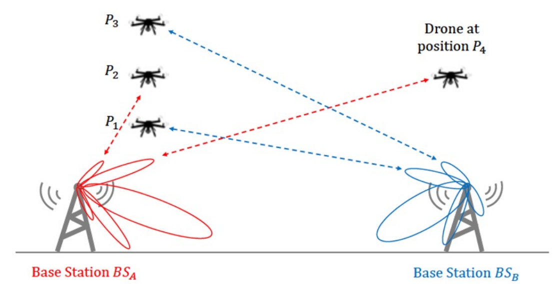
Challenges

- Down-titled antennas (weak signal at high altitude, null of nearby BS and sidelobe of farther BSs)
- Frequent & pingpong handovers
- Mobility models
- Strong LoS UAV-BS (interreference to neighbor BSs and UEs)
- Coverage hole and unavailable in remote areas

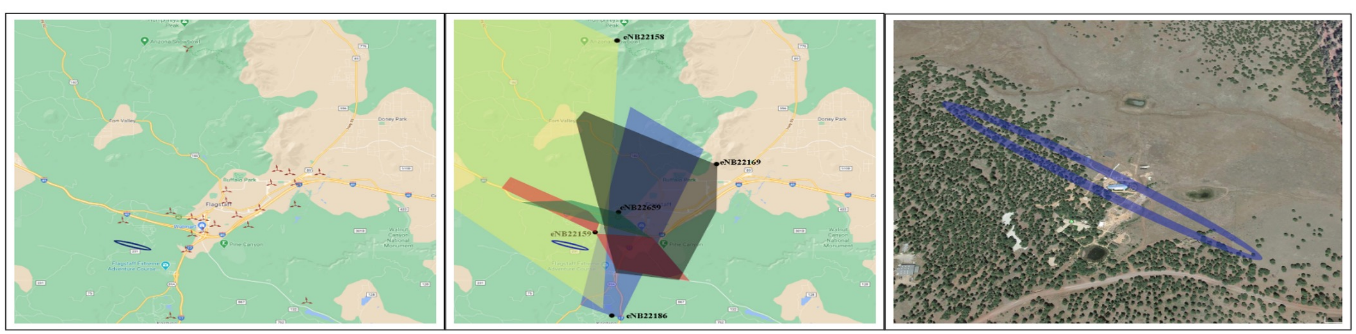
Inter-cell interreference

Fakhreddine , Handover Challenges for Cellular-Connected Drones, Jun 2019





Meil, et al. "Cellular-Connected UAV: Uplink Association, Power Control and Interference Coordination, Dec. 2019.

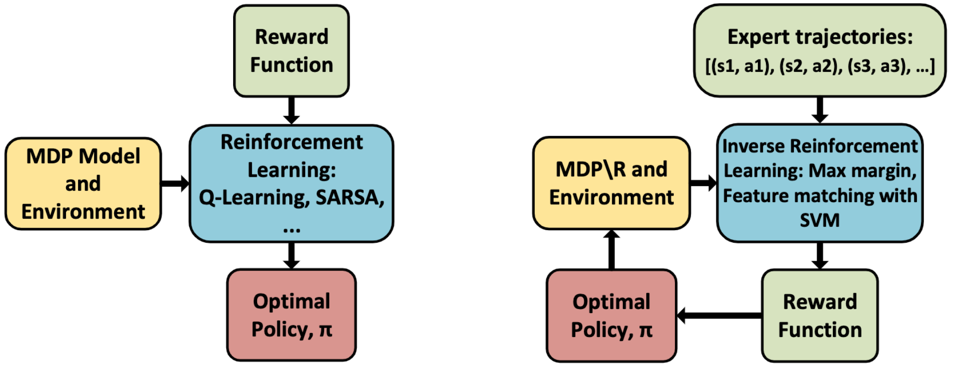


(a) Overall view (b) The captured signals (c) The test map

Gharib, Nandadapu, Afghah, "An Exhaustive Study of Using Commercial LTE Network for UAV Communication in Rural Areas" ICC Workshop on Integration of UAVs in 5G and Beyond, 2021.

