Spatiotemporal Profiling of Aerosol Particulates through Digital Inline Holography: A Synergistic Integration of GPU-Accelerated Reconstructions, Deep Learning Analytics, and Drone-Orchestrated Environmental Field Diagnostics

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ABSTRACT
Nearly 30% of all farmers face an invisible but relentless adversary: the widespread dispersion of aerosol particles like pollen and spores (Hetzel et al., n.d.). For far too long, policymakers and the public have overlooked farmers, overlooking the critical issue of aerosol particle dispersion. Stemming from the COVID-19 pandemic, this issue affects agriculture, public health, and the environment. These particles contribute to respiratory problems, reduced agricultural efficiency, and ecological impacts, yet current diagnostic tools often lack the precision to identify these aerosols (Singh & Kumar, 2022). This paper discusses the integration of Digital Inline Holography (DIH), which offers an innovative method to address these concerns. It has the potential to transform the understanding of aerosol behavior. Current techniques like laser diffraction have limitations when it comes to studying aerosols. So, can DIH actually enable more precise and versatile aerosol characterization? Yes, DIH actually provides sharper imaging and faster analysis and is more cost-effective, making it a better tool for understanding particle behavior in multiple settings. This project is designed to develop a novel DIH system to analyze aerosols with unprecedented precision. It extracts detailed 3D particle information through just four key steps: recording, 3D reconstruction, particle segmentation, and 3D tracking. This system uses a laser-based holographic setup, GPU-powered processing units, and pattern recognition algorithms to integrate holography and machine learning algorithms for particle data processing. The project will also go over DIH's potential in drone-based aerosol sampling. The results indicate that DIH, integrated with other innovations such as drone technology, successfully mapped aerosol concentrations and particle size distributions in multiple settings, identifying particles ranging from approximately 10 to 1,000 micrometers in diameter. Additionally, DIH's real-time capabilities provide an efficient method for large-scale environmental monitoring, catching aerosol oscillations that traditional methods often miss. This novel approach allows for better predictive modeling of airborne contaminants, aiding in pollution control and agricultural disease prevention. The results indicate that DIH can accurately monitor airborne contaminants, presenting meaningful refinements in agricultural efficiency and public health medications. This research highlights DIH's capability to address real-world issues by improving air quality monitoring, tracking respiratory aerosols for disease prevention, and studying spore and pollen spread in agrarian settings. By combining DIH with machine learning and automation, this study paves the way for future breakthroughs in aerosol characterization, ensuring more effective environmental management and safeguarding public health.

KEYWORDS
Digital Inline Holography (DIH), Aerosol particles, Farmers, Public Health, Agriculture, Machine Learning Algorithms, Air Quality Monitoring, Spore and pollen spread, 3D Particle Information, Respiratory Problems, COVID-19 Pandemic

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1. INTRODUCTION

Since the COVID-19 pandemic, concerns have been brought to global attention about a silent but pervasive threat: particulate matter (PM), a key factor in both indoor and outdoor air quality that directly affects farmers, their crops, and the environment (Piscitelli et al., 2022). Among these aerosols — pollen, spores, and other large particles — lie hidden contributors to respiratory illnesses, declining agricultural productivity, and ecological disturbances (Gupta et al., 2024). These aerosols are not only a challenge for farmers but also a growing issue for public health and environmental stability, creating an urgent need for effective diagnostic tools.

Aerosols like pollen and spores have long been underestimated in their broader impacts. While much focus has been placed on PM smaller than 10 µm due to their prolonged airborne presence and health implications, emerging research reveals that larger particles can also remain suspended and present significant risks (Thangavel et al., 2022). In agricultural settings, these larger aerosols are directly linked to reduced crop yields, as they can act as vectors for harmful pathogens or trigger allergic reactions in workers exposed to them for prolonged periods. Furthermore, the resurgence of infectious diseases tied to aerosols, such as the spread of respiratory pathogens or the rising concerns about aerosol-based transmission of human papillomavirus (HPV), underscores the importance of understanding and managing aerosol dynamics in the modern world (Ahmad et al., 2024). This emerging crisis highlights the need for innovative solutions to monitor, analyze, and mitigate aerosol-related threats.

Despite their critical role in shaping air quality and influencing ecosystems, current diagnostic tools fall short of addressing the full scope of the aerosol challenges. Techniques like laser diffraction and aerodynamic particle sizing, while valuable, lack the precision and real-time capabilities required to analyze non-spherical or irregular particles with high resolution or detect various particle behaviors in dynamic environments (Sauvageat et al., 2020). This gap in diagnostic technology leaves vulnerable populations, including farmers and those with respiratory sensitivities, at risk.

The urgency of the issue is compounded by climate change, which exacerbates aerosol production through increasing wildfires, dust storms, and changes in agricultural practices. These environmental shifts contribute to greater aerosol dispersion, pushing existing diagnostic methods to their limits ("Yes, Climate Change is Raising the Risks," 2024). At the same time, urbanization and industrial activities heighten exposure to airborne particles, further elevating public health risks. Current policy frameworks and mitigation strategies fail to adequately address the multifaceted nature of aerosol dispersion, leaving farmers and communities to grapple with its consequences.

This project takes a significant step forward by introducing Digital Inline Holography (DIH) as a transformative tool for precise, real-time monitoring and analysis of aerosol particles. DIH leverages advanced imaging techniques and computational power to overcome the limitations of traditional methods, providing a comprehensive understanding of aerosol behavior in a wide range of contexts. By enabling the detailed tracking and characterization of particles of all shapes and sizes, DIH opens new pathways for mitigating the adverse effects of aerosols on agriculture, public health, and the environment.

Above all, this project aims to bridge the gap between research and actionable solutions in a world increasingly shaped by the interplay between environmental and health crises. Integrating DIH with cutting-edge technologies like machine learning and drone-based sampling can address pressing issues such as improving air quality monitoring, mitigating respiratory risks, and supporting agricultural resilience in the face of aerosol dispersion challenges.

