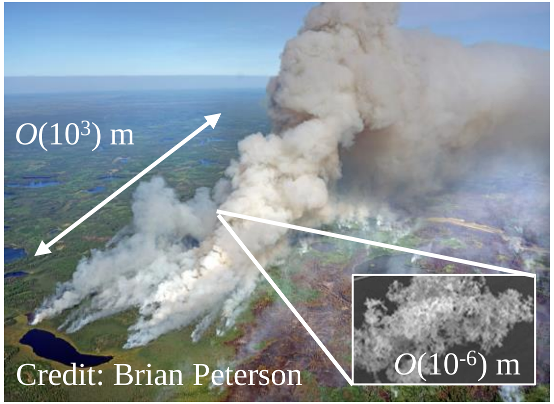
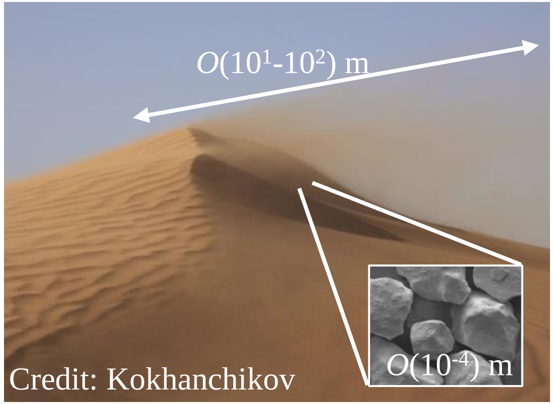
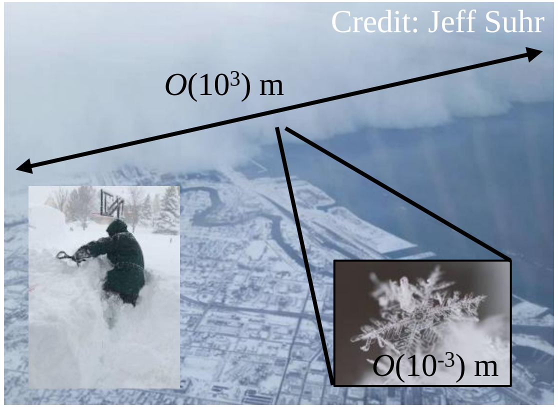
# 3D Characterization of Smoke Plume Dispersion Using Multi-view Drone Swarm

# *Introduction*

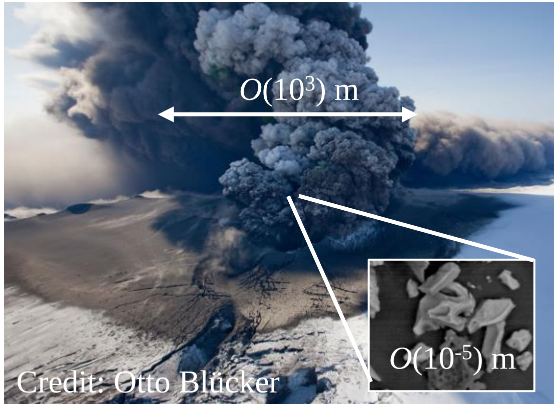
# Atmospheric Particle Transport



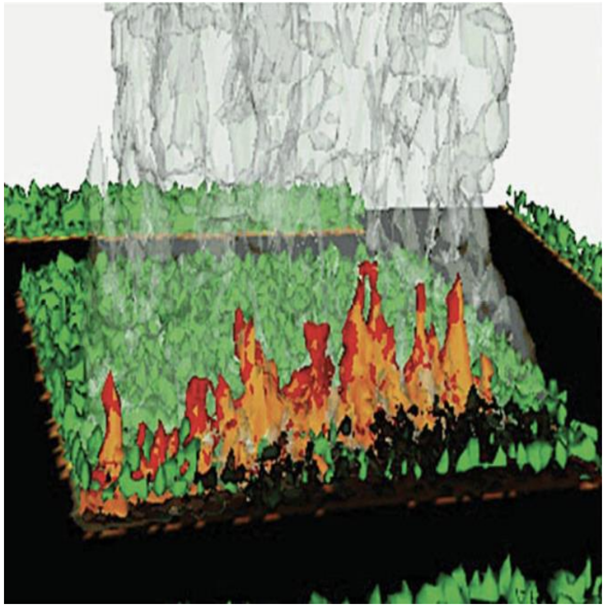

- **Particle transport is involved in many atmospheric processes**
  - Wildfires: air quality, climate impacts (Jaffe 2020)
  - Sand/dust storm: landscape evolution, climate modeling (Kok 2018)
  - Snow saltation: snow accumulation forecast (Pomeroy 1990)
  - Volcanic eruptions: air quality, climate, ecology (Brown 2012)
- **Characteristics:** span from microscale (particles) to kilometer scale
- **Difficult to reproduce in the lab with environmental factors**
- **Challenge: tools to measure large-scale dispersion dynamics**



# Significance and Effects of Prescribed Burning

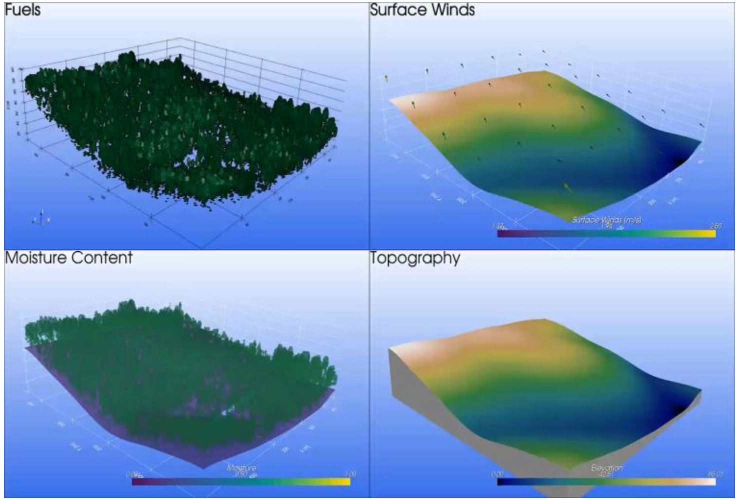
- Prescribed or controlled burns offer multiple benefits in maintaining healthy ecosystem: they promote prairie plant growth, limit invasive species, and prevent severe wildfires by reducing excess bio-fuel.
- Effective smoke management essential to minimize air quality impacts and ensure public safety
- Between 2012 – 2021, 43 prescribed burns in U.S. has escalated to wildfires (kutv.com)

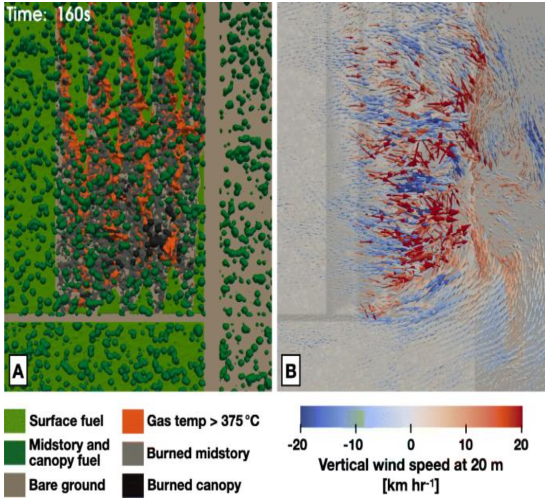
# Significance of Particle Dispersion Dynamics in Prescribed Burning

