1 Motivation

We propose a collaborative, multi-disciplinary research program focused on the integration of autonomous unmanned aerial systems (UAS) into prescribed wildland burn projects. This work brings together experts from the areas of forest management and ecology, uncertainty quantification, evidential sensor fusion and data-driven modeling and control, to enable autonomous aerial robotic systems to integrate with and assist humans in an unstructured, uncertain and hazardous fire environment. Integration is targeted during pre-burn reconnaissance, burn monitoring and control, and, post-burn survey. We expect to minimize the risks involved to human agents by providing real time situational awareness and prognostics of fire evolution. In the long term, this work will aid in the management of the wildland-urban interface, monitoring and suppression activities of unplanned wildfires as well as other hazardous phenomena. It is also expected to help improve wildfire forecasting models through retrospective data analysis.

Fire regimes describe the spatial and temporal patterns and ecosystem impacts of fire across the landscape, including their severity and frequency [1]. The type of fire regime is determined by factors of climate, weather, ecosystem type (vegetation), ignition agents, and human influences [2]. It is predicted that climate change will increase fire frequency and severity in regions that become hotter and drier [2] as the result of more available fuels. Fuel availability is influenced by fuel moisture, density, and size. Regarding fuels, the amount, type, continuity, structure, and moisture level are critical elements of fire occurrence and spread [3].

Wildfire activity has been increasing in the United States, beginning with abrupt changes that began in the mid-1980's. Higher temperatures and drought brought on by climate change has increased the potential for wildfire by altering forest structure and changing moisture regimes [4]. According to data published by the National Interagency Fire Center (NIFC [5]), the 20-year, 15-year, 10-year, and 5-year averages of total acres burned annually over the past 2 decades are 5.7, 5.8, 6.2, and 6.5 million acres, respectively. The average number of fires each year during this period dropped from a 20-year average of 25,320 fires to the past 5-year average of 23,507 fires, indicating that the average size of these fires have been increasing. The fact that these fires have been increasing in size and engulfing more communities, causing increased destruction of structures and higher fatalities [6] has resulted in greater attention from the research community in understanding fire initiation, behavior, and spread. According to estimates by the U.S. Census Bureau, in 2019 76% of the U.S. population resided in the eastern U.S., a region that has experienced the greatest increase in the wildland-urban interface [7]. The wildland-urban interface (WUI) is now the fastest-growing land use in the United States [7]. Future fire probability forecasting shows dramatic increases in fire probability in some parts of the eastern U.S. due to climate change [8], combined with the increased WUI can set the future stage for more catastrophic fires in the eastern U.S. This was recently demonstrated by the 2016 fires near Gatlinburg, Tennessee, that burned 17,900 acres, caused 14 fatalities, destroyed 2,460 buildings, and roughly $2 billion in damages [9].

There is no doubt that fire seasons are lengthening for temperate and boreal regions, including the temperate hardwood forests of the eastern U.S., and this trend should continue in a warmer world [2]. Predicting the future trends of fire severity and intensity are difficult to determine owing to the complex and non-linear interactions between weather, vegetation, and people, and it becomes necessary to acquire improved fire data. One of the key differences between vegetative fuels of the western and eastern U.S. is the fuel chemistry. Different species display differences in flammability, with some forests being more flammable than others [10–12]. In addition to climate, this affects the availability of fuels for ignition. In general, coniferous forests of the West tend to be more flammable than broadleaved forests of the East due to relatively lower ignition temperatures of extractives in coniferous foliage [13]. These differences alone will produce different fire behavior. Since future predictions show dramatic increases in fire probability in the eastern U.S. where the greatest occurrence and expansion of the WUI exists, more attention needs to be given to understanding the factors of fire behavior and spread in eastern forests. This project aims to determine how slope, aspect, ambient air temperature, relative humidity, fuel composition, and fuel moisture in temperate hardwood forests influence fire intensity and rate of spread.

While an environment with unstructured uncertainty invariably entails hazardous encounters, it presents the right context for autonomous agents to take over dangerous and repetitive tasks from humans [14]. An important long-term goal of the proposed research program is to aid and advance the situational awareness and decision-making capabilities of unmanned aerial systems (UAS) through improvements in mission planning and the integration of sensing technologies, process modeling, prediction and control tools. UAS flight over regions with burning vegetation carries elevated risks due to unsteady and turbulent airflow, higher temperatures and variable density of air. These effects lead to uncertainties in the flight dynamics, affecting both the translational and rotational motion of the platform. Data from onboard sensors may also be corrupted due to these effects. Therefore, it becomes critical to ensure nonlinearly stable and robust flight, with guaranteed stability margins. It also serves as motivation to obtain stable and robust data-driven learning and control schemes for the UAS, that identify unknown dynamic disturbance inputs based on applied (known) control inputs and sensor output data obtained in real time. The motivation stems from the lack of guaranteed stability and robustness in the majority of existing data-driven learning/identification and control schemes for autonomous unmanned vehicles from input-output data, which in turn limits their integration in hazardous environments. Our algorithm design work will be complemented by platform development and integrated via hybrid simulation and in-situ verification methods. The integration will occur during all stages of prescribed burn projects as mentioned above.

Partnerships. This project consolidates an existing interdisciplinary collaborative partnership in research, mentoring and education between PI Kumar at the Department of Mechanical and Aerospace Engineering (OSU) and PI Williams at the School of Environment and Natural Resources (SENR, OSU). It further expands the partnership by bringing in PI Sanyal from the Department of Mechanical and Aerospace Engineering at Syracuse University, who is a domain expert in data-driven modeling and control and will serve to increase the robustness of UAS activity in a wildland fire environment. Additionally, the proposed project will strengthen and diversify our stakeholder involvement. The team has a synergistic relationship with the Ohio Department of Natural Resources, Division of Forestry (ODNR-DF). We will expand the ODNR partnership by providing autonomous UAS support during all stages of the prescribed burn efforts, including pre-burn planning and reconnaissance, burn monitoring and control and post-burn survey. This approach will accelerate research and expand existing community outreach and education efforts.

2 Intellectual Merits

Intellectual merits of this work are anchored in the advancement and integration of autonomous unmanned aerial systems (UAS) with wildland fire management projects. Developed methods and materials will enhance situational awareness and enable autonomous risk-aware decision making in the face of unstructured uncertainty in a hazardous environment.

- Quantification of Unstructured Uncertainty for Decision Making: A complex environment presents hard to characterize obstacles that induce path-dependent resource constraints, e.g. heat loading or other perceived threats. Resource constrained path planning is NP-hard and they have not been studied under environmental uncertainty. We will study them as path-dependent integral chance-constraints. The autonomous agent will deliberately assume mission appropriate risk for path-planning. This will enable the discovery of "keyhole trajectories," through which highly cost-effective paths can be found.