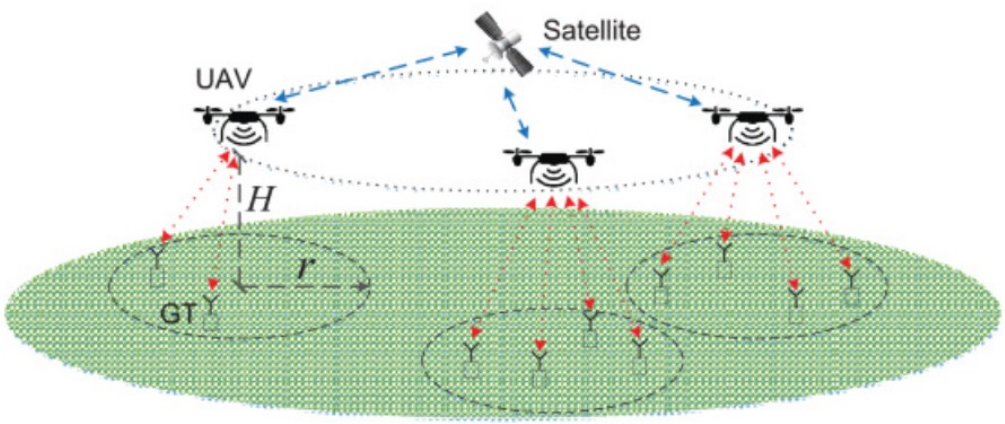
Communication-aware UAV Planning

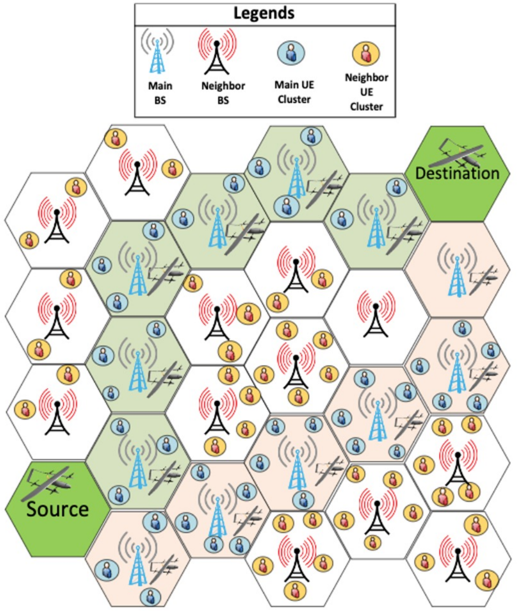
- Joint Path Planning, task management and communication optimization
  - Task completion
  - Shortest path
  - Interreference to UEs
  - Maintain connectivity
- Complex reward to account for path planning, task completion and communication



(a) Reinforcement learning approach

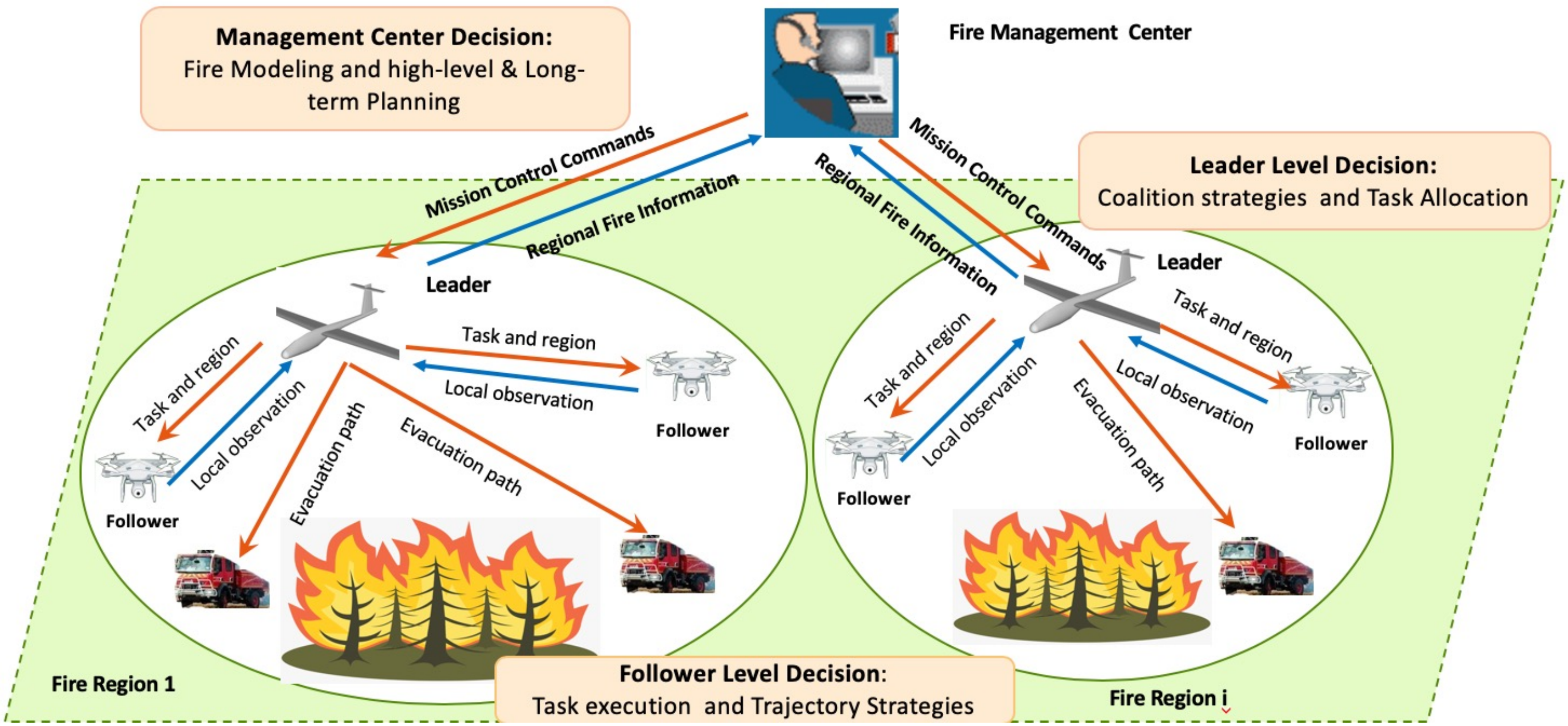
(b) Apprenticeship learning using Inverse RL