2. LITERATURE REVIEW

This project is specifically designed to provide long-term indoor and outdoor air quality management with a focus on seamless, autonomous, and uninterrupted operation. DIH has shown time and time again to understand and manage particles in the air, but its current uses face different roadblocks that limit its potential. For example, Joel Kuula and colleagues designed a lensless DIH sensor that achieved an impressive 70-90% accuracy in particle sizing. Yet, their method required directing particles onto an adhesive coverslip for a 30-second impaction period and depended heavily on cloud processing, which proved inefficient and reliant on frequent manual work (Kuula et al., 2020). Similarly, Eric Sauvageat developed a real-time pollen monitor using DIH in a flow channel, processing air at 40 liters per minute (Sauvageat et al., 2020). However, it was specifically designed for pollen, relied on pre-concentration steps, and used elliptical fitting models, limiting its use for other purposes. Kim et al. (2022) introduced a smartphone-based digital holographic microscopy (S-DHM) sensor capable of real-time particulate matter estimation using built-in phone hardware to build on these advancements. While portable and cost-effective, this solution fell short of classifying particles or leveraging S-DHM's full potential to extract morphological and phase data. Simply put, all these technological innovations were constrained by limitations that hindered their ability to meet the needs of long-term air quality management fully.

There is an innovation, other than DIH, that is actually used to track aerosol particles: laser diffraction. This method analyzes particle sizes by measuring light scattering. This technique directs a laser beam through an aerosol sample, where particles scatter light at angles that correspond to their size. Detectors capture the angular intensity of scattered light, which is processed to calculate particle size distributions (Volckens & Peters, 2005). Laser diffraction is substantial for quickly analyzing huge numbers of particles — sometimes thousands per second — with high accuracy. That's why it's a popular choice in agrarian settings. However, it struggles with irregular shapes like pollen or spores, because the process relies on light scattering evenly. Irregular shapes disrupt measurements, reducing reliability. The technique often inaccurately represents complex shapes and PM smaller than 10 µm due to its assumption of sphericity (Thangavel et al., 2022). For example, Peter Fisher's team found a 10–20% error rate when measuring irregular particles like fibers or clusters (Fisher et al., 2017). Laser diffraction also demands precise alignment and calibration of the optical setup, making it even harder to deploy in dynamic or uncontrolled environments (Kulkarni, 2023).

Beyond laser diffraction, another alternative to DIH that has been explored is phase Doppler anemometry (PDA). PDA utilizes the Doppler shift of scattered light from particles to determine their velocity and size in a fluid stream. This method has been extensively used in industrial applications such as spray characterization and combustion diagnostics. However, PDA struggles with high particle concentrations, leading to signal overlap and potential inaccuracies ("Measurement Principles of PDA," 2024). Moreover, its reliance on expensive optical components makes it less accessible for widespread environmental monitoring applications.

In addition to particle characterization, DIH has been applied in various fields such as biomedical imaging, oceanography, and combustion studies. In biomedical contexts, DIH has been used to analyze blood cell morphology and detect pathogens in fluids (Kaur et al., 2022). However, Gao and Yuan's (2022) research states that limitations in image resolution, as well as the complexity of biological samples, have hurt its widespread use in clinical settings. Similarly, oceanographic studies have used DIH to track plankton dynamics and particulate distribution in water bodies. However, obstacles such as optical distortions caused by water movement and varying refractive indices have restricted its efficacy (Davies et al., 2021). These limitations highlight the need for further advancements to enhance DIH's capabilities across multiple domains.

While DIH presents a promising approach to aerosol analysis, its implementation in real-world scenarios often falls short. To achieve optimal results, technological refinements and integration with complementary methodologies are required. This project successfully finds a cohesive algorithm for DIH and tests it in various settings.

3. MATERIALS

The main resources required to ensure the feasibility of this project included a drone, a computer, a Charge-Coupled Device (CCD) camera, a GPU, and a laser — all of which were already available (Kreuzer & Pawlitzek, 2003). A prototype had already been created, utilizing all of these resources. YOLOv8 (You Only Look Once, Version 8), the latest YOLO model with a CSP backbone, PANet neck, and anchor-free detection head, was implemented for efficient multi-scale object detection. Simply put, it improved accuracy and speed with dynamic scaling, optimized loss functions, and PyTorch-based modularity for detection and segmentation (Mehra, 2024). **Below are all the materials that were used throughout the entire project, from the creation of the DIH sensor to its integration with other innovations:**

Table 1. Summary of Hardware and Software Needs for the Feasibility of the Project

Hardware	**Software**
Laptop	YOLOv8 (You Only Look Once version 8)
Coherent laser source (532 nm wavelength laser)	Python
Charge-Coupled Device (CCD) camera	MATLAB
Graphics Processing Unit (GPU) - NVIDIA RTX4070	LabVIEW
High-resolution intensified camera (customized for aerosol imaging)	PyTorch
Drone	OpenCV
Objective lens	TensorFlow
Optical alignment tools (mirrors, beam splitters, optical mounts)	AWS Lambda
Wind tunnel	Google Colab
Mouthpiece setup	SQL databases
Onboard microcontroller	Digital holographic reconstruction algorithms (based on Fourier Transform methods)
Cloud storage solution (AWS)	COMSOL Multiphysics (for airflow simulation)
Solid-state drives (SSDs)	Blender
Particulate Matter (PM) sensor (PMSA003I)	ImageJ
Volatile Organic Compounds (VOC) sensor (SGP30)	Particle segmentation algorithms (K-means clustering)
Carbon Dioxide (CO_2) sensor (SCD-30)	Deep learning-based 3D reconstruction algorithm (NumPy)
Temperature and Humidity Sensors	Optical flow algorithm for drone feedback control (C++) - Schlieren imaging
Power Supply Units (battery packs, adapters)	Gerchberg-Saxton Algorithm
Tripod	Autodesk Fusion 360

4. METHODS

Taking all these insufficiencies into account — from different uses of Digital Inline Holography (DIH) to other innovations with the same goal — a full-throughput algorithm has been developed to utilize DIH in agricultural settings through a straightforward four-step process: recording, 3D reconstruction, particle segmentation, and 3D tracking. DIH is an emerging, cost-effective, and compact method for particle characterization. The proposed DIH system offers a portable, affordable approach to particle characterization. This imaging-based method uses a digital camera to record holograms — interference patterns created when particle-scattered light interacts with the un-scattered portion of a coherent light source. Label-free characterization is also possible with DIH, which works over a wide depth of field and provides phase information, including refractive index, 3D location, and morphological data. The process is straightforward: a coherent, collimated laser generates a planar reference wave, which is directed through a particle-containing region, similar to laser diffraction. These particles scatter light, producing spherical object waves for any particle size. A hologram forms by recording the intensity of combined reference and object waves with a digital sensor. This hologram encodes interference patterns containing spatial data about the particles. Using digital reconstruction, 3D particle locations can be extracted from holographic data. Recording a time series of holograms enables the reconstruction of particle trajectories, allowing measurement and analysis of dynamic particle properties. The feasibility of this solution is supported by a structured diagram and a blueprint that have already been developed.