- Learning Evidence for Environmental Situational Awareness: Multi-source data in a harsh environment is subject to interpretation (hot = fire or ash or hot shrubs?) and has a high conflict rate. When combined with repeatedly poor priors from ad-hoc process models, Bayesian information fusion can suffer, taking with it all downstream decision loops. We will construct new sensor belief functions that accurately reflect ignorance contained in hypotheses related to the environment. Evidential information fusion will effectively handle sensor epistemic uncertainty and allow reliable integration in an environment where not all data is trustworthy.
- Koopman Autoencoders for Weather Situational Awareness: UAS will be able bypass computational heavylifting to generate in-time micro-level local conditions that are nearly impossible to derive from aviation weather services or other atmospheric simulation-centric solutions. This will be achieved by enabling physics-informed learning of dynamics directly on the wind-related observable space as described by Koopman operator theory.
- Robust, Real-Time Data-Driven UAS Control: Efficient and reliable operations of autonomous vehicles with uncertain dynamics in real time requires nonlinearly stable and robust learning and control schemes that use available knowledge of applied inputs and observed outputs, to estimate (learn) the unknown inputs *even without prior training data or persistent excitation.* Primary requirements for reliability are: (1) computational efficiency, speed and accuracy in learning the unknown (disturbance) inputs; (2) stability to changes in input and output data; and (3) robustness to sudden changes in the system dynamics. We will meet these requirements through the design of Hölder-continuous and finite-time stable disturbance observers and data-driven control schemes. The unknown (disturbance) force and torque inputs will be represented using an *ultra-local model*. These schemes will provide guaranteed stability and robustness in autonomous operations of UAVs with uncertain but Lipschitz-continuous dynamics, if the control constraints are met. The control scheme will maintain actuator constraints, and warn the operator when these constraints are close to being violated due to large disturbance inputs.
- Environmental Impact on V&V: For extended periods of operation, UAS will perform beyond visual line of sight. Edge-computing, multi-modal sensing, task management and radio-based unmanned traffic management (UTM) system will form a testbed for integrating both aerial and ground-based autonomous systems in a physically hazardous environment.
- Prognostics for Eastern Forests: The majority of research on wildland fire behavior has focused on western forests, and less so on eastern forests. Differences in forest composition and structure, and differences in fuel composition and characteristics may translate into differences in fire behavior. This work will help to delineate any differences as well as similarities of fire behavior between eastern and western forests.

3 Broader Impacts

This research broadly impacts autonomy in UAS. But more importantly, the proposed partnership accentuates the right context for autonomous UAS. The decision making ability of autonomous agents has often been questioned, and such criticism is usually justified. Instead of potentially putting humans in danger, a better context for autonomous vehicles, and indeed, autonomous flight, is to take humans out of missions that involve danger and/or repetitive, stressful actions. This proposal is concerned with such roles for autonomous UAS in demanding environments. Robotic systems are already in operation for environmental and infrastructure monitoring, emergency response, homeland security, precision agriculture, land management, and transportation of goods. The science developed in this project will benefit these platforms, as well as applications involving other unstructured phenomena/environments with poorly modeled dynamics and/or anomalous interactions between sensors and their objects of interest. Examples include space and cislunar domain awareness (SSA), surveillance tracking, disaster response etc., where environmental uncertainty and/or unpredictable target behavior can create misleading or contradictory data. Our risk-versus-reward tradeoff strategy will help assess the merits of a particular rescue mission vis-à-vis the nature of the emergency, e.g. risk can be deliberately increased if the objective is to rescue humans trapped in an unfolding disaster. Our data-driven modeling, learning and control algorithms will find application where identification of unknown processes and systems play an important role, including robotics, smart cities, autonomous vehicles, medical devices, power grids, wireless and internet communications, and civilian and military logistics. Safe, reliable, and efficient learning and memory algorithms for complex processes and systems can have a large economic impact from the widespread deployment of these algorithms in applications like manufacturing, health care, and infrastructure. By avoiding data-intensive and labor-intensive methods for learning in poorly-known and dynamic systems and processes, human resources could be focused on higher level planning and execution of tasks that depend on these processes. This would enable applications of this research to realize the twin goals of greater societal and economic benefits.

The results of this work will be brought into the classroom to educate future natural resource managers on the aspects of fire behavior in general and specifically fire behavior in eastern forests. This work can provide more insight to fire behavior in eastern forests that can provide further guidance as to how best manage fuels in the wildland-urban interface. Findings from this research will be disseminated through conferences and journals in applied mathematics, controls, and cyber-physical systems conferences. Moreover, research results from the proposed research will be shared through collaborative work between the PIs and their collaborators in academia, as well as automotive and aerospace industry. The PIs will also work closely with the National Society of Black Engineers, the Society for Hispanic Engineers, and the Society of Women Engineers to identify students from under-represented groups with compatible interests to participate in this research.

4 Proposed Research

This proposal presents multidisciplinary integration of autonomous UAS through environmental characterization, evidential sensor fusion, autonomous mission planning and data-driven model learning, control and in-situ V&V. Specific research tasks are described in the sections below.

4.1 Environmental Situational Awareness

Trustworthy situational awareness is key to integration of autonomous systems in a fire hazard. We focus on two aspects of the operational environment that are especially relevant for UAS viability: (a.) rapid ("in-time") forecasting of local wind conditions, and, (b.) characterization of unstructured, dynamic obstacles through unsupervised learning.

4.1.1 Forecasting Local Winds through Data-Driven Reduced Order Modeling

UAS operations require current micro-level (< 1 *m spatial resolution*) conditions as well as short-range forecasts to allow sufficient decision lead-time [15]. Online data from the Aviation Weather Center does not meet these standards, especially in locally prevalent hazardous conditions, e.g. local "firestorms" can cause rapidly escalating wind conditions [16]. The full extent of available high resolution weather simulations, combined with onboard sensor and IMU data must be employed in a computationally scalable manner to create sufficiently accurate short-range forecasts [17–19].

We propose to employ the theory of the composition operator (Koopman operator) [20] for this prediction problem. Consider the following general, unknown structure of discretized atmospheric dynamics: $\mathbf{x}_{k+1} = \mathbf{F}_t(\mathbf{x}_k)$, $\mathbf{x} \in \Re^N$. The Koopman operator allows us to transform finite

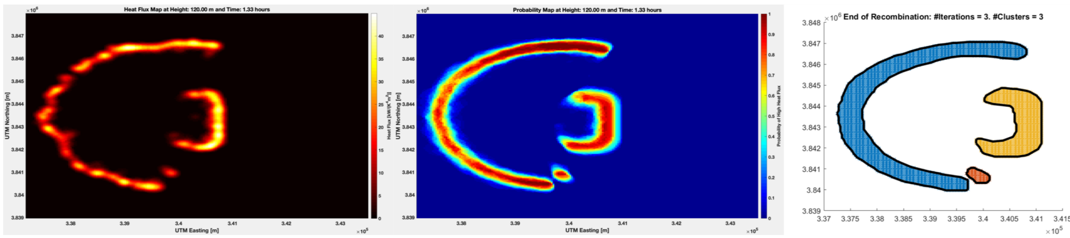

Figure 1: Left: Computed heat flux at flight level (FL $\sim 400\ ft$). Center: Probability distribution of flux $\geq 5\ kW/m^2$ at FL. Right: Unsupervised clustering to identify nominal obstacle boundaries.

dimensional nonlinear differential equations to an infinite dimensional linear operator that acts on a space of all possible *observable functions* of the state [21–24]. While it was originally developed for measure preserving (Hamiltonian) systems, the field has advanced to encompass dissipative systems, e.g. recent reduced order modeling of the Navier Stokes equations [22, 23, 25, 26]. Our premise is that due to insurmountable difficulties in emulating the true nature of local wind conditions, one must transform the state-space (pressure, temperature, water vapor pressure fields) to the directly "observable space". This includes *wind speed and direction*, on which the Koopman operator (KO) corresponding to the unidentified dynamics, $\mathbf{F}_t(\cdot)$ can be constructed through data-driven spectral analysis. Typically, the space of observables is much higher dimensional than the unobservable state, but its evolution is locally linear. Linearity motivates data-driven *reconstruction of the KO* for $\mathbf{F}_t$ through spectral analysis [27], resulting in special observables, namely the KO eigenfunctions [22].