Shamsoshoara, Mousavi, Afghah, Guvenc, "joint Path Planning and Power Allocation of a Cellular-Connected UAV using Apprenticeship Learning via Deep Inverse Reinforcement Learning, submitted 2022.
Namvar, Afghah, I. Guvenc, "Heterogeneous Drone Small Cells: Optimal 3D Placement for Downlink Power Efficiency and Rate Satisfaction", submitted, 2022.
Namvar, Afghah, "Heterogeneous Airborne mmWave Cells: Optimal Placement for Power-Efficient Maximum Coverage, IEEE INFOCOM Workshop, 2022.

Wildland Fire Observation, Management, and Evacuation using Intelligent Collaborative Flying and Ground Systems

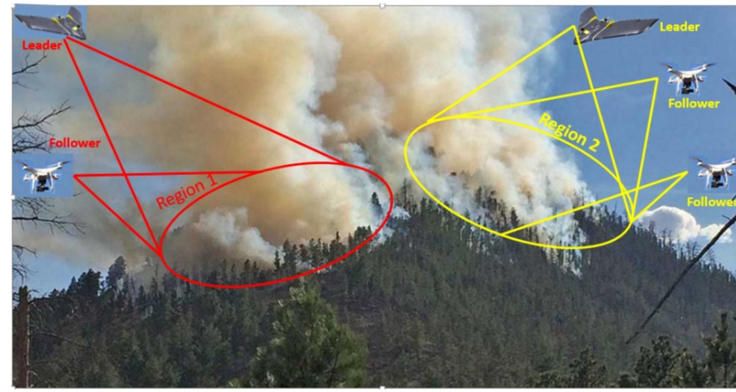


Agile Coalition Formation for Drone-based Forest Fire Monitoring

Dynamic Environment

Dynamic Tasks

Environment Conditions



Allocating the tasks among the heterogenous agents, when dealing with

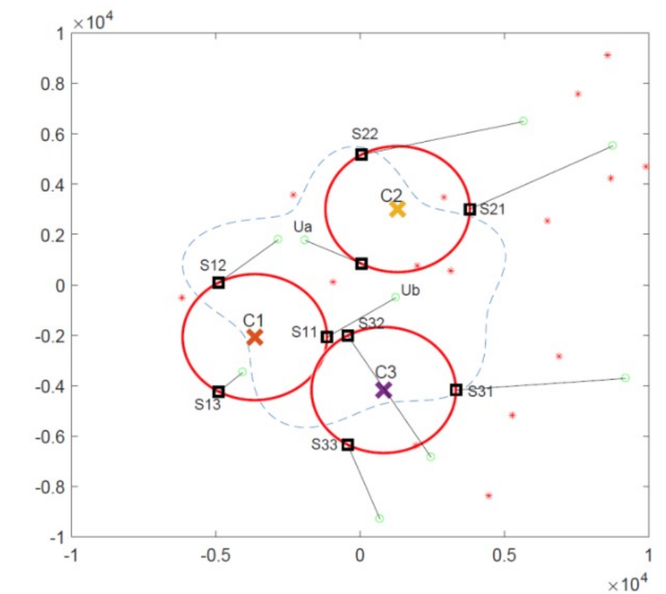
Partial Observation

Communication Constraints

Limited Resources

Limited Computation Capability

Agent Constraints



Fixed-wing UAVs (*leaders*): provide the fire profile.