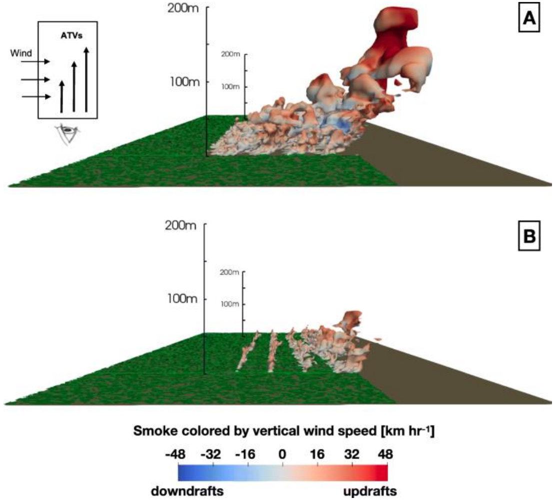


- Monitoring and controlling large prescribed burns is challenging due to the complex particle dispersion dynamics, which can have severe consequences if not well understood.
- Researchers are developing simulation methods to predict fire and smoke dispersion dynamics before controlled burns
- This data will aid in analyzing effects and determining resources needed for safe operation

# Methods for Fire and Smoke Dispersion analysis on Prescribed Burning



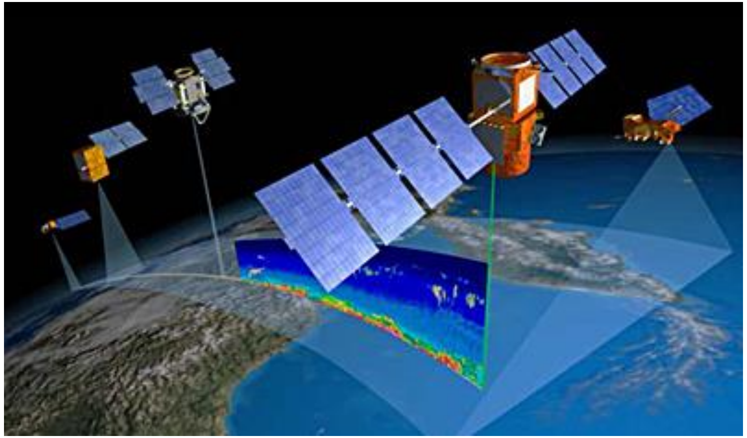



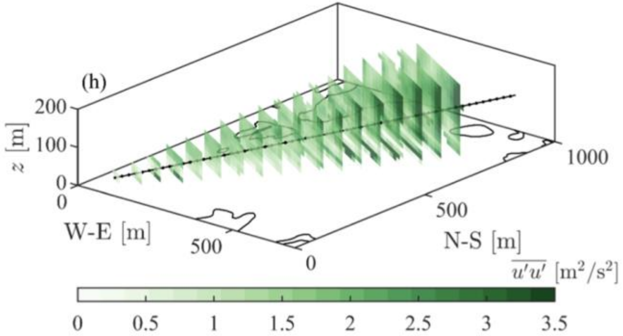

- ➢ Current methods focus on simulating fire and smoke particle behavior by taking 3D fuels map (vegetation structure, topography, moisture content) and wind predictions as input (Mell, W et al. 2021)
- ➢ These methods use models like QUIC-Fire and FIRETEC to make predictions. (Linn, et al. 2020)
- ➢ However, these techniques lack:
  - Validation by comparing predicted particle flow to actual plume dispersal behavior
  - Dynamic 3D Ground truth data of particle dispersion
  - Ability to predict on regions with unmapped 3D Fuels data

# Current Tools for Field Measurements of Large-scale Particle Transport

**CALIPSO satellite mapping aerosols**

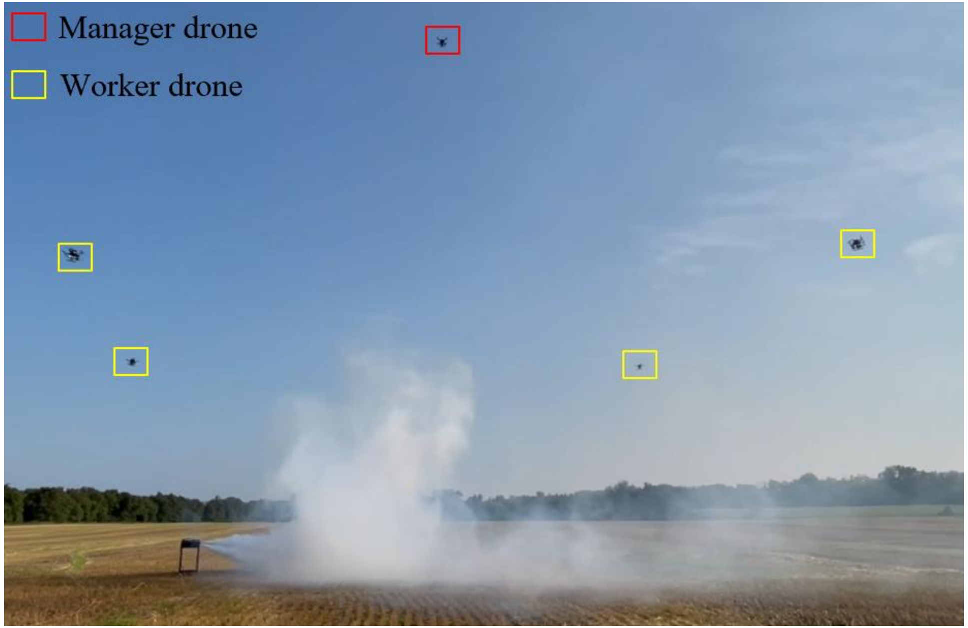


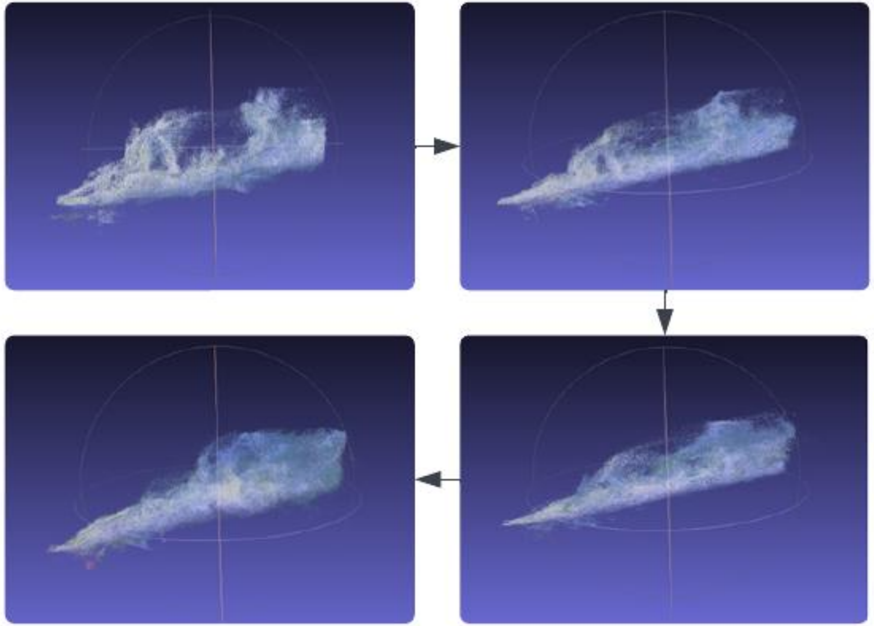
**LIDAR Flow Measurement Techniques**




- Current field tools (e.g., remote sensing, Lidar) do not have sufficient spatial and temporal resolution to capture the highly dynamic flow associated with the particle transport (Sokolik et al. 2019, Prichard et al. 2019)
- Cannot provide accurate mapping of the detailed particle information (e.g., size, concentration, morphology, types, etc.), which is critical for their dispersion dynamics (Beckett et al. 2022)