If successfully uncovered, the finite dimensional KO spectral representation will help express the desired observable function (in this case, wind speed and direction) either directly in terms of the Koopman eigenfunctions or their projection (modes) [22, 23, 28, 29]. In recent years, several deep learning techniques, e.g. autoencoder variants, have been employed [24, 30–33]. We will combine multi-sourced wind data to generate micro-level short range wind speed and direction forecasts. The High Resolution Rapid Refresh model (HRRR-v2) developed at the National Centers for Environmental Prediction (NCEP@NOAA) [15] provides hourly updates with a 3 km resolution over the continental United States. This is to be combined with onboard sensor data that correlates attitude hold control inputs to local wind disturbances [17]. Unlike most studies that target steady state behavior through reduced order modeling, the objective here is to extend the current conditions to reliable short term forecasts. In addition to the usual identity and reconstruction losses, physics-informed losses will be included to accelerate convergence to modes dominant in the near term [33–38]. We have successfully performed this work for the prediction of electric current fields in kinetic plasma simulations for space explosions [39, 40].

4.1.2 Learning Unstructured Obstacles

We will characterize *physical*, *predicted* and *perceived* keep out zones (obstacles, regions of threat or retarded situational awareness) as obstacles with probabilistic boundaries. For example, Fig.(1):left depicts predicted flight-level heat flux. The center image shows probability contours of heat flux exceeding the critical value of 5 kW/m^{-2} for onboard equipment. Unsupervised clustering of this data is crucial because it will separate obstacles from each other so that flight space (solution domain for motion planning) can be maximized.

Our proposed approach builds upon the well known *k-means* (Lloyd's) algorithm [41]. Optimal unsupervised clustering will be achieved through a two-step recursion. In the first step, the outcome of *k-means* clustering is subject to repeated splitting based on statistical measures of member clusters (e.g. Mahalanobis distance of each point with respect to parent ensemble statistics).

Recognizing that this may cause "oversplitting", a second level of recursion is to be added that identifies cluster pools on the basis of *statistical recombination favorability.* Early results of this learning approach is shown in Fig.(1)(Right), which correctly identifies three distinct clusters in the probabilistic heat-flux data. Finally, clustered obstacle data will be converted to computationally digestible probabilistic representations, using appropriate parametric cumulative distribution functions (cdfs), including heavy tails depending on the quality of situational awareness. E.g., consider a polygon probabilistic perimeter:

$$\bigcap_{i=1}^{N}\left(\bigcup_{j=1}^{M_i} P\left(a_{i,j}x + b_{i,j}y > (c_{\mu,i,j} + \zeta_{i,j})\right) \geq 1 - \epsilon_i\right),$$

Here, $c_{\mu,i,j}$ is the mean value of the parameter c. of the polygonal keep-out zone, $\zeta_{i,j}$ (ξ_i) is the random variable with zero mean representing the uncertainty in those parameters, and ϵ_i is the *prescribed level* of risk violation. Thus for a prescribed risk parameter ϵ_i, the polygonal constraint can be converted to an equivalent deterministic form: $\bigcap_{i=1}^{N}\left(\bigcup_{j=1}^{M_i} a_{i,j}x + b_{i,j}y > c_{\mu,i,j} + F^{-1}_{\zeta_{i,j}}(1-\epsilon_i)\right)$, where $F_{\zeta_i}(\cdot)$ represents the cumulative distribution function. We will treat both spatial chance-constraints and the much more difficult resource-chance-constraints, that manifest as path integrals in motion planning.

4.2 Onboard Guidance Navigation & Control

4.2.1 Resource Chance-Constrained Planning

We propose graph-based chance-constrained path planning for an environment with dynamic, unstructured fire hazards. *Chance-constraints* (CC) [42] offer an appropriate probabilistic architecture to incorporate uncertainty in unstructured/partially known or intangible obstacles, e.g. hot regions, gusty regions, GPS denied regions [43–47]. We will extend this construct to <u>resource-constraints</u>, in which constraints manifest as a probabilistic <u>path dependent</u> "load" that accumulates over time. Probabilistic resource-constrained path planning is a problem of immense importance but scant progress. In contrast to "instantaneous" constraints, such as physical obstacles, resource constraints accumulate as a path-dependent load over time and lead to an NP-hard optimization problem [48–51]. Consider a UAS flying over a hot area characterized by contours of heat flux, e.g. shown in Fig.(2)(Left). In this "obstacle", the heat flux itself does not pose a threat to the robotic agent. It is the aggregate effect of spending time within the hot region that must be monitored and limited. The path-integral of heat flux aggregates to temperature rise, which can be directly correlated to safety of onboard equipment. Similar aggregate, aka *integral*, aka *path loading*, aka *resource* constraints can be posed in the context of noise limits in urban flight, cumulative exposure to harmful elements like weather phenomena, chemicals, radiation, etc. General accumulation of vehicle damage or vehicle exposure is proposed to be modeled by the binary function $\delta(t)$, such that "$\delta(t) = 1$" represents a compromised vehicle. The resultant **chance** constraint is: $P(\delta(t) = 1) \leq \epsilon$, where, damage ($\delta(t) = 1$) occurs due to the path-dependent accumulation of a detrimental load:

$$\underbrace{\text{“}\delta(t) = 1\text{”}}_{\text{“damage”}} \;\equiv\; \int_0^t \underbrace{\mathcal{F}_{\mathcal{L}}(\mathbf{y}(\tau), \mathbf{u}(\tau), \tau)}_{\text{rate of damage}}\, d\tau \;\geq\; \underbrace{\mathcal{L}^\star}_{\text{loading limit}} \tag{1}$$

The rate of damage is given by the function $\mathcal{F}_{\mathcal{L}}(\cdot,\cdot,\cdot)$ and is context dependent. In the case of flight over fire, it represents a normalized heat flux as follows

$$\mathcal{F}_{\mathcal{L}}(\mathbf{y}(t), \mathbf{u}(t), t) \;=\; \frac{A}{mc_p}\phi(\mathbf{y}(t)) \tag{2}$$

the variables above have the usual meaning (m = vehicle mass, A = incident area, c_p = heat capacity, $\phi(\cdot)$ = heat flux). Heat flux is allowed to be negative (cooling effect), allowing the