A digital inline holography (DIH) system was manually built using a coherent laser source, a high-resolution camera, and machine learning algorithms to analyze aerosol particles in real-time. The process began with a laser generating a planar reference wave, which located particles to create holograms. These holograms were then reconstructed to extract 3D particle locations, and machine-learning algorithms were implemented to monitor and track particles based on size, shape, and motion. This system significantly improved the ability to observe and understand how aerosols behaved in various real-world situations. **Below is the diagram illustrating the simple process of the system:**

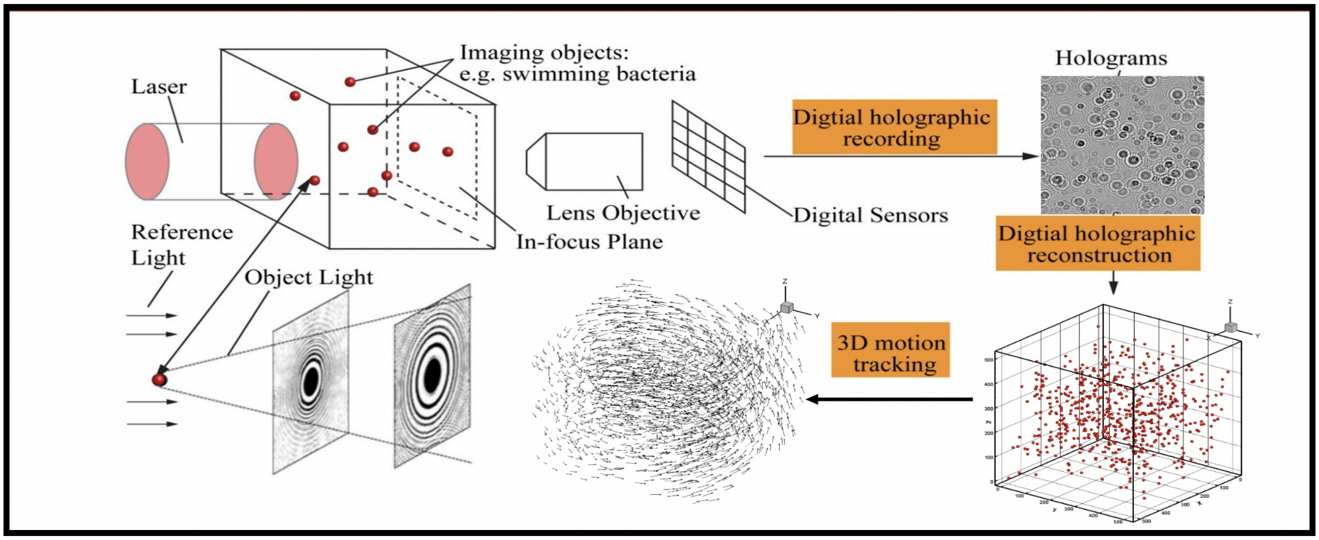

Figure 1. Below is a step-by-step explanation of how this DIH system works:

The process begins with a coherent light source, typically a laser, which generates a monochromatic and coherent light beam. This laser light is directed towards the object of interest, such as swimming bacteria, within the imaging region. The object interacts with the incident light, causing a portion of it to scatter (object light) while the unscattered portion continues as reference light. This configuration ensures interference when these two elements interact downstream (Baird, 2014). The coherent nature of the laser is key to creating holograms because it guarantees phase stability. This coherence makes it possible to impose reference light and object waves to create holograms (Hecht, 2010).

Once the light interacts with the object, it passes through a lens objective that focuses it onto an imaging plane. The lens objective guarantees that the details of these interactions are captured with unprecedented consistency by enhancing the scattering patterns from the object. The in-focus plane is important since it is a reference for subsequent digital reconstructions (Priest et al., 2021). The objective lens system in this configuration must be optimized to focus the scattered light onto the digital sensor plane and have high numerical opening capabilities to capture diffraction patterns accurately (Sohn & Silver, 2014).

At this stage, the interference pattern formed by the object and reference light is captured on a digital sensor, such as a CCD camera (Paschotta, n.d.). This interference pattern, or hologram, encodes the scattered light's amplitude and phase. Unlike traditional photography, which captures only light intensity, holography records the light field's wavefront. Digital holograms revolutionize the field by enabling computational processing, rather than optical reconstruction, to recover 3D information. This process relies on the sensor's quality and resolution to accurately capture the intricate interference patterns (Uppal, 2024).
As soon as the hologram is recorded, computational algorithms process it to create a 3D image of the object. Laser diffraction and Phase Doppler Particle Analyzer (PDPA) techniques, which

measure droplet size and velocity, convert the captured 2D hologram into a digital 3D representation (Wu et al., 2021). Digital reconstruction can extract the 3D location of particles and retrieve phase and amplitude data, enabling the observation of different focal planes without physically refocusing. This makes it simple to observe objects at various depths (Zhou et al., 2022).

Finally, the reconstructed 3D data is used for motion tracking. Advanced image processing algorithms use sequential frames to track the motion of dynamic systems like swimming bacteria in three dimensions. This provides quantitative data on velocity, trajectory, and spatial distribution, which is useful for research in particle tracking. DIH represents intricate patterns in ways that traditional imaging techniques cannot (Matthews et al., 2024).

Throughout this entire process, five case studies have been executed to test the viability of the DIH sensor, with each case study differing in its own way. **Below is an overview of each case study that was performed:**

Case Study I Overview:

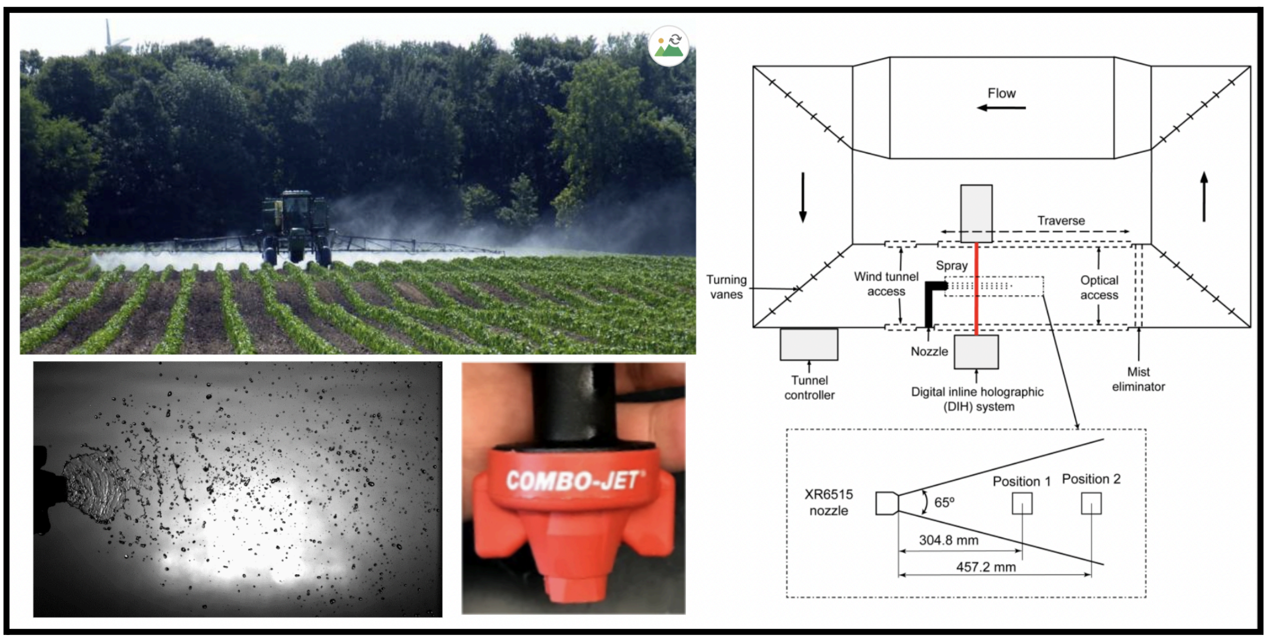

Figure 2: Overview of the First Case Study on Pesticide Spray Characterization. Below is an explanation of this case study:

This first case study focuses on pesticide spray characterization, which is super important in agriculture because it affects both how well pesticides work and how much they impact the environment. Getting the right droplet size distribution is key to drift control, which means making sure pesticides land where they should — on crops — and don't spread to unintended areas, such as nearby water sources or other plants. If pesticide droplets drift too much, they can harm the environment, waste money, and even pose health risks ("Factors Affecting Pesticide Drift," 2018). To tackle this issue, farmers use different methods to control droplet sizes, such as oil emulsion additives, air inclusion technology, and nozzle design. Adding oil to the spray makes the droplets heavier, which helps them stay on target, while air inclusion technology creates larger droplets that don't get carried away as easily by the wind. Nozzle design also plays a huge role, as different nozzles can change how the spray spreads, how fast it moves, and how evenly it covers the crops (Whitford et al., n.d.).

Even though these methods help, traditional tools like laser diffraction and Phase Doppler Particle Analyzers (PDPA) aren't always reliable for measuring how well they work. Laser diffraction works by shining a laser through the spray and measuring how the light scatters to estimate droplet size. However, it assumes all droplets are perfectly round, which they usually aren't, leading to inaccuracies (Headley, 2025). PDPA, which measures droplet size and speed using light shifts, struggles when there are too many droplets packed together, making it hard to get clear data (Vulgarakis Minov et al., 2016). This is where Digital Inline Holography (DIH) steps in as the most efficient and effective tool to use. DIH provides a much sharper, real-time look at the spray, capturing tiny details that other methods miss, and it works better with irregularly shaped particles. It's also more affordable and portable, making it a great fit for agriculture.

To get a better understanding of how pesticide sprays behave, this study used a wind tunnel setup, which creates a controlled environment to test sprays without worrying about weather conditions messing things up. The wind tunnel helps simulate real-world conditions, and the turning vanes inside guide the airflow smoothly, ensuring it's even across the entire spray area. A tunnel controller adjusts the speed of the air to mimic different conditions, while a mist eliminator cleans up any extra spray that could build up and interfere with the test. The system also includes a traverse mechanism, which moves the DIH system across the spray area to collect data from different points, giving a complete picture of how the spray changes as it moves.

The XR6515 nozzle was used in the experiment because of its 65-degree spray angle. This wide-angle helps cover a larger area efficiently, but it also means there's a higher risk of drift if not handled correctly. That's why two specific measurement positions were chosen: 304.8 mm and 457.2 mm from the nozzle. By measuring these two distances, it was possible to see how the droplets spread out and whether they stayed the right size or broke apart too quickly.

The DIH system in the experiment captures super-detailed holograms of the spray droplets at different spots, giving farmers a ton of useful info about droplet size, shape, and how they move through the air. These holograms are processed using powerful algorithms that create 3D images of the droplets, allowing farmers to track their motion and behavior over time. Unlike traditional methods, DIH gives a much clearer and more accurate picture of how sprays actually work, helping to fine-tune pesticide applications for better results.

The top left image in the figure shows a tractor with spray booms applying pesticides across a farm field. This highlights why getting the spray just right is so important for large-scale farming. The bottom left image gives a closer look at the spray droplets, showing how they spread out and the challenges in controlling them. The bottom center image features a "COMBO-JET" nozzle, which is designed to create optimized spray patterns that balance coverage and drift control. Along with this nozzle and the XR6515 nozzle, other nozzles were tested at the same altitude and direction, which will be further explained in the results section (pp. 18 - 22).

Overall, this case study shows how DIH can provide a much better way to analyze pesticide sprays compared to older methods. Collecting detailed data at different distances helps farmers understand how well different spray techniques work, ultimately leading to better pesticide use, less waste, and a lower environmental impact.