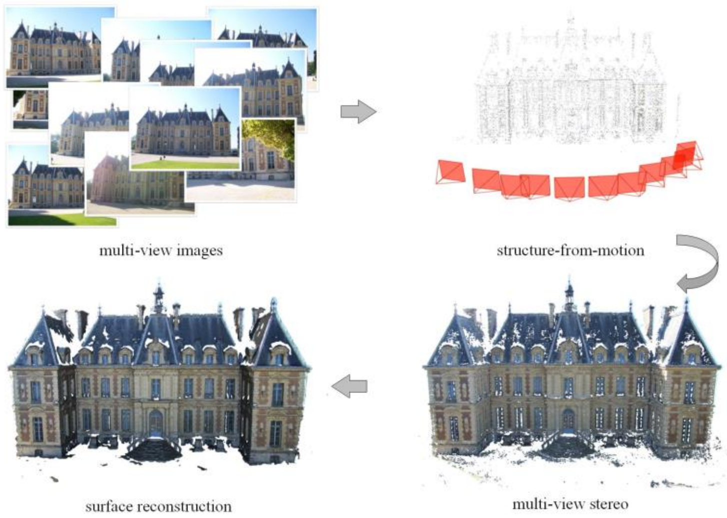
# Objectives



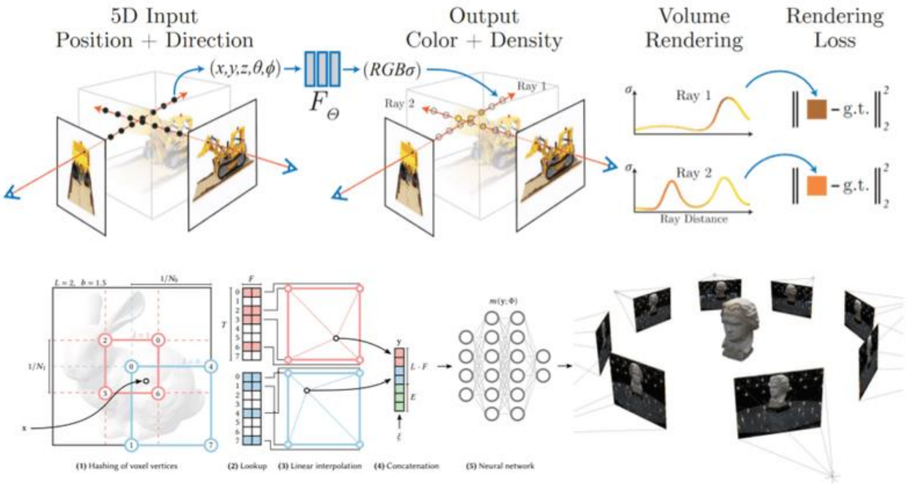



- **Our solution**: deploying a drone fleet for multi-perspective imaging of atmospheric dispersion plumes to analyze flow dynamics and participle transport → **3D reconstructions of plume dispersal dynamics**
- **Outcomes:** serve as ground truth model; inform drone operation; provide guidance on hazard response

# Summary of State-of-Art Research in 3D Reconstruction



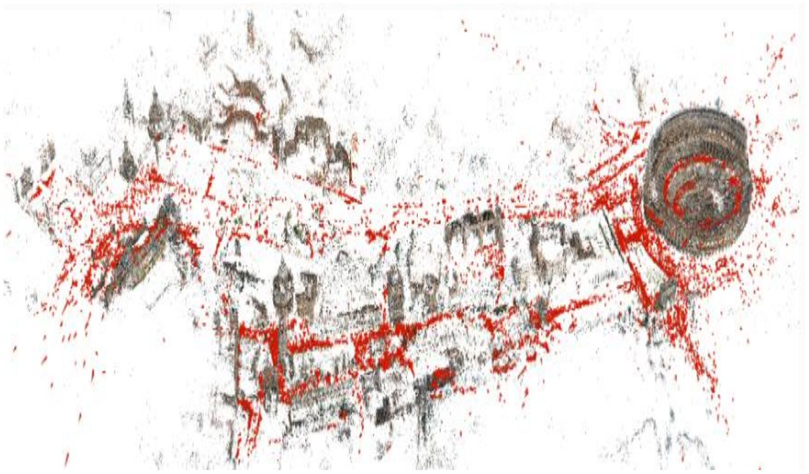

Structure from Motion Reconstruction

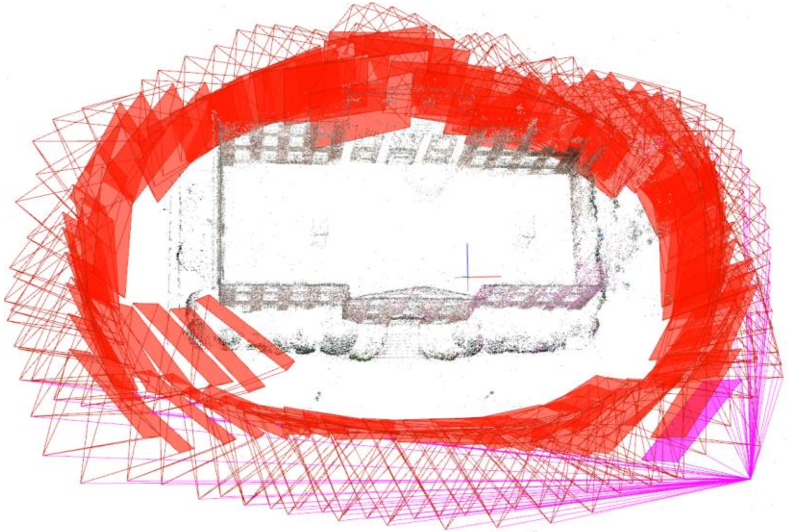



NeRF Reconstruction

- No existing work on 3D reconstruction of particle transport with multi-view images from the drones
- Impactful milestone techniques on 3D reconstruction of static objects using multi-view images
  - 3D reconstruction using Structure from Motion(SFM) and Multi-View Stereo(MVS) (Schonberger 2016)
  - Scene reconstruction using Neural Radience Fields(NeRFs) (Mildenhall 2021)