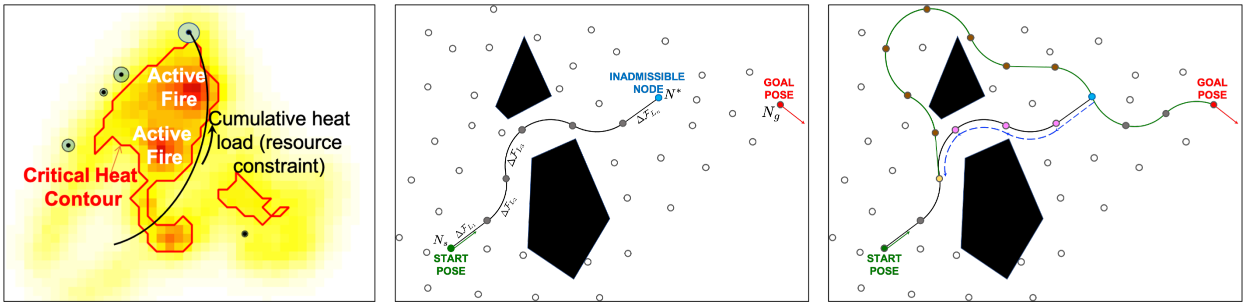

Figure 2: Hybrid A^* Path Planning with Backtracking

planner to perform load-shedding by interspacing flight through hot regions with flight over cooler areas. We will develop novel kinematically admissible hybrid-A^* graph methods to solve resource chance-constrained optimal planning. State-of-the-art directional graph search does not consider probabilistic resource constraints. Even for deterministic resource constraints, they do not yield optimal paths because node *inadmissibility* due to resource constraint violation is path dependent [51,52]. In Fig.(2) (Center), inadmissibility of node N^* occurs due to the integrated load over the shown path: $\sum_{k=1}^{n} \Delta\mathcal{F}_k$. The proposed approach is based on the following principles:

- Node-inadmissibility is path-dependent. In fact, an entire section of the search space can get blocked-off because of such indirect violations. In Fig.(2) (Center), the blue node violates the cumulative loading constraint due to the path taken to arrive at it (gray nodes).
- Graph search must backtrack from an inadmissible node, with an appropriate stopping condition (Fig.(2): blue node → yellow node). All nodes (and their posterity) shown in the backtracking path (blue, pink and yellow) belong to the *closed* set (*visited* set) and must be released into the search space. Directional search resumes (at the yellow node) by picking the second best node, causing a redirection of the graph search.
- Research will focus on stopping criteria and minimal time backtracking. Cascading constraints will be considered. Convergence proofs will be developed for optimality of the forward path.

4.2.2 Evidential Multimodal Sensor Fusion

Our proposed evidential platform for multi-source data fusion is suitable for an environment typified by high incidence of poor priors in the Bayesian sense. Each sensing modality, as well as the forecasting agent (if available), serves as an "expert" that furnishes its beliefs about various process related propositions. We will employ learning algorithms to construct these beliefs from field data, which will be fused via evidential reasoning to properly quantify and incorporate <u>sensor ignorance</u>. E.g. when the process is "fire", we have the following contributing *experts*:

i.) Fire Perimeter Forecaster (if available): $\mathbb{F}$. FARSITE [53,54] or BehavePlus [55,56];
ii.) On-Ground Temperature Sensors (if available) or Satellite Imagery (if available): $\mathbb{T}$;
iii.) Online RGB (vision) sensors onboard UAS: $\mathbb{V}$;
iv.) Online IR sensors onboard UAS: $\mathbb{R}$.

A possible frame of discernment for evidence combination is $\Theta = \{V,\ F,\ S\}$, where V is all fuel (vegetation), F is fire and S represents all nonburnable elements. Each element can be further divided depending on available data, e.g. $V = \{\text{Maple}, \text{Oak}, \text{Poplar}\}$, $S = \{\text{Ash}, \text{Boulder}, \text{Water}\}$. Expert data is interpreted as *evidence* regarding relevant fire related propositions, e.g. in a given cell of a rasterized model, what is the evidence supporting belief in the proposition "{Fire}", or "{Ash}", or, "{Fire OR Ash}"?

The degree of belief that a particular proposition $A \subseteq \Theta$ is true is derived from the current evidence in support of A. This numerical "amount" of belief for any proposition A supplied by an expert E is the so called mass-number, $m_E(A)$. The evidential framework (Dempster-Shafer) differs from Kolmogorov's formalism because $m_E(\Theta) \neq m_E(V) + m_E(F) + m_E(S)$. In fact, $m_E(\Theta)$ is the *ignorance* of E and $m_E(\Theta) = 1$ represents complete ignorance [57, 58]. This guard-rail allows an expert to implicitly refrain from participating in information fusion when its data is not trustworthy. Expert assigns their "lower" (belief: $Bel_E(A) = \sum_{B \subseteq A} m_E(B)$) and "upper" (plausibility: $Plaus_E(A) = \sum_{B: B \cap A \neq \phi} m_E(B)$) degrees of support to each proposition, which will be combined [59,60], as proposed in Fig.(3) (top panel).

We will develop belief assignment models for temperature, vision and IR sensors. This work is under progress [46, 61, 62] and will be refined in this project. For example, temperature readings provide a *predictive* presence of fire and make use of a wildfire's propensity to increase the surrounding temperature of the non-burning fuel, referred to as its *heat aura* [63]. Physics will be combined with empirically known sensor variability to assign belief values [46,61,63]. On the other hand, the vision/IR sensors behave in a more direct manner. Environmental features display particular color signatures [64]: see Fig.(3)(Bottom), which shows the R, G and B component intensity values of an image taken by a UAS during a prescribed fire in Marion OH (2019). Work so far has conducted <u>manual</u> quantification in terms of match distance discrepancy [65]) of specific quantities of interest, e.g. $\Sigma(R, G, B)$ against an idealized set of fire, fuel and ash distributions [62, 66]. Belief assignment results for the vision expert are shown in the bottom of Fig.(3). The proposed research will make sensor information more reliable in the presence of ambiguity by conducting field tests for robust visual and IR belief assignment.

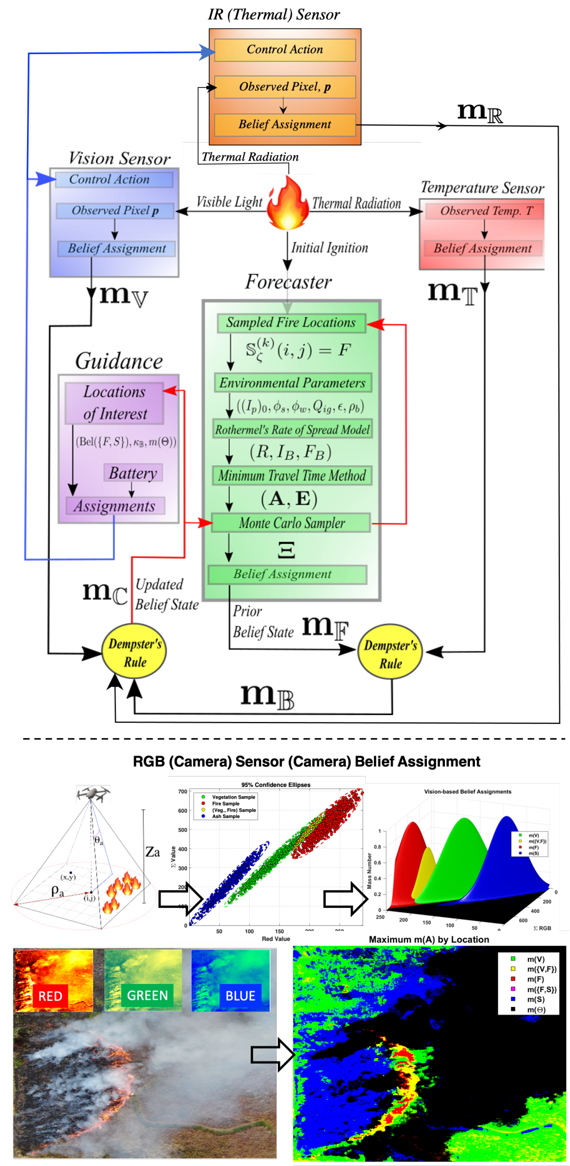

Figure 3: Top: A Multi-Expert Evidential Information Fusion Framework in a Wildfire. Bottom: Belief Assignment for a Vision Sensor