Rotatory UAVs (observers): real-time video coverage

Select the best follower UAVs to maximize:

$$v(\mathcal{C}_k) = \sum_{l=1}^{N_r} \gamma\Big(\sum_{j=k_1}^{k_S} \mathbf{r}_j^l\Big/R_k^l\Big),$$

subject to: $\mathbf{p}_j \geq P_k$, for $j = k_1, k_2, \ldots, k_S$,

$d_{jk} \leq D$.

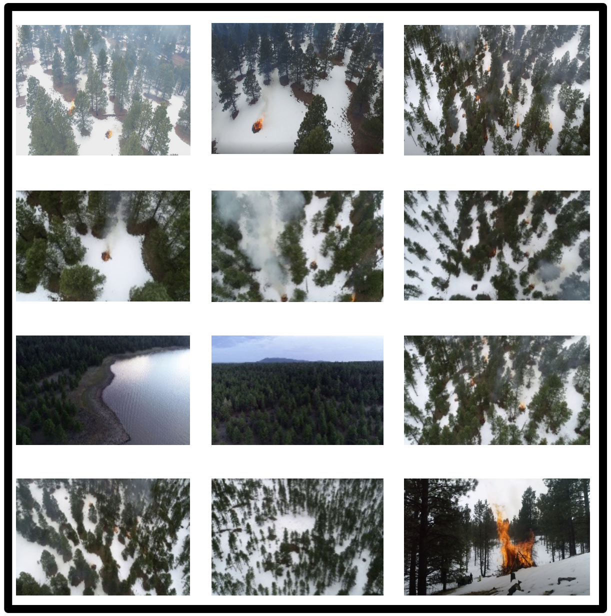
F. Afghah, Ashdown, et al. "Wildfire Monitoring in Remote Areas using Autonomous Unmanned Aerial Vehicles ", IEEE INFOCOM Workshop 2019.