Case Study II Overview:

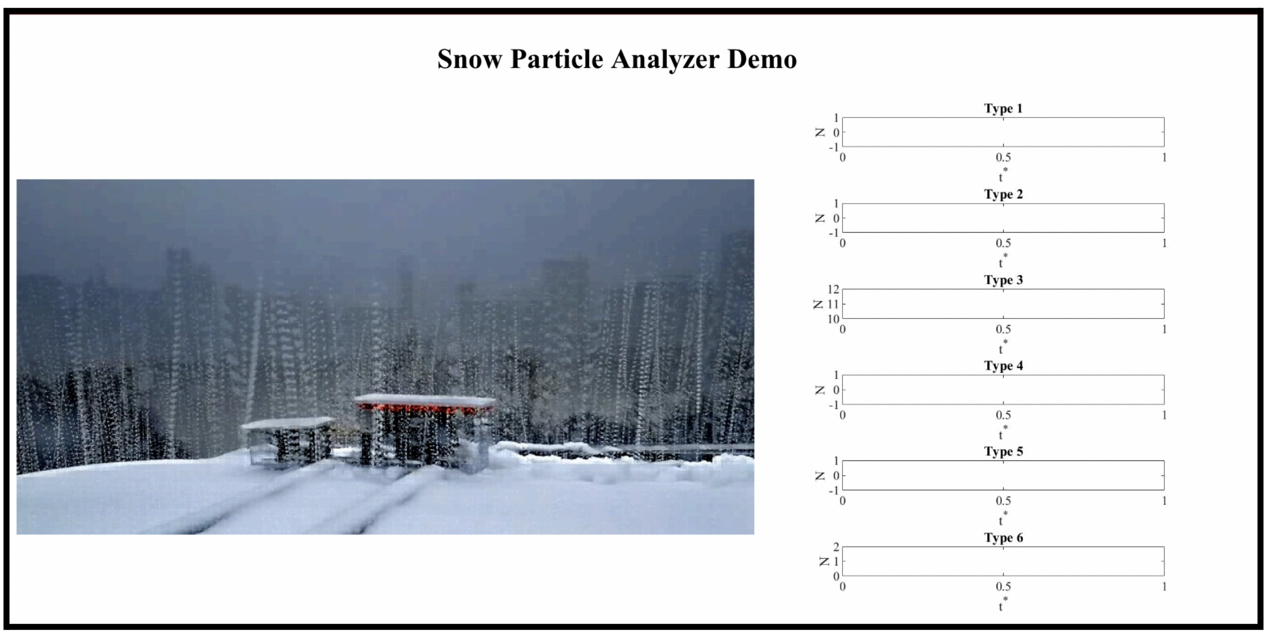

Figure 3: Overview of the Second Case Study on Snow Particle Analysis. Below is an explanation of this case study:

This case study looks at how different types of snow particles can be detected and analyzed in real-time during a snowstorm using a compact and durable setup. The study took place in a park — Staring Lake in Eden Prairie, Minnesota — where snow can vary significantly in density and structure, making it challenging to analyze. The goal was to show how Digital Inline Holography (DIH) can provide high-resolution, real-time details about snowflakes — something that traditional methods struggle with. What's efficient is that all the equipment used for this study was sourced from home, making it a cost-effective and accessible way to study snow particles. Snow comes in many shapes and sizes, which can impact things like road conditions, visibility, and infrastructure (Abrahamsson et al., 2018). That's why being able to analyze snow accurately is super important.

Older methods like optical microscopy and laser diffraction aren't always great at capturing the fine details of snowflakes, especially in real-time. That's where DIH technology comes in — it provides a more efficient and reliable way to study snow particles. The setup for this experiment was built to handle the harsh Minnesota winter and included a laser to light up the snowflakes, a CCD camera to capture their details, a weatherproof case to protect the equipment, a GPU-powered processing unit for quick 3D image creation, and machine learning algorithms to analyze and classify the snowflakes.

The snow particle analysis followed four main steps to break down everything in detail. First, the recording phase involved capturing holograms in real-time as the snowflakes passed through the laser beam, recording their shape and position. Next, the 3D reconstruction step turned those holograms into clear 3D models of the snowflakes. Then came particle segmentation, where machine learning helped sort snowflakes into different types based on their size, shape, and structure. Finally, the 3D tracking phase allowed the system to follow the movement of snowflakes over time to see how they behave under different conditions.

The diagram in the figure categorizes the snowflakes into six distinct types, each with unique characteristics that help in understanding their impact on snowfall dynamics. Some of the types were smaller and simpler in shape, allowing them to fall quickly and significantly reduce visibility during the snowstorm. Others, which appeared more frequently, had more intricate structures and varied in size, showcasing the natural diversity of snowflakes and their influence on accumulation. Certain types were larger and more complex, with detailed patterns that caused them to fall more slowly and build up on surfaces more easily. Finally, there were irregular particles that often broke apart due to environmental factors like wind, contributing to the scattered nature of snowfall. Analyzing these different formations provides valuable insights into how snow accumulates, how it affects transportation and visibility, and what steps can be taken to mitigate its impact. All specific details regarding these types will be discussed further in the results section (pp. 22 - 23).

The DIH system was set up in an urban area (Staring Lake Park) during a snowstorm to capture as much variety in snowflake shapes as possible while avoiding interference from buildings or other objects. Some important things to consider during deployment included placing the system at the right altitude to catch snowflakes falling at different speeds, keeping the electronics from freezing, and making sure all data was continuously saved for later analysis. The system's compact size made it easy to transport and set up, which means it could be used for other studies in the future.

Compared to traditional methods, the DIH system provided much clearer and more detailed images of snowflakes. Plus, it's small and durable enough to be used outside in rough weather without any issues. Another huge advantage is that it’s way more affordable than expensive lab equipment and can provide real-time data without needing to collect and prepare samples first.

This case study proves that DIH technology can completely change the way to study snow and any other environmental particles. It makes it easier to track and understand snowfall patterns, which can help improve snow removal strategies, weather forecasting, and overall preparedness for heavy snow conditions.

Case Study III Overview:

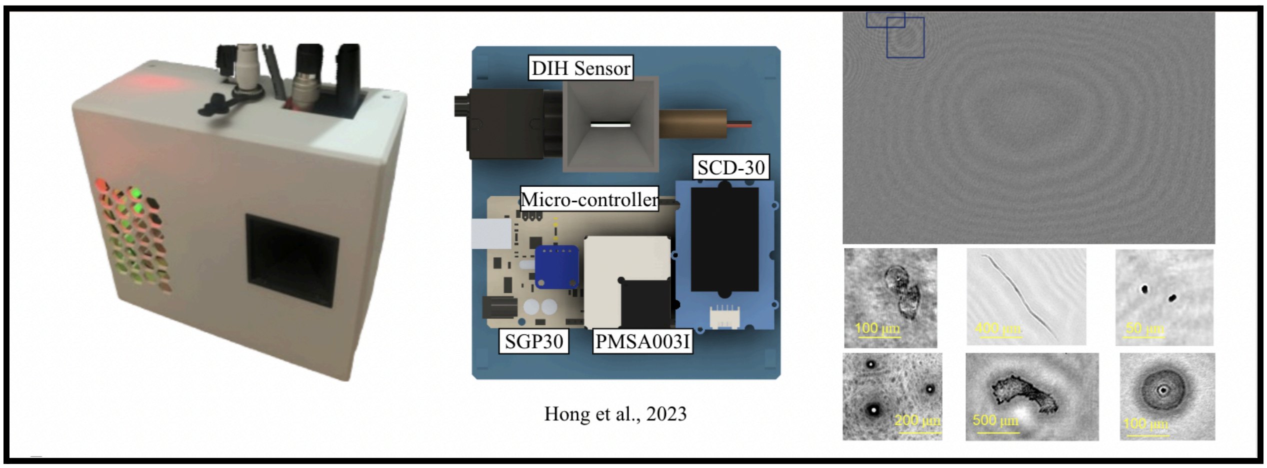

Figure 4: Overview of the Third Case Study on Air Quality Monitoring. Below is an explanation of this case study:

This case study focuses on the development and testing of an in-house air quality monitor designed to provide real-time analysis of airborne particles. The system consists of several key components that work together to detect and classify particles in the air, making it an efficient and reliable solution for air quality monitoring. The setup includes a Digital Inline Holography (DIH) sensor, which acts as the primary imaging tool to capture high-resolution images of particles ranging in size from 2 µm to 1 mm within a 3 mL sample volume. The DIH sensor is a lensless system, allowing it to provide clear and detailed particle imaging without the need for complex optical components.

In addition to the DIH sensor, the system is equipped with multiple environmental sensors to gather comprehensive air quality data. These include a PM (particulate matter) sensor, a VOC (volatile organic compounds) sensor, a CO_2 sensor, as well as temperature and humidity sensors, which all work together to monitor various environmental conditions. All these components were additional purchases made outside of home resources to enhance the system's capabilities. The data collected from these sensors provide a holistic view of air quality, making it easier to identify trends and potential issues in different environments.

The core of the system features an onboard microcontroller, which acts as the main control unit, managing data flow between the sensors and processing components. A PMSA003I sensor is included to detect fine particulate matter, while an SGP30 sensor helps in tracking volatile organic compounds in the air. The SCD-30 module is responsible for measuring CO_2 levels, ensuring accurate monitoring of air quality changes. These components were also acquired externally to complement the system and ensure accurate and efficient air quality measurements. All these components are carefully integrated to work together efficiently.

One of the most significant features of this air quality monitor is its onboard GPU processor, which utilizes deep learning algorithms to analyze captured data in real time. The GPU enables high-speed processing for particle classification, counting, and size measurement, allowing the system to process air at a rate of 26 liters per minute (L/min). The analyzed data is then automatically backed up to cloud storage, providing secure and accessible records for further analysis or review.

On the right side of the diagram, several images showcase the types of particles analyzed by the system, highlighting the diversity of airborne contaminants it can detect. These images display particles of various sizes, with measurements such as 50 µm, 100 µm, 200 µm, 400 µm, and 500 µm, offering a glimpse into the system's ability to capture and distinguish between different types of particulate matter. The detailed particle images confirm the monitor's capability to identify a wide range of particles, from microscopic debris to larger airborne contaminants, which will be discussed in more detail in the results section (pp. 23 - 25).

Overall, this air quality monitoring system provides a compact and cohesive solution for real-time environmental analysis. Its combination of DIH technology, deep learning-based processing, cloud storage capabilities, and additional monitors makes it an effective tool for tracking air pollution, detecting harmful particles, and improving overall environmental awareness.

Case Study IV Overview:

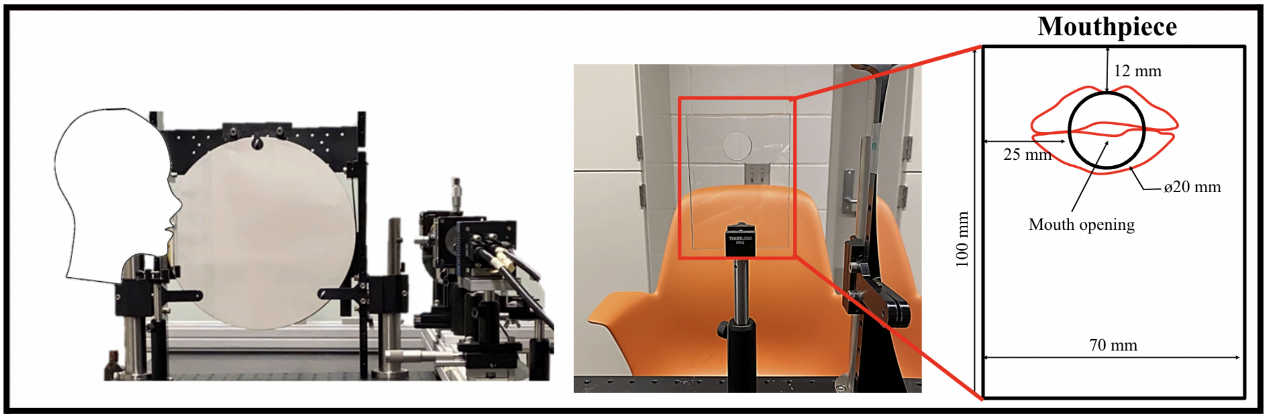

Figure 5: Overview of the Fourth Case Study on Respiratory Aerosol Analysis. Below is an explanation of this case study:

This fourth case study goes into respiratory aerosol analysis, which is super essential for understanding how tiny particles, or aerosols, are produced when people breathe and talk. These aerosols can carry germs, allergens, or pollutants, which makes studying them a big deal for public health, especially when it comes to spreading diseases (Fennelly, 2020). The goal of this study is to figure out how aerosols form and spread in different breathing scenarios. To do this, advanced imaging techniques are used, combining Schlieren imaging — an optical method that helps visualize air density changes by detecting how light bends — to track airflow, and Digital Inline Holography (DIH) to capture super-detailed images of the aerosols in real-time (Rolfe, n.d.). The DIH system can detect aerosol sizes, particularly ranging from 0.5 to 100 µm, which covers everything from super fine to larger respiratory particles. This size range matters because smaller aerosols (under 10 µm) can stay in the air for a long time, while bigger ones (over 10 µm) settle down more quickly (Tang et al., 2020).