4.3 Data-Driven Modeling and Control

Finite-Time Stable Disturbance Observer

Our approach is based upon recent advances in rapid finite-time stable (FTS) Hölder-continuous disturbance/uncertainty observers that accurately estimate (unknown) disturbance forces and torques acting on a known physics-based model of the dynamics of the UAS coupled with a data-driven robust feedback control scheme, as given in Co-PI Sanyal recent work [67]. This combined scheme can be thought of as a combination of a real-time (and really fast) machine learning scheme with a robustly stable control scheme. The two novel directions in the proposed research in this direction will be: (1) develop disturbance observers based on the preliminary work in [67], for the Lie group of rigid body translational and rotational motions SE(3); and (2) design control schemes for rotorcraft UAS dynamics that take into account their underactuation in translation, and rotor thrust constraints.

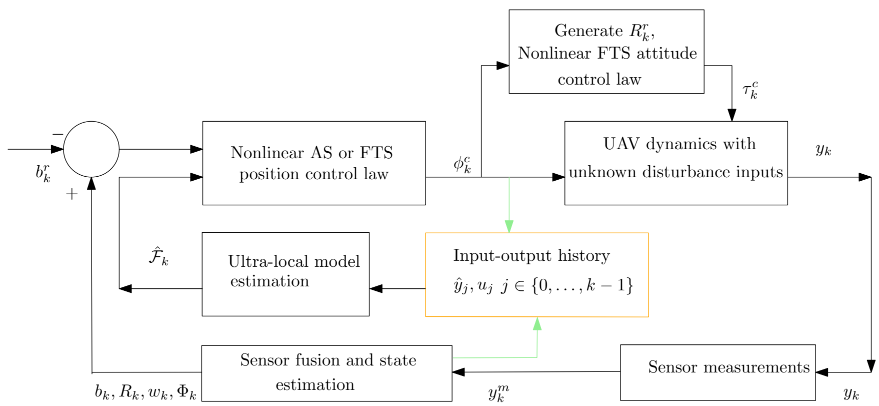

Figure 4: Block diagram representing our proposed nonlinear autonomous control framework for UAS with uncertain dynamics.

Consider a UAS flying through a region of unsteady aerodynamics, such that its instantaneous configuration (pose) is given by its position vector in an inertial frame $\mathcal{I}$ is denoted by $b = (x, y, z) \in \mathbb{R}^3$ and its orientation (attitude) denoted by $R \in \mathrm{SO}(3)$, characterized as the rotation matrix from a body-fixed frame $\mathcal{B}$ to inertial frame $\mathcal{I}$. Also, SO(3) is the 3-dimensional Lie group of rigid body rotations. The instantaneous pose is therefore described by $g = (b, R) \in \mathrm{SE}(3)$. The kinematics of the UAS is given by: $\dot{b} = v = R\nu$ and $\dot{R} = R\Omega^\times$, where, $v \in \mathbb{R}^3$ and $\nu \in \mathbb{R}^3$ denote the translational velocity in frames $\mathcal{I}$ and $\mathcal{B}$ respectively, and $\Omega \in \mathbb{R}^3$ is the angular velocity in frame $\mathcal{B}$. The cross-product operator $(\cdot)^\times : \mathbb{R}^3 \to \mathfrak{so}(3)$ maps 3-vectors to skew-symmetric 3×3 matrices, which is also the Lie algebra $\mathfrak{so}(3)$ of SO(3). The dynamics (kinetics) of a rotorcraft UAS with a body-fixed plane of rotors is given by: $m\ddot{b} = m\dot{v} = (f^c R - mg)e_3 + \phi^d$, $\;J\dot{\Omega} = \tau^c - \Omega^\times J\Omega + \tau^d$. Here, $e_3 = [0\ 0\ 1]^{\mathrm{T}}$, $f^c \in \mathbb{R}$ is the scalar thrust force and $\tau^c \in \mathbb{R}^3$ is the control torque created by the rotors, and $m \in \mathbb{R}^+$ and $J = J^{\mathrm{T}} \in \mathbb{R}^{3\times 3}$ are the mass and inertia matrix of the UAS respectively. The disturbance force and torque are denoted ϕ^d and τ^d respectively, which are mainly due to unsteady aerodynamics in this application. A block diagram of the overall robust feedback control framework is given in Fig.(4). The dynamics model is expressed in discrete time for real-time identification of these disturbances and their compensation for tracking control [68, 69] as shown below:

$$b_{k+1} = b_k + w_k,\ mw_{k+1} = (f_k^c R_k - mg)e_3 + \phi_k^d, \tag{3a}$$

$$R_{k+1} = R_k \exp(\Phi_k^\times),\ J\Phi_{k+1} = \tau_k^c + \exp(-\Phi_k^\times)J\Phi_k + \tau_k^d, \tag{3b}$$

where the discrete time variables are denoted with a whole number subscript $k \in \mathbb{W}$, corresponding to a sampling instant t_k. These equations are obtained in the form of a Lie group variational integrator, and the matrix exponential in Eq.(3b) is evaluated using the Rodrigues formula for numerical efficiency [69, 70]. If the sampling period $t_{k+1} - t_k = \Delta t$ is constant, then setting $w_k = v_k \Delta t$ and $\Phi_k = \Omega_k \Delta t$ gives a first order integrator. The unknown disturbance inputs $\chi_k = (\phi_k^d, \tau_k^d) \in \mathbb{R}^6$ will be learnt in real time according to an observer law of the form:

$$\hat{\chi}_{k+1} = \mathcal{D}(\|e_k^\chi\|)e_k^\chi + \chi_k, \quad \text{where} \quad e_k^\chi = \hat{\chi}_k - \chi_k,\ \hat{\chi}_0 = \chi_0 \text{ is given}, \tag{4}$$

and $\mathcal{D} : \mathbb{R}^+ \to \mathbb{R}$ is a Hölder-continuous function designed to make this observer finite-time stable (FTS), as in [67]. For each k, $\chi_k = F(f_k^c, R_k, \tau_k^c, \Phi_k)$ will be obtained from known (or filtered) inputs and states, to estimate (and predict) the disturbance inputs at instant $k+1$. Here $F(\cdots)$ denotes the known terms on the RHS of the dynamics in Eqs.(3) from the physics-based model of

UAS dynamics. The FTS disturbance observer so designed will converge in finite time to a bounded neighborhood of the zero error vector (i.e., $e_k^\chi = 0$) if the rate of change of the disturbance inputs is bounded (i.e., $0 < \|\chi_{k+1} - \chi_k\| < B^\chi$). It will converge to $e_k^\chi = 0$ if the χ_k is constant.