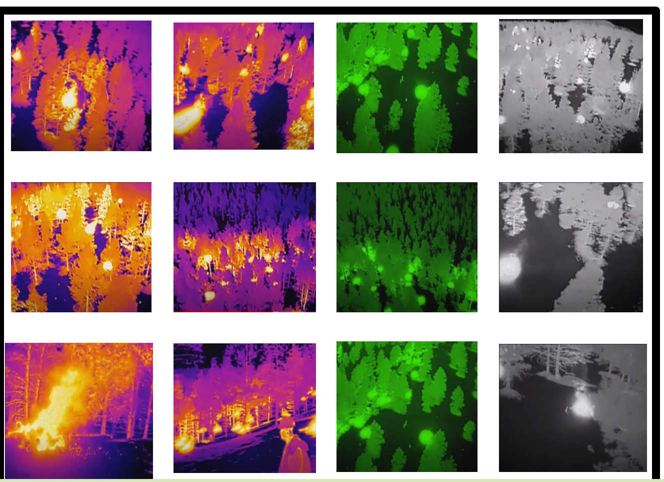
Wildfire Detection and Mapping

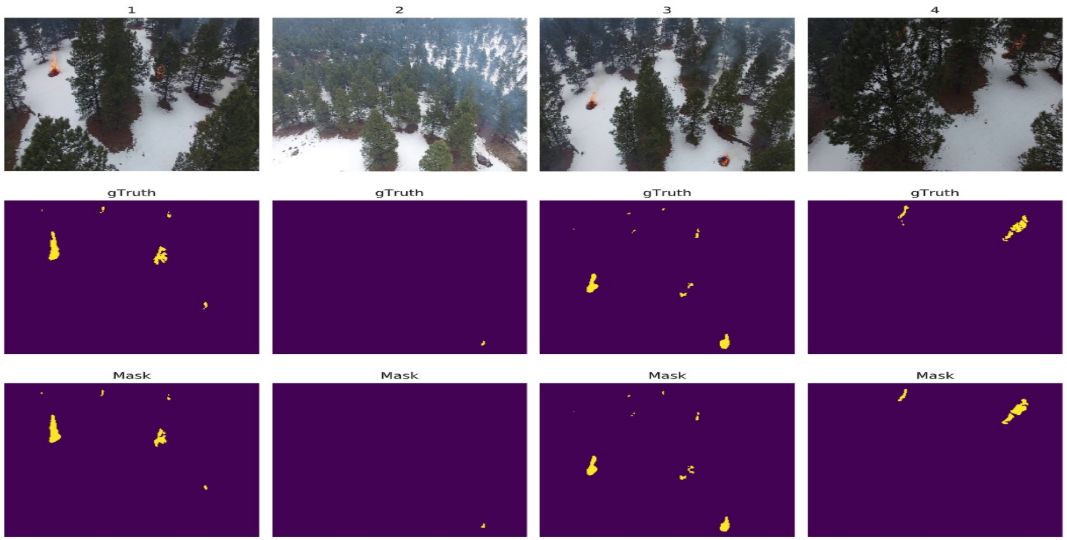
	Satellite-based	Drone/aircraft-based	Sensor-based
Pros:	Global coverage, Routinely collected	Limited operation due to lack of standards, Limited models and datasets	Limited coverage Limited lifetime
Cons:	Low spatial and temporal resolution, Low accuracy in smoke and cloudy sky unable to detect low-intensity early-stage fires	Agile detection, High resolution, Autonomous operation in remote areas	Cost-efficient, Fast detection

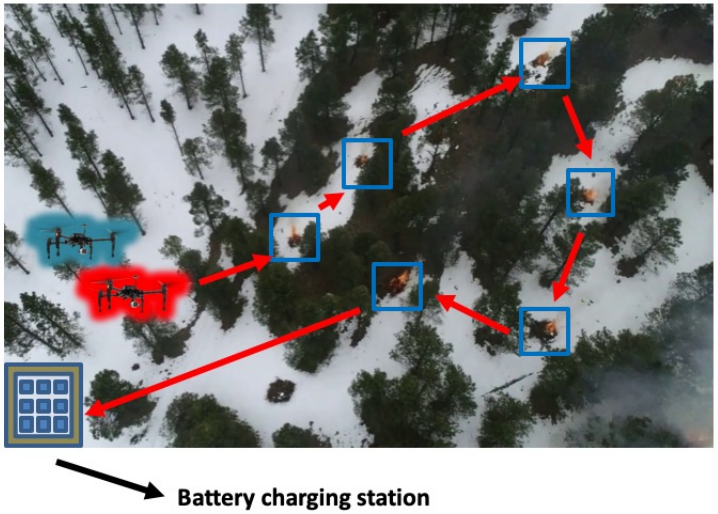
usatoday.com, Australia Fire, Jan. 2020
https://vigilys.com/

FLAME I Dataset
Fire Luminosity Airborne-based ML Evaluation









Shamsoshoara, Afghah, et al, “Aerial Imagery Pile burn detection using Deep Learning: the FLAME dataset”. Computer Networks, March 2021.

FLAME2 Dataset

Dataset Name	Collection Method	RGB/IR	Perspective	Fire Area	Labeling Type	Num of Images	Year	Supplemental Data
DataCluster Labs' Fire and Smoke Dataset [26]	Cellphone videos	RGB	Terrestrial	Mixed[a]	Fire or Smoke/No Fire or smoke	7000+ frames	2021	N
AIDER[b] [27] [28]	Search Engines	RGB	Aerial	Mixed	Fire/No Fire	1000 images	2020	N
Dataset for Forest Fire Detection [29]	Search Engines	RGB	Mixed[c]	Rural	Fire/No Fire	1900 images	2020	N
Fire Detection by Dhruvil Shah [30]	Search Engines	RGB	Terrestrial	Mainly Urban	Fire/No Fire	3225 images	2020	N
FireNet [31]	Search Engines	RGB	Terrestrial	Mixed	Bounding Boxes	502 images	2019	N
Fire Detection From closed-circuit television (CCTV) [32]	CCTV	RGB	Terrestrial	Mixed	Fire/no Fire Smoke/no Smoke	864 frames	2019	N
Furg Fire Dataset [33] [34]	Search Engines	RGB	Terrestrial	Urban	Bounding Boxes	365,702 frames	2018	N
CAIR's Fire Detection Image Dataset[d] [35]	Search Engines	RGB	Terrestrial	Mainly Urban	Fire/No Fire	651 images	2017	N
Mivia's Fire Detection Dataset [36] [37]	CCTV	RGB	Terrestrial	Mixed	Fire/No Fire	62,690 frames	2014	N
FLAME[e] [7]	Drone Footage	Mixed[f]	Aerial	Rural Pile Burns	Fire/No Fire and Masking	47,992 frames	2020	Minimal[g]
FLAME 2[h] [20]	Drone Footage	side-by-side Dual RGB/IR	Aerial	Rural Prescribed Burns	Fire/No Fire Smoke/No Smoke	53,451 frames	2022	Yes[i]