# Feature matching approach: Structure-from-Motion Revisited[2016]

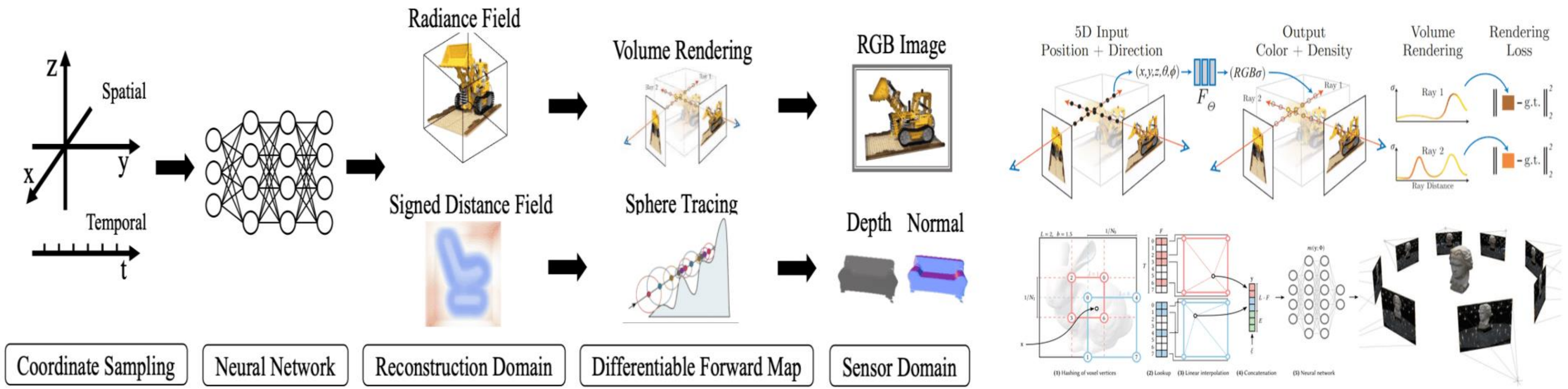




- Structure from motion reconstructs 3D models from 2D image sequences using feature tracking and photogrammetry to simultaneously estimate camera poses and 3D structure (Schonberger 2016)

- **Limitations:**
  - As SFM depends on feature matching, most dispersion plumes won't have any matchable features creating a problem in reconstruction

# Deep Neural Network approach: Neural Radiance Fields for View Synthesis




- **NeRF:** A method to synthesize novel photorealistic views of complex scenes by optimizing a continuous 5D neural radiance field representation from a sparse set of input images (Mildenhall 2021)
- **Limitations:**
  - Computational complexity scales with number of sampling points along rays making it difficult to implement in real time
  - Robustness to scenes with transparent objects or overfitting to sparse views not analyzed

# Deep Neural Network based approach: D-NeRF for dynamic scenes


- **D-NeRF:** Represents a dynamic scene as a sequence of neural radiance fields rather than a single static NeRF (Pumarola 2021)
- This allows modeling of non-rigid motion and deformation in the scene over time
- **Limitations:**
  - D-NeRF may have difficulty generalizing to new or unfamiliar scenes that differ significantly from its training data.

# RoDynRF: Robust Dynamic Radiance Fields

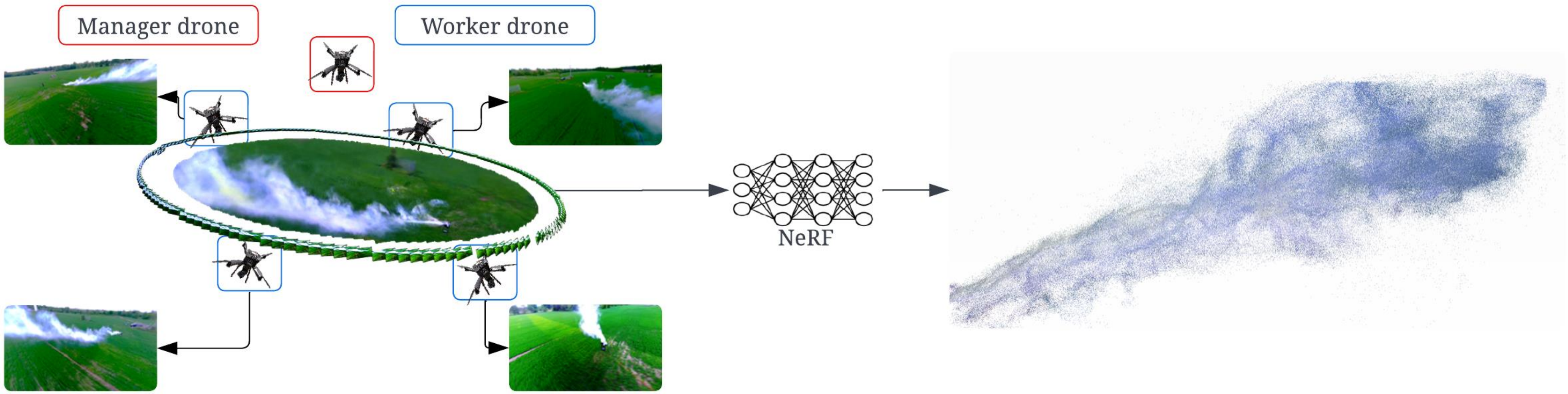
- **RoDynRF** : A novel method for dynamic view synthesis from monocular videos without requiring known camera poses (Liu 2023)
- **Limitations:**
  - Still faces challenges in very complex dynamic scenes
  - Requires longer training time (about 28 hours on an NVIDIA V100 GPU) compared to some existing methods

# Need For Multi Drone Imaging Approach

- Challenges we face when reconstructing an atmospheric dispersion plume:
  - Plume lack necessary feature points for 3D reconstruction using SFM/MVS
  - NeRF algorithm developed for static objects whereas in our case plume is dynamic in nature
  - The D-NeRF algorithm developed for reconstructing dynamic objects only works well on pre-trained models and faces issue with unseen scenarios
- While the NeRF and D-NeRF algorithms can reconstruct the dispersion plume, they are limited in spatial and temporal resolution
- A multi-view imaging solution is essential to overcome these limitations, as multiple views provide significantly improved spatial and temporal resolution compared to a single view
- Considering the slow temporal variation of large dispersion plumes, multiple drones can capture image sequences circling the area of interest from different views
- This enables us to reconstruct a sequence of plume models using NeRF pipeline

# *Methodology*

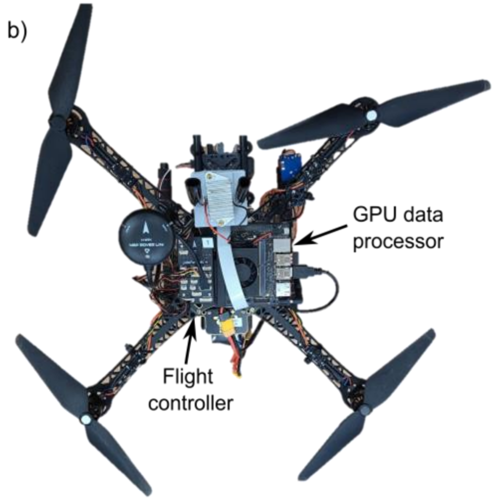
# Overview




- Position the master drone on top of the dispersion plume
- Command four worker drone to their desired locations surrounding the dispersion plume
- Worker drones circle around the plume to collect data
- Processing the data to create a sequence of 3D reconstructions to study the dispersion dynamics