Control Design

The control scheme can compensate for the above learned disturbances while tracking a desired trajectory given by a an autonomous guidance scheme (Sec.(4.2.1)). This trajectory tracking scheme can also be designed to ensure asymptotically stable (AS) or FTS convergence of tracking errors to a desired bounded neighborhood of the zero vector, as in [68,71,72]. For a given reference position trajectory in time $b^r(t)$, we obtain $b_k^r = b^r(t_k)$ and $w_k^r = b_{k+1}^r - b_k^r$, by sampling. A feedback tracking control law ϕ_k^c is designed to track w_k^r where the controlled translational dynamics satisfies:

$$m e_{k+1}^w = \bar{\phi}_k^c - mge_3 + \phi_k^d - m w_{k+1}^r, \text{ where } e_k^w = w_k - w_k^r \text{ and } \bar{\phi}_k^c = f_k^c R_k e_3 - \hat{\phi}_k^d. \tag{5}$$

We will design a feedback law for ϕ_k^c based on an appropriately designed Lyapunov function $V(e_k^b, e_k^w)$ such that its first difference satisfies:

$$\mathcal{L}_{\mathcal{F}(\cdots)} V(e_k^b, e_k^w) < 0, \text{ where } \mathcal{F}(\cdots) := \mathcal{F}(\bar{\phi}_k^c, \phi_k^d, w_{k+1}^r) := \bar{\phi}_k^c - mge_3 + \phi_k^d - m w_{k+1}^r, \tag{6}$$

and $\mathcal{L}_{\mathcal{F}(\cdots)}$ denotes the (finite) first difference along the discrete flow given by $\mathcal{F}(\cdots)$. The particular form designed for this first difference will determine whether the resulting control scheme leads to AS or FTS convergence of the tracking errors $(e_k^b, e_k^w) \in \mathbb{R}^6$. Next, a reference attitude $R^r \in \mathrm{SO}(3)$ to be tracked is generated that satisfies:

$$R_k^r = \exp(\alpha_k v_k^\times) \text{ s.t. } \alpha_k \in (-\pi, \pi], \ \|v_k\| = 1, \ R_k^r e_3 = \phi_k^c / \|\phi_k^c\|, \text{ and } \phi_k^c = \bar{\phi}_k^c + \hat{\phi}_k^d. \tag{7}$$

The selection of R_k^r satisfying Eq.(7) is not unique unless the third component of the unit vector v_k is set to zero; [72,73] give appropriate choices for the reference attitude. As rotorcraft UAS with a fixed plane of rotors are underactuated, with the attitude control being an inner loop to generate the required thrust direction for the outer loop position control, we will use a FTS attitude control scheme in discrete time that generates a control law for $\bar{\tau}_k^c := \tau_k^c - \hat{\tau}_k^d$, using an approach similar to that in [69].

4.4 Study of Fire Behavior and Spread

We aim to study the effects of physiography, fuel characteristics and weather conditions on fire behavior and spread. The Ohio Department of Natural Resources, Division of Forestry (ODNRDF) regularly burn the state forests in the fall and spring as part of their oak forest management. For this study, two burns will be scheduled - one during the second year and one during the fourth year of the proposed study. Due to the intensity of field work and the finicky nature of fire weather and conditions, it is best to not schedule burns the same year. Working with ODNRDF, forests located in southern or southeastern Ohio that are identified for scheduled burning will be selected, and 10 hectares will be isolated within each forest for study purposes. These forests reside in a part of Ohio that lies on the unglaciated Appalachian Plateau, which consists of steep hills and valleys and is the most rugged area in the state. The 10 hectare study areas will be selected such that it has opposing/opposite aspects to capture the influence of aspect on fire behavior. If possible, the forest in the second burn will have aspects different than the forest of the first burn.

Figure 5: Top: Burn site in Pomerene Forest. Bott. **L**: LAD-DCS UAS *Falcon* in a prescribed burn. Bott. **R**: Past ODNR Burn in Richland Furnace Forest.

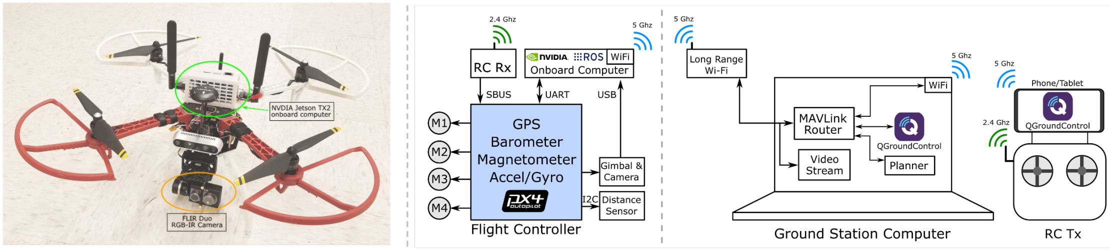

Figure 6: UAS Architecture and System Integration

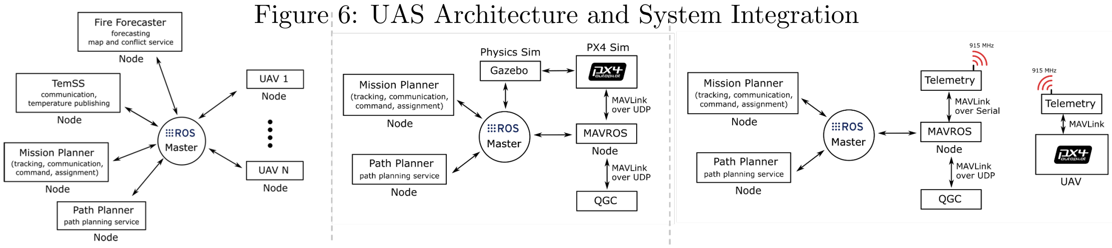

Figure 7: ROS Integration and Vehicle Emulation with Gazebo

For each burn, pyrometers (offline) will be placed 15 m apart across and downslope to create a gridwork across the different aspects. They consist of aluminum tags painted with temperature-sensitive paint (Tempilaq®) and attached to a metal pin at 0, 20, and 40 centimeters above the ground [74]. Placement of aluminum tags at different height locations serves as an indicator of flame height. On each aluminum tag, temperature-sensitive paints will be applied, each with a different melting point from 93°C to 982°C, as a means to record the fire temperature [74–79]. Pyrometers will be installed before the burn and collected immediately after the burn. Online temperature sensing nodes (identified as TemSS in Fig.(7)) will be placed in uniform distribution over the burn area for guiding UAS flight. At the time of fire ignition, the relative humidity and dry bulb temperature will be measured with the Kestrel 5500FW Fire Weather Meter Pro LiNK for the purpose of acquiring the fuel moisture index [81]. These measurements will be recorded every 15 minutes once the fire is started and until the burn is completed. Wind speed and direction will likewise be recorded at the start of burn ignition and every 15 minutes with the same Kestrel 5500FW Fire Weather Meter Pro LiNK until the burn is completed. UAS burn monitoring and control support will be provided by sensing and communications systems described in Sec.(4.5).