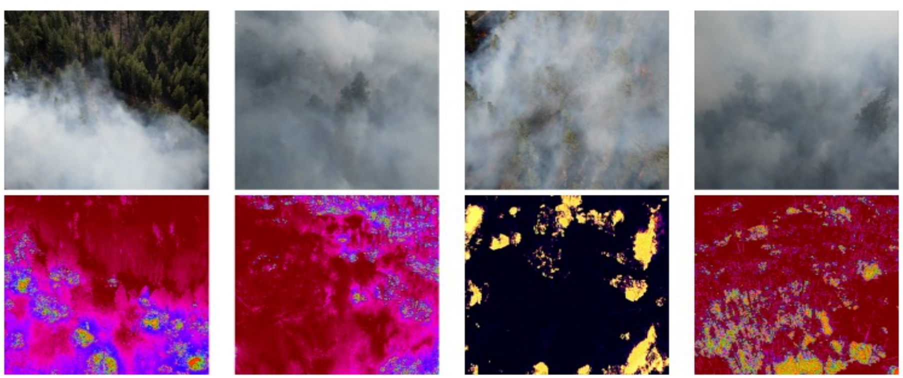
Feature	Application
Side-by-side RGB/IR Images	Georectification, orthomosaicking, Fire frontline monitoring, terrain feature with IR input (especially in the smoky sky)
Labeled by experts	Ground-truth for supervised learning fire classification
Pre-fire and during fire footage	Fire detection, segmentation and fire modeling
Supplementary data (weather information, georeferenced pre-burn pointcloud data points)	Fire modeling and fire management

Hopkins, Bryce and O'Neill, Leo and Afghah, Fatemeh and Razi, Abolfazl and Watts, Adam and Fule, Peter and Coen, Janice, "FLAME 2: Fire detection and modeLing: Aerial Multi-spectral imagE dataset, **IEEE Dataport**, Sep. 2022. doi: https://dx.doi.org/10.21227/swyw-6j78.

FLAME2 Dataset

- Kaibab National Forest, Arizona, adjacent to the South Rim of Grand Canyon National Park, November 2021.
- Flame Length: 0.25–0.75 m (occasionally reaching 5–10 m)
- Spread rate: 300–600 m/hr

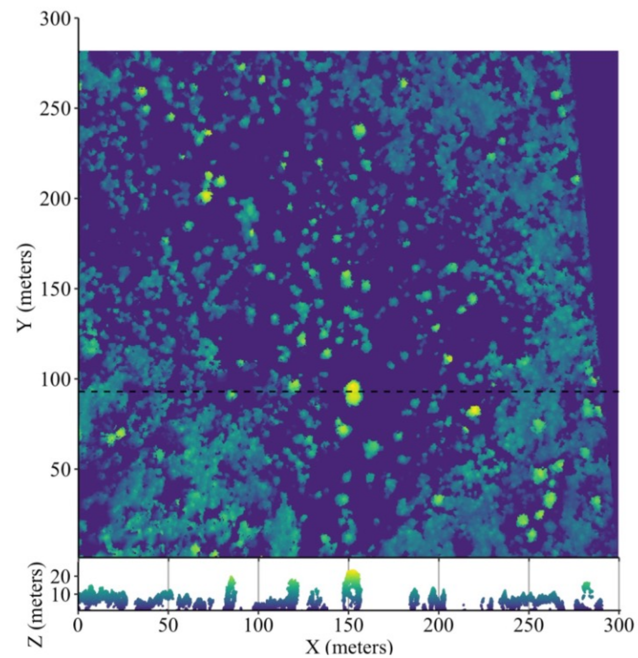
Image Dateset
Side-by-side RGB/IR fire images collected by Mavic 2 enterprise



Example of frame pairs from FLAME 2, where the IR frame provides information that is obscured by smoke in the RGB frame

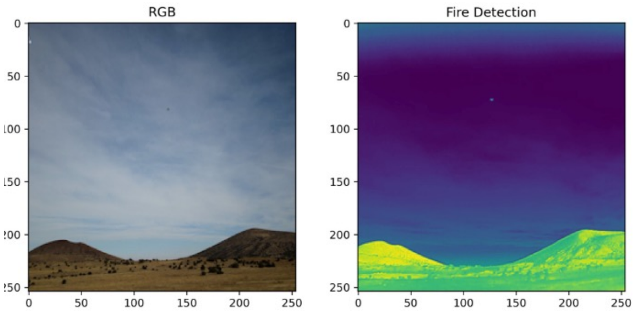
Supplementary Data

- Georeferenced RGB pointcloud of preburn area
- Weather information
- LiDAR point clouds and Digital Elevation Models (DEMs).