# Hardware Overview


Master Drone



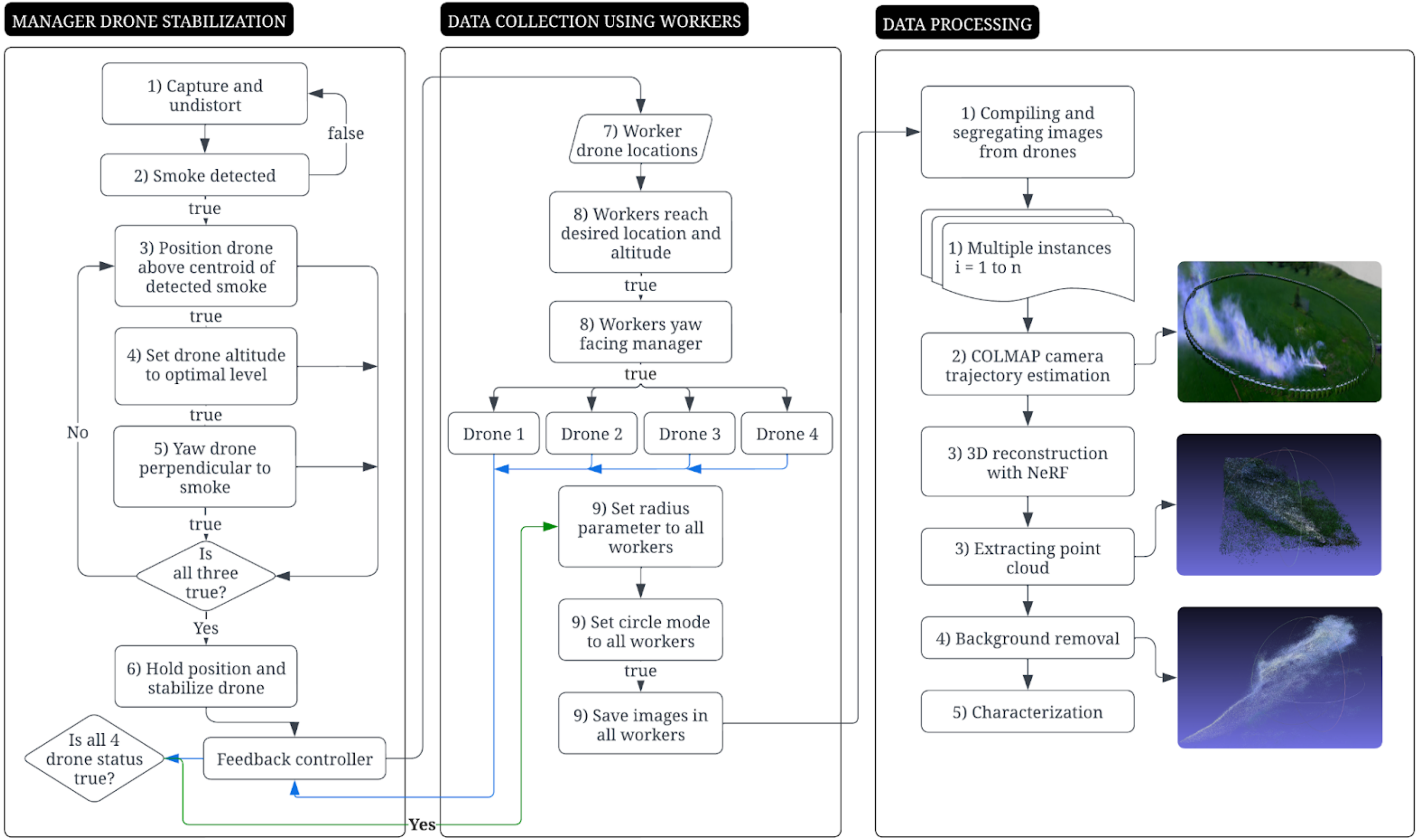

Worker Drone

- Most of the drone components used are similar to Bristow et al., 2023 with slight modifications
- **Camera**: Machine vision camera used for smoke detection, tracking, swarming and dataset collection for 3D reconstruction
- **Software**: The onboard computer runs ROS Noetic and MavROS, facilitating inter-sensor communication within the drone, drone-to-drone communication, and autonomous operations.

# Hardware Overview


- **RTK (Real-Time Kinematic):** A high-precision satellite navigation technique that provides centimeter-level positioning accuracy in real-time by using carrier phase measurements from GNSS signals.
- The triangulation between RTK base station, RTK enabled GPS and Satellites helps achieve this level of precision

# Overview Flowchart



# Phase-1: Master drone positioning

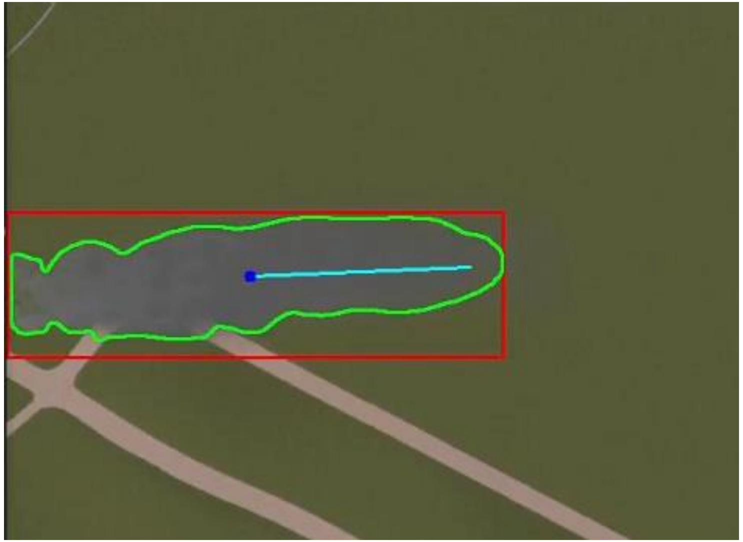
- **Image un-distortion:** The camera always has a distortion in its image and for 3D reconstruction and positioning we must use an un-distorted image
- To un-distort the image we calibrate the camera to find the camera matrix and distortion coefficient and undistort the image

# Phase-1: Master drone positioning



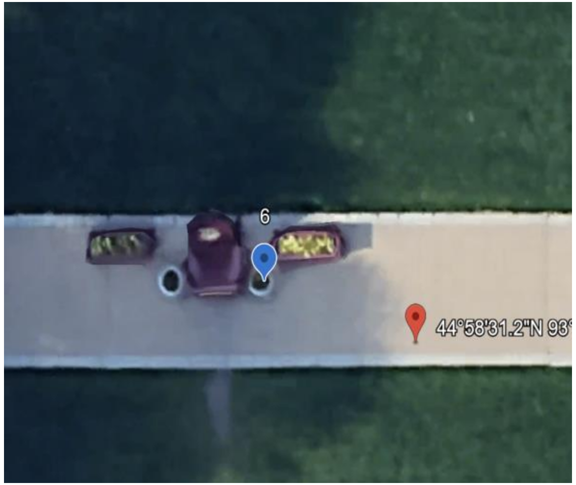
- **Detecting the plume:** Detecting the plume using yolo-v8 segmentation model
- **Centering the drone:** The drone tracks and centers on the plume's centroid, adjusting its position until the centroid is within a threshold of the image center
- **Setting the right altitude:** The drone adjusts its altitude based on the segmented smoke's area, ascending when it exceeds an upper threshold and descending when below a lower threshold, until reaching the optimal range