The experimental setup, shown in the figure, is carefully designed to keep things consistent. A special mouthpiece helps control airflow during the tests. The mouthpiece has a 20 mm opening, which is pretty close to the average size of a human mouth when breathing normally or talking. The overall dimensions — 70 mm wide and 100 mm tall — give the structure stability and make sure the airflow stays even. The 25 mm spacing represents how deep the mouth opening goes. The 12 mm lip thickness helps mimic real breathing conditions as naturally as possible. These precise measurements ensure the experiment is feasible and produces accurate results.

One big challenge in studying respiratory aerosols is that regular breathing doesn't produce a lot of them, which makes it hard for traditional techniques to pick them up (Jayaweera et al., 2020). According to Monroe et al. (2022), "Generated particle concentrations were significantly higher than those observed by human coughing. This was done to simulate 'worst-case' scenarios and amplify the aerosol signal that escaped the enclosure, facilitating reliable measurements, since realistic coughing and tracheal operations release aerosol concentrations that are difficult to measure." Simply put, traditional aerosol detection tools often struggle because the particles are just too sparse compared to those generated by coughing or sneezing. With DIH, that's not a problem — it provides super sensitive and real-time 3D tracking of aerosols, giving a clear and detailed picture of how they behave.

To take things a step further, Schlieren imaging is used alongside DIH to visualize the airflow. This technique is essential for spotting even tiny changes in air movement caused by the warm, moist air that is exhaled. It works by using a special optical setup that highlights shifts in air density, making it possible to see how air moves around a person's face when they breathe or talk. Combining Schlieren imaging with DIH gives a full picture of how air and aerosols travel, which is super useful for understanding how respiratory particles spread in different situations.

This study is particularly relevant when it comes to airborne disease transmission, like during the COVID-19 pandemic, where understanding how aerosols move can lead to better protection strategies. The data from this study helps improve things like face masks, ventilation systems, and even guidelines for social distancing by showing exactly how aerosols behave in different conditions; these findings will be detailed further in the results.

The combination of Schlieren imaging for airflow tracking and DIH for detailed aerosol analysis provides an accurate, in-depth understanding of aerosol production and dispersion. The findings could have a big impact on healthcare, workplace safety, and public health policies, helping to reduce the risks of airborne diseases and improve overall air quality strategies.

Case Study V Overview:

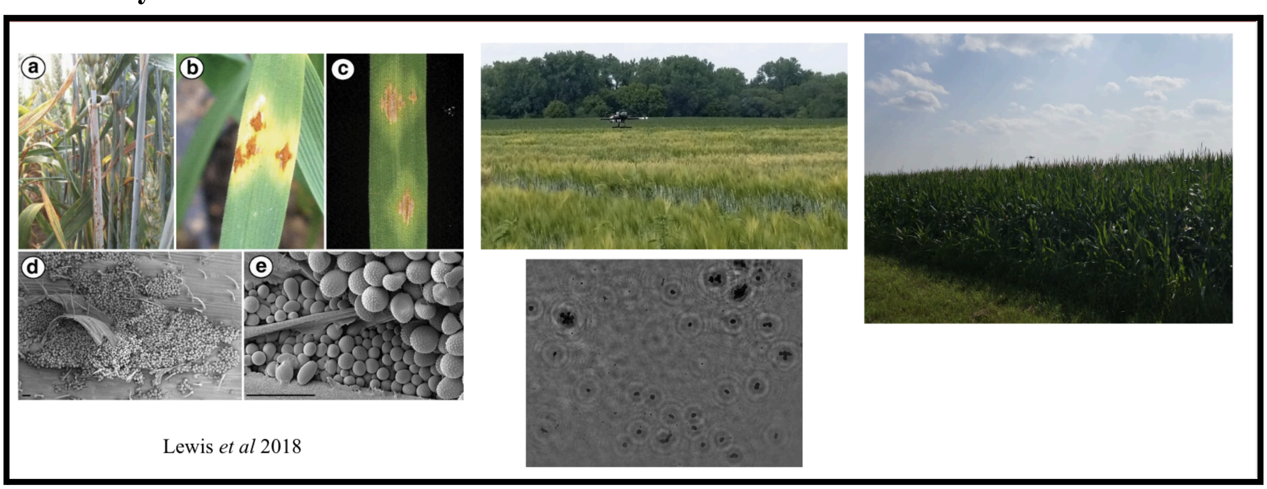

Figure 6: Overview of the Fifth Case Study on Autonomous Drone for Aerosol Sampling. Below is an explanation of this case study:

This fifth and final case study focuses on drone-driven spore and pollen detection, an innovative approach to monitoring plant health and airborne particles in agricultural environments. The goal of this study is to use Digital Inline Holography (DIH) technology mounted on drones to detect stem rust spores in wheat fields and corn pollen in large-scale farming areas. These airborne particles play a crucial role in agricultural productivity — stem rust spores can severely impact wheat yields by spreading fungal infections, while corn pollen is essential for successful pollination and crop growth (Lahlali et al., 2024). Understanding how these particles spread and behave can help farmers optimize planting strategies, improve yields, and prevent the spread of harmful pathogens.

To achieve this, the study tested both single- and multi-drone operations, examining different sampling methods to find the most effective way to collect and analyze airborne spores and pollen at Cedar Creek, MN. The drones were deployed over the crop fields, capturing data under real-world conditions to evaluate their performance in this environment. The images in the figure above provide an overview of the study setup and findings. The top middle image shows the drone in action, flying over wheat and corn fields to collect data. These drones were equipped with DIH sensors and a CCD camera to scan large areas efficiently, offering a bird's-eye view of pollen and spore dispersion patterns.

The labeled images (a, b, c) depict different stages of stem rust infection on wheat leaves, ranging from early signs to more advanced infections, which can spread via airborne spores. The microscopic images (d, e) show high-resolution scans of spores and pollen particles, highlighting their structure and distribution. The DIH data, shown in the bottom middle, provides a clear visualization of detected corn pollen particles, confirming the effectiveness of the technology in capturing even microscopic particles. The system was able to identify and track pollen sizes with high precision, distinguishing them from other airborne contaminants.

One of the most interesting aspects of this study is how DIH technology was used to provide real-time insights into the presence and movement of these particles. Traditional methods, like manual sampling and lab analysis, can be time-consuming and inconsistent. However, with DIH-equipped drones, farmers can quickly and accurately monitor their fields, making informed decisions on crop management and disease prevention in real-time.

Overall, this case study goes over the power of combining drone technology and DIH imaging to revolutionize agricultural monitoring. The ability to detect spores and pollen remotely with high accuracy can lead to better disease management, optimized fertilization schedules, and improved crop yields. This paves the way for smarter, data-driven farming practices, helping farmers stay ahead of potential threats and maximize their productivity.