4.5 Systems Integration and Verification of GN&C

4.5.1 Integration

Intermittent communication loss and latency are significant challenges in a wildfire environment. Our base flight platform (Fig.(6):Left) carries the NVIDIA Jetson TX2 [82] single board computer due to which it is capable of performing computer vision tasks on board. The Jetson TX2 module is mounted on the Orbitty Carrier board [83] to receive power and provide access to peripherals such as USB and serial port (UART) for connection with a PX4 board. We will integrate sensor fusion (Sec.(4.2.2)) and data-driven control (Sec.(4.3)) tasks with the PX4 autopilot through Linux based ROS. Our ground station will run a ROS master that connects to several nodes such as mission planner node, path planner node and various UAV nodes. It will also connect other nodes each running processes like the fire forecaster and TemSS (Temperature Sensors) as shown in Fig.(6). The PX4 ecosystem provides a ROS package called MAVROS [84]. It contains a library to instantiate a node that connects to MAVLink devices and act as interpreter between the MAVLink messages and equivalent ROS messages. Fig.(7) shows the ROS architecture for interfacing the physical UAV or a simulated UAV (Gazebo) with the mission and path planner.

Here, the mission planning node is the primary node which is responsible for performing high level tasks such as keeping track of the UAVs, executing multi-agent mission periodically, computing assignment pairs and fetching optimal paths. It is not practical to test the ROS based software without risking unexpected vehicle take-off or loss of node connectivity due to software bugs. With propellers removed, it is not possible to test any mid-flight commands and behavior. Therefore, we propose to test ROS based software in simulation.

4.5.2 V&V

Randomized techniques with performance bounds will be employed in the simulation approach. We will address coverability (exhaustiveness of scenario search) and realism with the key goal of achieving quantifiable trust in the verification results. A mixed approach for V&V is proposed that focuses on exhaustive simulations through scenario generation. The corroborative V&V framework proposed by Webster et al. [85] will be employed, which seeks to bootstrap conclusions of one approach by another. Flight testing using dynamics simulator Gazebo will enable simulation-based testing. Simulated temperature resource-chance-constraints will be tested in field tests using Gazebo. The MAVROS node provides a link to connect the simulated PX4 to the ground control station, QGroundControl. These tests will help build up to the biannual in-situ validation tests in presence of the stakeholders during prescribed burns.

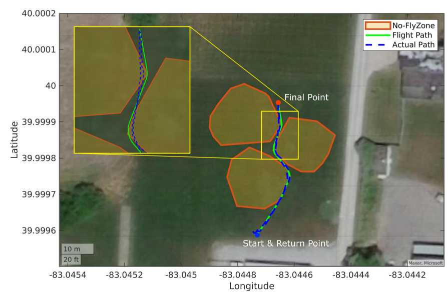

Figure 8: UAS tracking in field tests in Columbus Metroparks

5 Previous Relevant Work by Members of Proposal

For each PI, see the collaboration document and respective biosketch.

6 Risk & Mitigation

▶ **Student Safety:**
About a dozen student volunteers (school, UG, grad) will participate in prescribed burns. Student safety will be the foremost priority: fire safety protocols will be followed, including debriefing prior to and on day of burn, providing all students with the federally required personal protection equipment, and requiring all students to have completed certified prescribed fire training. Participants will be connected through hand-held radio communication.

▶ **Escaped Burns:**
We remain aware of the risk of possible escape of prescribed burns and the possible dispersion of smoke into human-sensitive areas. ODNRDF always has a prescribed burn plan in place for each burn that is conducted, which includes all necessary resources and tactics in the event of an escaped burn and how smoke is to be managed. State law requires that certified burn managers, which have training on escaped burns, manage prescribed burns. All ODNRDF prescribed burns have multiple burn managers present, and Co-PI Williams who is also a certified prescribed burn manager will be present on the burn conducted in this proposal.

▶ **Weather/Unforeseen Circumstances:**
The primary challenge will be the ability to conduct a given prescribed burn. It is possible that weather conditions necessary to conduct a prescribed burn safely does not occur during a 2 - 3 month window to burn in the fall. Indeed, a burn can be called off at an hour's notice due to sudden changes in wind, precipitation and/or humidity. If a fall burn cannot be conducted then the burn will be moved to late winter/early spring. The 48 month window of this project creates a realistic likelihood of being able to conduct multiple successful burns.

7 Evaluation

▶ **Metrics for Evaluation of Algorithms in Field-Tests:**

Each element of the algorithmic framework for UAS missions will be evaluated against meaningful success metrics. These metrics include accuracy (performance quality), computational efficiency (response speed) and robustness (handling off-nominal conditions). Weather situational awareness (local winds: Sec.(4.1.1)) will be evaluated over a spatial resoution threshold of $< 1\ m$. Retrospective analysis of on-board sensing data and corrective flight-control torque time histories will be used for evaluation of accuracy. Obstacle situational awareness (Sec.(4.1.2)) will be evaluated against statistical and information theoretic clustering accuracy metrics [89]. These include *purity*, $p > p^*$, p^* to be determined (TBD), the *rand index*, $R > R^*$, R^* TBD and an appropriately normalized mutual information, $MI > m^*$, m^* TBD. The speed of clustering is bounded above by path-planning update requirements (see next). The path-planning update rate requirement is relatively benign (matching the time-scale of a wildfire), set nominally at 0.1 Hz. This must include clustering, obstacle characterization and solution of the resource-chance-constrained optimal path (Sec.(4.2.1)). We will perform convergence analysis of the proposed backtracking graph search, with the objective of proving local/global optimality. Robustness of the planner (Sec.(4.2.1)), data-driven disturbance observer and controller (Sec.(4.3)) will be evaluated in simulation (via Gazebo dynamics) and with hardware-in-the-loop field tests. Tests of speed and accuracy will graduate upwards, starting at ideal environmental conditions and working up to realistic scenarios. We will pay special attention to waypoint hitting radius. The evidential sensor fusion framework is responsible for generating target locations for path-planning (e.g. maximum sensor conflict and relevant fire hypotheses). Its accuracy will be assessed in terms of large scale metrics such as mean radial error (helps assess accuracy of fire perimeter), representation error (was higher belief assigned correctly?) [90]. Estimation robustness will be assessed via confidence threshold values, tested against benchmarking data sets (e.g. see Sec.(6.3) in Ref. [90]).

▶ **Evaluation of Prescribed Burn Outcomes:**

Fire temperature will be recorded at the ground surface level. We will determine how slope steepness and location (lower, mid, upper), slope aspect, surface fuel composition (by species group), fuel loading of fine fuels (biomass), fuel moisture (measured as fuel moisture index) during the burn, air temperature, and relative humidity affects the fire intensity and rate of spread. All pyrometers measuring fire temperature will be georeferenced. A GIS-produced map will display the layers of fire temperature, flame height, slope steepness, forest canopy closure, fuel load, and fuel composition across the landscape by aspect. These factors will be correlated and modeled with fire temperature to determine the relationships that exist. Fire temperature measured on the ground will be used as ground-truthing for data collected by UAS. The data collected will be placed into the Rothermel surface fire spread model [91,92] and the subsequent predictions of fire intensity and rate of spread will be compared with the results of the analyzed data in this study.