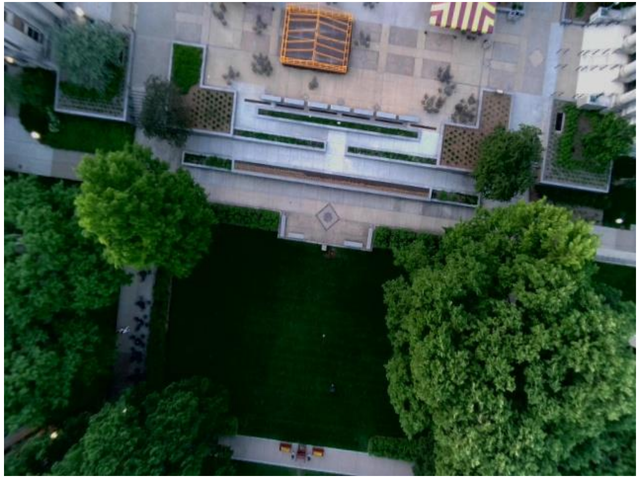
# Phase-1: Master drone positioning

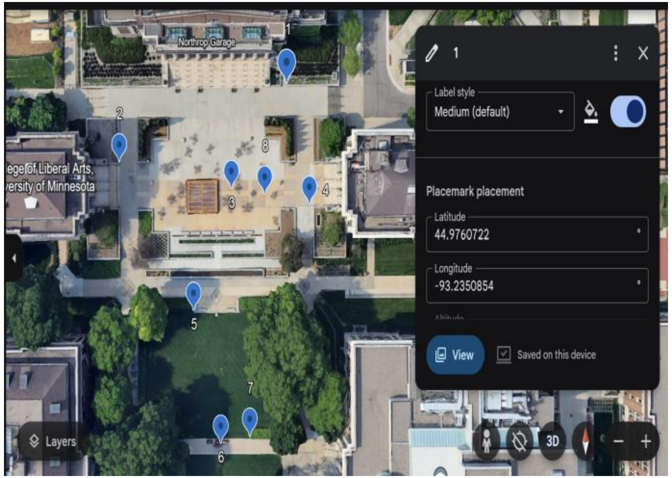


- **Setting the desired yaw:** Yawing the drone perpendicular to the flow of the dispersion plume
  - The segmented mask's covariance is calculated, yielding eigenvectors that indicate the plume's flow direction relative to the image
  - Using the drone's current heading, we calculate and execute the desired yaw adjustment.
- **Re-initiation of all the three process and the drone becomes stable**