normalized preburn elevations, effectively mapping out canopy altitudes

FLAME Detection



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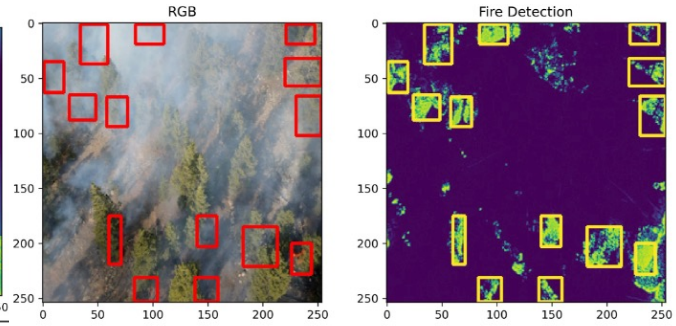

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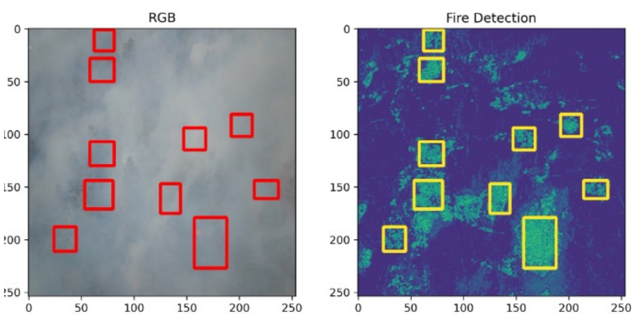
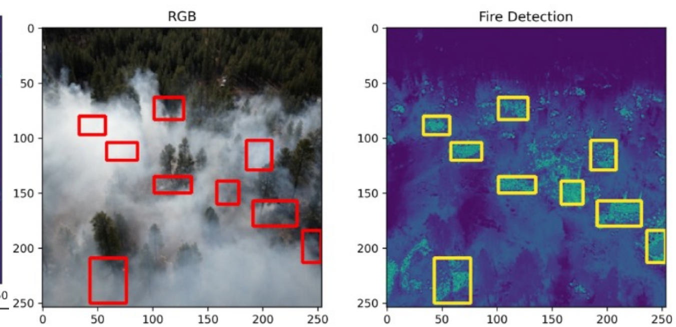