The slope and aspect will be measured and recorded at each pyrometer location. The forest canopy density will be measured with a GRS Densitometer and recorded prior to the burn. The forest litter depth to mineral soil will be measured at each pyrometer location. Quantification of fuel around the pyrometers will follow the procedure of Ref. [80]), which covers 1-hour through 1000-hour fuels. An additional sample of forest litter will be collected down to the mineral soil from the 0.1 m^2 sub-sample plot in the 1 m^2 fuel sample plot described in [80]. This litter sample will be sorted by species category (white oak, red oak, hickory, maple, etc.) in the lab and oven-dried at 60°C for 72 hours to determine the proportional biomass by species composition. Pre-burn reconnaissance flights will be validate the fuel loading distribution across the burn area.

▶ **Evaluation of Educational Objectives:**
To evaluate the effectiveness of our new cross-disciplinary course material, we will participate in the *Course Design Institute* (CDI) at the OSU University Institute for Teaching and Learning (UITL). This is described in detail in Sec.(8.1) below, with focus on the *backward-design approach*.

8 Education and Outreach

We will integrate field experiences in UAS autonomy and prescribed wildland burns to develop cross-disciplinary educational material suited to upper level undergraduate and graduate students, fire-management professionals, and general public outreach. There will be lasting impact on two fields that have traditionally been disparate.

8.1 Educational Objectives and Tasks

Course modules will be created under the umbrella of *Robotic Missions in Wildland Fires.* These will include detailed notes and recorded video lectures spanning the following interdisciplinary topics: fire ecology, fire weather environment and fire behavior, detection and monitoring, designing and conducting a prescribed burn, principles of axiomatic theory of probability, stochastic process modeling, evidential information fusion, assimilation of uncertainty in robotic trajectory design and data-driven modeling and control. Fire models will include NEXUS, FARSITE, and BehavePlus.

A **co-taught pilot course** built on the above topic will be offered in Fall 2023, as a cross-listed course between MAE (OSU and Syracuse) and SENR (OSU), aimed at the senior and early graduate student level. It will train students to become fire behavior analysts and provide advanced baseline fire behavior knowledge to be utilized in future work or research. Our audience includes students of engineering and SENR; professionals of wildfire management, ecology and firefighting departments; and, the general public, especially residents in the vicinity of prescribed burns and wildfires. All video lectures will be produced with assistance from the OSU Office of Distance Learning. Co-PI Sanyal is also committed to authoring a monograph on guidance, navigation and control schemes for autonomous unmanned aerial vehicles and their formations.

Participation in UITL Programs
At OSU, the University Institute for Teaching and Learning (UITL) aims to integrate and enhance ongoing efforts in teaching at Ohio State, and to elevate visibility and importance of such work to the institutional level. The PI's commit to participating in UITL's *Course Design Institute* (CDI), in order to engage in design of the cross-disciplinary course based on evidence-based principles of how people learn. CDI will help us implement *backward design* [93], in order to first identify specific, student-centered goals and objectives before we finalize the content, organization and delivery. PI Kumar has had positive experience working with UITL in the past and this project creates the perfect opportunity to renew this partnership.

Engagement with K-12 Columbus Schools
The PI's team has a successful partnership with local schools in terms of hosting school students in his Lab for summer internships. Even during COVID, high school students have worked with PI Kumar. School students absolutely love research on aerial robotics, as well as environmental science. The proposed project is a mouth-watering combination of the two and we expect interest to be very high. We will sponsor student-driven projects in which graduate students will design computational and field-test challenges and mentor high-school students towards completing them. We have strong existing partnerships with two schools: a) the Metro Early College High School (MECHS), which was established through a collaboration between OSU and the Battelle Memorial Institute, and, b) the Columbus Academy. We will contribute projects to MECHS' *Early College Experiences (ECE)*, which are hands-on opportunities for juniors and seniors to earn high school

credits, participate in internships, and take college coursework. All projects and internships will be offered to students from underrepresented and underserved communities and encourage them to pursue higher education in engineering. We will invite two high-school students to participate in the preparation and execution of prescribed burns. They will travel with our group to the burn site and assist in our UAS mission activities. At least one of these two students will be selected from underrepresented groups. We will work with the National Society of Black Engineers, the Society for Hispanic Engineers, and the Society of Women Engineers to identify candidate students.

Prairie Burns

To maximize opportunity for experiential learning, we will participate in the annual tall-grass prairie burns at the Larry R. Yoder Prairie Learning Laboratory at OSU's Marion campus. In 1987, the Prairie was designated an Ohio natural landmark and has grown to 11 acres at the present time. We have a "gentlemen's agreement" to burn parts of this prairie every year. This project will consolidate the ENR 3335 course series (Wildland Fire Management and Lab) at OSU, which conducts the burn on the prairie and fulfills the Federal S-130, S-190, L-180, and I-100 requirements for Red Card (Wildland Fire Incident) certification.

8.2 Public Outreach

Public outreach material, including pamphlets and PSA videos, will be created that provide timely information about prescribed burns and describe their benefits to the resident community. The content will include connection of prescribed burns to ecosystem health, wildfire suppression and climate change. These materials will be developed with the help of MAE and SENR students and distributed through local and online/social media channels.

9 Results from Prior NSF Support

I. ECCS-1254244/EPCN-1700753: "CAREER: An Integrated Hybrid Forecasting Framework for Increased Wind Power Penetration". PI: Mrinal Kumar. Duration: 02/15/2013 - 01/31/2019, Amount: $400,000. **IM:** 1.) meshless variational approaches to solve high dimensional Fokker-Planck equations; 2.) adaptive closed-loop Monte Carlo framework for uncertainty forecasting with guaranteed convergence. **BI:** Increase wind penetration in the power-grid by reducing the risks associated with it, methodologies also relevant for predictive analytics of other complex systems, e.g. space situational awareness and tracking complex phenomena such as wildfires. **Accomplishments:** Two Ph.D., one post-doc, two MS and numerous UG and school students. 16 peer reviewed articles (6 journal: Refs. [86,87,94–97]) and 10 refereed proceedings: Refs. [98–107]).
II. CMMI-1563225: "A Novel Computational Framework for Chance-Constrained Optimal Control". PI: Anil Rao, Co-PI: Mrinal Kumar. 09/2016 - 01/2021, Amount: $398,917. **IM:** A novel approach for chance-constrained optimal control (CCOC) involving highly accurate approximations of complex chance constraints has been developed that can be readily integrated into nonlinear programming software. **BI:** Impacts a wide variety of CCOC problems including human motion, cyber-physical systems, financial systems, optimal air-traffic control, underwater vehicle control etc. **Accomplishments:** 2 Ph.D. students. 10 publications (4 journal [42, 45, 108, 109] and 6 conference [43, 44, 46, 66, 110, 111]), 2 best-paper awards, two AFRL Faculty Summer Fellowships.
III. CNS 1739748: "CPS: Medium: Enabling Multimodal Sensing, Real-time Onboard Detection and Adaptive Control for Fully Autonomous Unmanned Aerial Systems." PI: Qinru Qiu, Co-PI: Amit Sanyal. 10/2017-9/2021, $600,000. **IM:** Fast onboard waypoint allocation, trajectory generation and nonlinearly stable control using computer vision and AI (DNN/DRL) in GPS-denied and/or cluttered indoor environments [68,69,112–114]. **BI:** Advances UAV technology and benefits machine intelligence through higher autonomy and reliability in operations. **Accomplishments:** 2 recently graduated PhD and 1 current PhD student partly supported by this grant.