# Phase-1: Master drone positioning

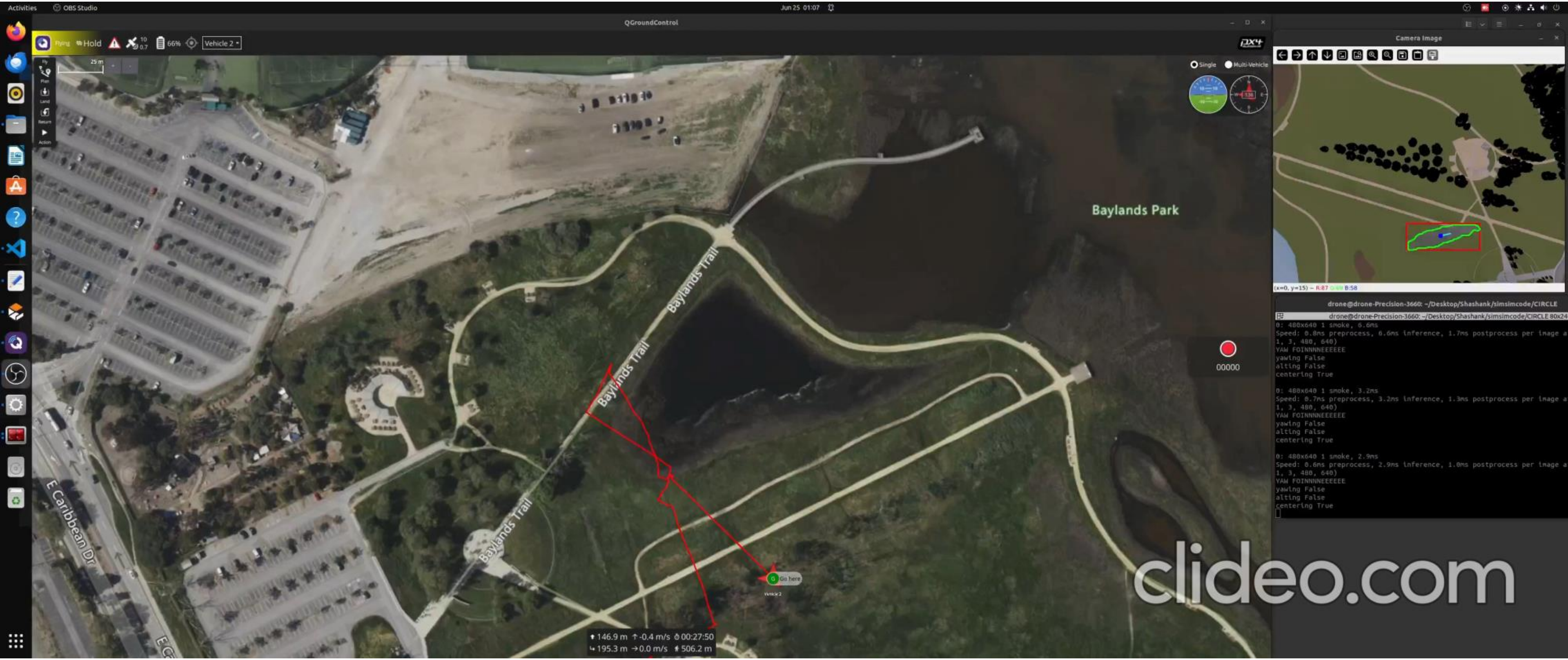




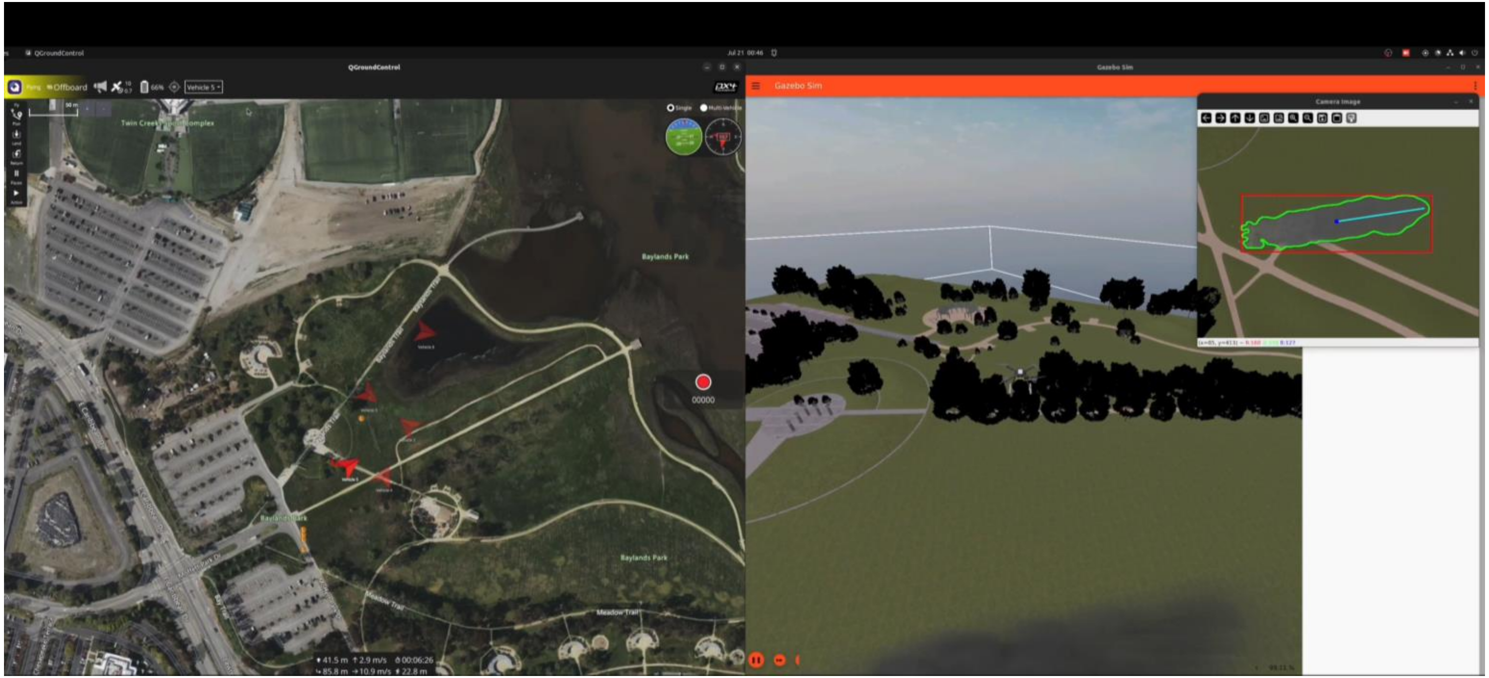

- **Mapping 2D pixel of the image to GPS coordinates:**
  - Using the drone's GPS coordinates, altitude, and camera focal length, we calculate the real-world dimensions of the captured image in meters.
  - Using haversine formula we calculate the latitude and longitude of the corners in the image since we know the latitude and longitude of the center of the image
  - Using this we compute an affine transformation matrix, that maps every pixel to its GPS coordinates

# Phase-1: Master drone positioning in simulation



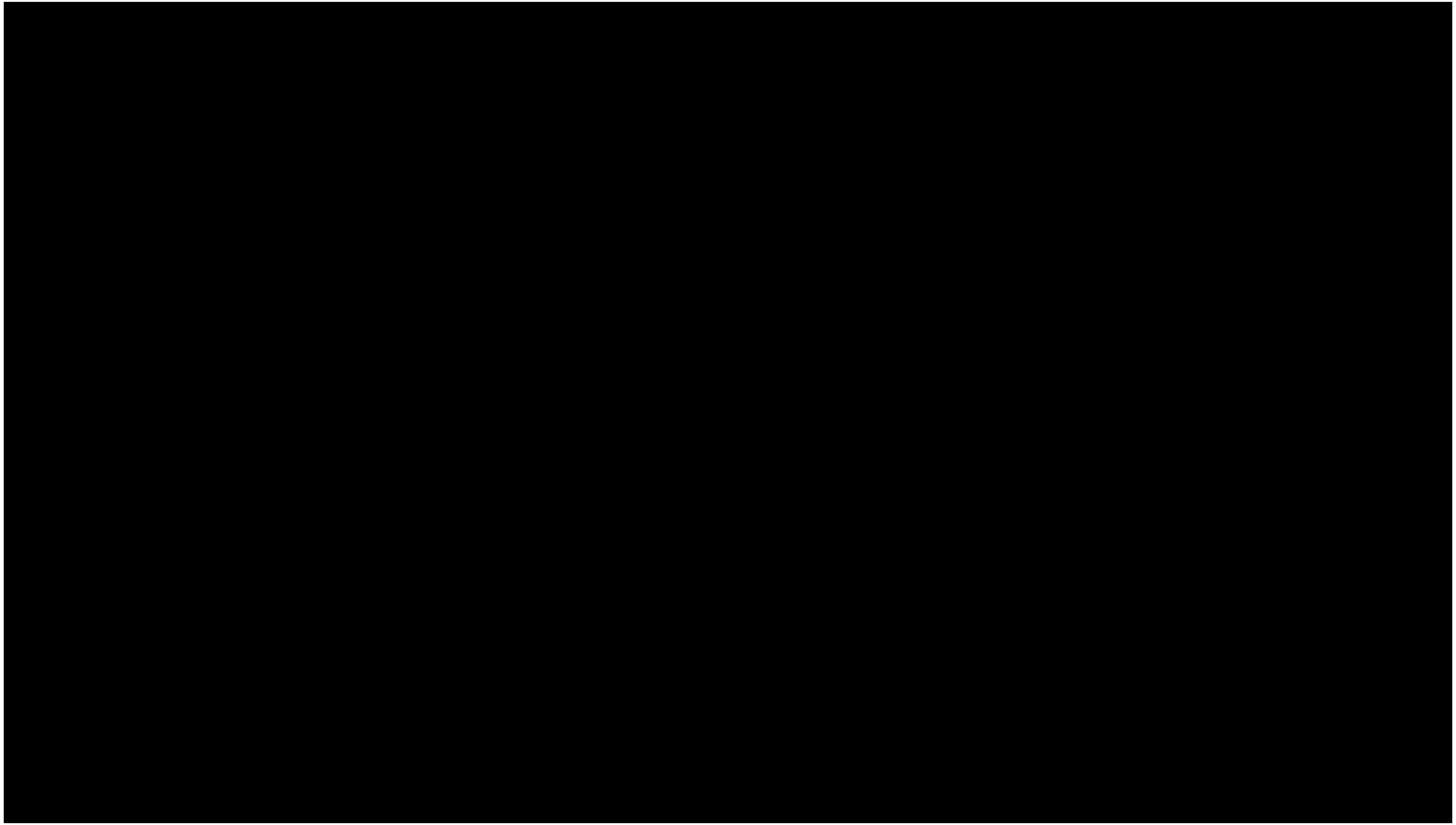
# Phase-1: Master drone positioning

# Phase-2: Data Collection in simulation




- **Swarming:** Precisely localizing and dispersing the drones at desired altitude and location to surround the plume from four sides and yaw it to face the master drone
- **Data collection for 3D reconstruction:** Navigating each drone simultaneously to adjacent positions in a circle while capturing image sequences to create a closed loop of images