ID = 16393 Class = 1

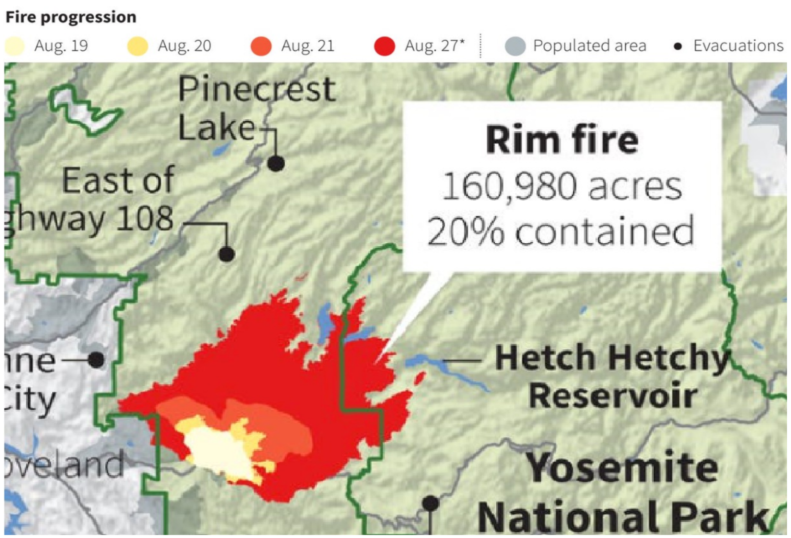


Model	Mode	F1 Score	Precision	Recall	Accuracy
Logistic	RGB	89.57	90.99	89.48	90.37
Logistic	IR	92.61	92.94	92.43	92.43
Logistic	Early Fusion	96.71	96.92	96.65	96.54
LeNet5	RGB	95.39	95.86	95.12	95.33
LeNet5	IR	92.3	92.19	92.79	92.15
LeNet5	Early Fusion	97.16	97.35	97.1	97.01
Flame	RGB	94.53	95.18	94.38	94.86
Flame	IR	86.81	87.47	86.91	85.79
Flame	Early Fusion	94.88	96.01	94.95	94.86
Flame	Late Fusion	95.24	95.84	95.61	94.95
VGG16*	RGB	99.92	99.9	99.93	99.91
VGG16*	IR	97.35	97.57	97.26	97.29
MobileNetV2*	RGB	99.36	99.33	99.42	99.35
MobileNetV2*	IR	97.51	97.65	97.43	97.38
MobileNetV2*	Late Fusion	99.82	99.78	99.87	99.81
ResNet18*	RGB	98.46	98.57	98.37	98.32
ResNet18*	IR	96.54	96.97	96.27	96.26
ResNet18*	Late Fusion	99.5	99.46	99.56	99.44

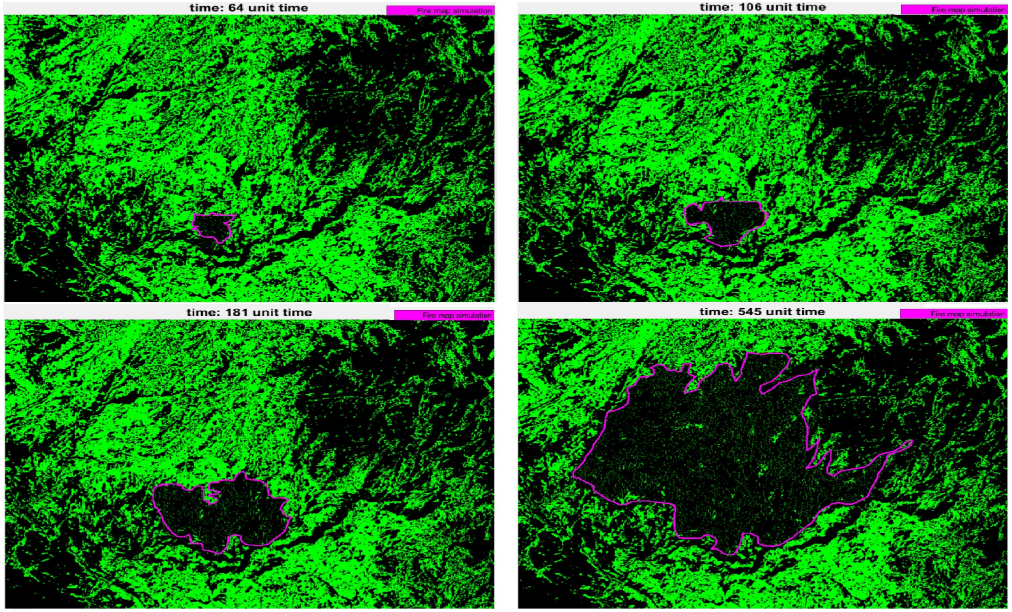
Xiwen Chen, Bryce Hopkins, Hao Wang, Leo O'Neils, Fatemeh Afghah, Abolfazl Razi, Peter Fule, Janice Coen, Eric Rowell, Adam Watts, "Wildland Fire Detection and Monitoring using a Drone-collected RGB/IR Image Dataset", IEEE ACCESS, 2022.

Fire Modeling

- Data driven fire modeling by extracting spatial distribution of vegetation from aerial images and incorporating it into the spread modeling
- Integrating instantaneous speed and direction of the wind, fire propagation rate of combustibles, the vegetation density, and the slope and aspect of the terrain



Rim fire progression from August 19 through August 27, 2013.
https://www.businessinsider.com/this-map-showshow-rapidly-the-yosemite-wildfire-spread-in-just-over-a-week-2013-8



Prediction of burned area by the our proposed method based on Rothermel's surface fire spread model

Razi, Afghah, et al, " Wildfire Spread Modeling with Aerial Image Processing", IEEE SwarmNet, WoWMoM 2020.

Acknowledgment

Collaborators:

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- Dr. Charles Kamhoua, ARL
- Dr. Kurt Turk, AFRL

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- Dr. Janice Coen, NCAR
- Dr. Adam Watts, USDA
- Dr. Abolfazl Razi, CU
- Dr. Pete Fule, NAU
- Dr. Kyriakos Vamvoudakis, Georgia Tech
- Dr. Eric Rowell, DRI
- Dr. Alireza Shamsoshoara, NAU
- Dr Nima Namvar, Charter Communications

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