# Phase-2: Data Collection



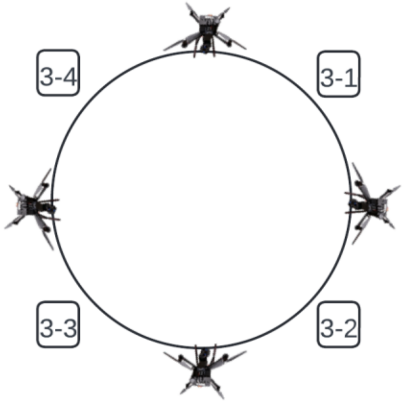
# Phase-3: Grouping data

- The data from all the drones are grouped into one folder named as images
- Nomenclature:
  - Images are named in the fashion "drone ID"_"circle_ID"_"frame_name"
  - For example: d_3_1_frame_00001.jpg, here d_3 means drone 3, _1_ indicates that it is the first circle made by the drone, _frame_00001.jpg indicates that it is the first frame on that circle
- The image file is used to compute the full trajectory of all drones at once
- This approach ensures that separate reconstructions yield results in the same coordinate frame
- If trajectories are grouped before computing the full trajectory, each one may end up in its own coordinate frame
- Having separate coordinate frames for each trajectory increases the likelihood of COLMAP failing to generate accurate trajectories for the drones
- Complete, relative alignment of trajectories enables easy manipulation to meet specific needs
- After estimating the trajectory, each circle is divided into quarter circles and grouped with other drones
- Additional overlaps between frames enhance spatial and temporal accuracy

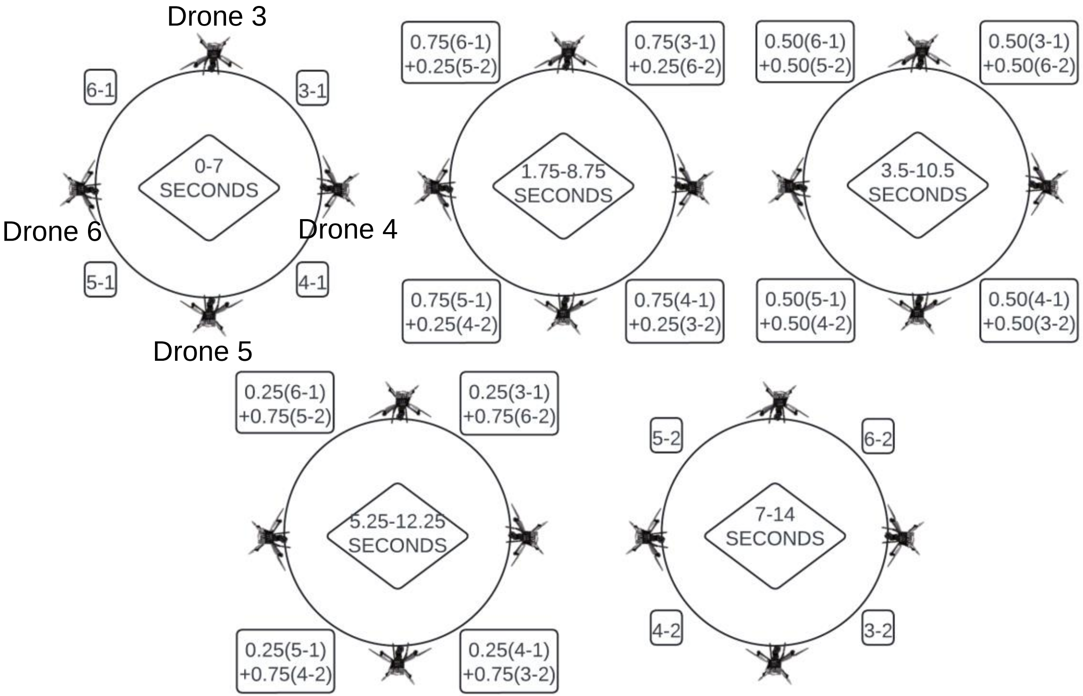
# Phase-3: Trajectory Estimation

- **Camera trajectory estimation via COLMAP:** feeding the sequence of images as input (Schonberger 2016)
  - Uses SIFT feature extraction, Exhaustive feature matching, Structure from motion, and Bundle adjustment to estimate camera poses
  - Uses background features for feature matching

# Phase-3: Creating Overlaps

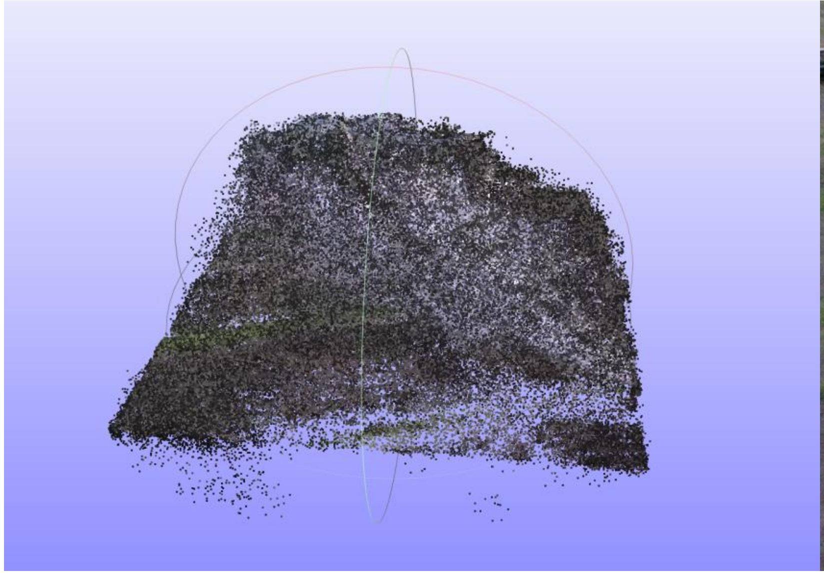



For a single drone 3 full circle




- 3-1 signifies the 1st quarter circle of drone 3 and like wise 3-2 signifies 2nd quarter circle of drone 3
- 0.75(6-1)+0.25(5-2) indicates 75 percent of the 1st quarter circle of drone 6 is take and 25 percent of the 2nd quarter circle of drone 5 is taken to make a full quarter circle.
- We can simplify and say that we have a reconstruction for every 2.8 seconds between 1-14

# Phase-3: 3D Reconstruction



- **3D-Reconstruction with NeRF:** By using computed COLMAP camera trajectory and image data
  - NeRF model is trained where all the 2D image data are projected as radiance fields to converge into 3D data which outputs RGB-D
  - The 3D data outside the enclosure region is cropped out
  - The cropped data is exported as point clouds

# Phase-3: Background Removal

- **Post processing:** Background removal with (yolov8+SAM, NB Gaussian model and DBSCAN)
  - YOLO-v8 detects smoke plumes in three random images from input data; SAM uses the bounding boxes to segment the plume
  - Mask and background data used to train a Naive Bayes Gaussian classifier to segment smoke plumes from point clouds (background removal)
  - Density-Based Spatial Clustering of Applications with Noise(DBSCAN) used to further filter outliers

# ***Results***

# Results 1-7 seconds

# Results 1.75-8.75 seconds

# Results 3.5-10.5 seconds

# Results 5.25-12.25 seconds

# Results7-14 seconds

# Characterization

- **Objective:** Demonstrate the drone-based 3D reconstruction system's ability to quantify plume parameters essential for controlled burns
- **Key Parameters:** Vertical and horizontal plume dispersion, and plume lifecycle, critical for plume modeling and prediction
- **Importance:** Accurate parameter quantification enhances understanding of smoke dynamics and supports effective controlled burn strategies and environmental assessments
- **Scaling:** Real-world coordinates are achieved by scaling NeRF model data using known trajectory diameters
- **Vertical Dispersion:** Maximum plume height tracked over time using z-coordinates in 3D data
- **Horizontal Dispersion:** Plume spread analyzed via x-axis projections and contour plots to visualize growth and influencing forces

# The End

**THANK YOU**