5. RESULTS

After a lot of testing, analysis, and fine-tuning, the results from each case study showed that the

Digital Inline Holography (DIH) sensor is reliable and works well in different environments. The findings prove that DIH can capture, analyze, and interpret aerosol particles with impressive accuracy in real-world settings. Each case study gave valuable insights into how DIH can make a big impact on particle diagnostics in agriculture, environmental monitoring, and public health. **Below is a detailed analysis of the findings from each conducted case study in order:**

Case Study I Results:

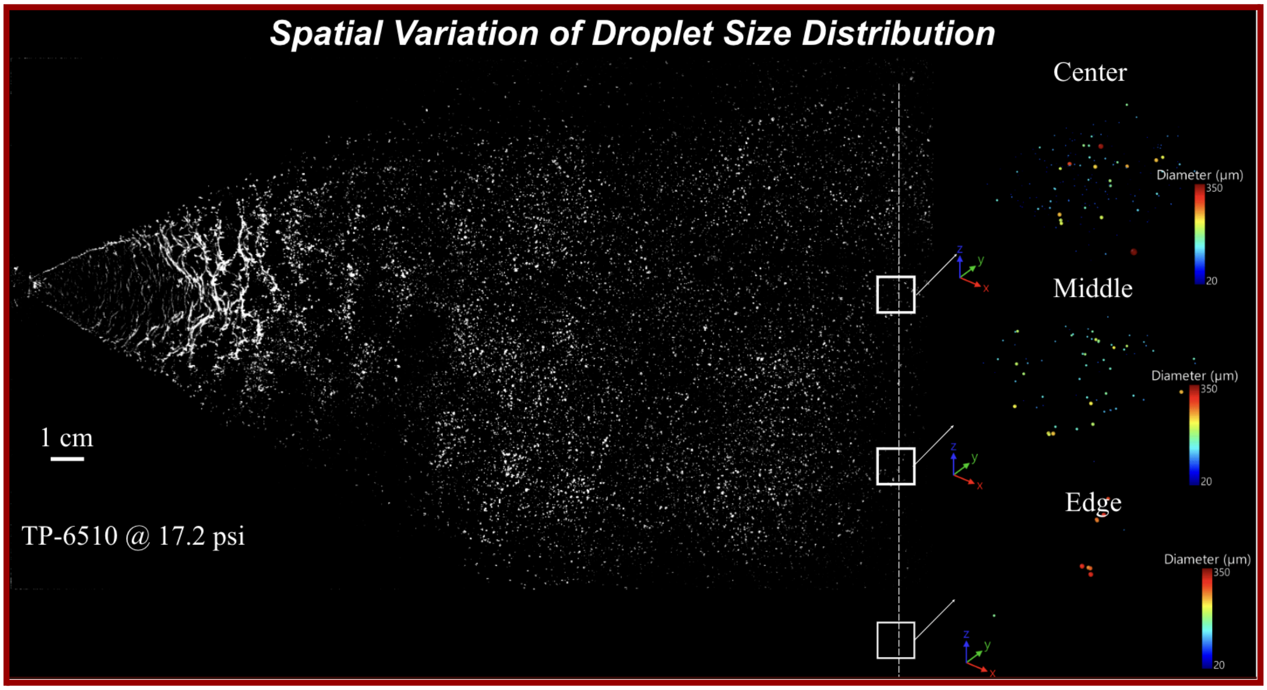

Figure 7: Results of Pesticide Spray Characterization Case Study. Analysis of Droplet Sizes

The results from this case study on pesticide spray characterization provide an analysis of how droplets behave as they move through the air, helping to understand their size distribution across different regions of the spray. Using Digital Inline Holography (DIH), the experiment captured a 3D visualization of the droplets as a laser scanned through the spray, offering near real-time insights through machine learning-based holographic reconstruction. Essentially, this simulation provided a highly detailed look at how the droplets disperse from the nozzle under controlled conditions.

The spray was generated using a TP-6510 nozzle at 17.2 psi — a typical pressure setting used in agriculture to achieve a good balance between coverage and drift control (Sumner, 2012) — and an XR6515 nozzle, as stated in the methods section. The figure shows how the droplets start densely packed near the nozzle and gradually spread out as they move further. The 1 cm scale bar provides perspective on how far the droplets traveled, showing a gradual dispersion pattern. This visualization demonstrates the effectiveness of the nozzle and pressure settings in controlling the spray pattern.

On the right side of the figure, the results are broken down into three key regions: center, middle, and edge. Each of these areas demonstrates something different about how the droplets behave. In the center region, the droplets are the largest, with some measuring 20 µm and others reaching up to 350 µm — dispersed from blue to red on the color scale. Larger droplets tend to stay within the intended spray zone, making them more effective for direct crop coverage. Moving to the middle region, the droplet sizes start to vary more, ranging from 50 to 250 µm, represented by a mix of green and yellow colors. This is where the spray begins to disperse more, but the droplets are still relatively effective. Finally, in the edge region, the droplets become much smaller — still with a diameter of around 350 µm — shown in red. These smaller droplets are more prone to drifting away from the target, which could lead to pesticide waste and environmental concerns.

The color scale used in the figure, ranging from 20 µm (blue) to 350 µm (red), provides a clear visual representation of how droplet sizes change across the spray. This color gradient helps quickly identify where the most significant variations occur. The largest droplets stay closer to the center, while the smallest ones tend to move toward the edges, highlighting the importance of nozzle placement and spray conditions in ensuring optimal pesticide application.

This entire study was conducted using a simulation-based approach, where powerful machine learning algorithms processed the holograms to generate a 3D representation of the droplets. This approach enabled the tracking of droplet movements and provided insights into their behavior in real-world conditions without the need for field tests. The machine learning algorithms used in the process ensured that the droplet sizes were accurately captured and analyzed in near real-time, providing insights that traditional methods like laser diffraction often miss.

So, what does all of this mean for farmers? Essentially, these results confirm that the spray is most effective in the center region where the largest droplets are found, ensuring proper coverage. However, as you move outward, the droplets become smaller and more dispersed. This means adjusting the spray settings or using additives to reduce drift has occurred. Farmers can use this information to fine-tune their spraying techniques, reduce waste, and ensure their pesticides are hitting the right targets while minimizing environmental impact.

Overall, this case study proves that DIH provides a much more accurate, detailed, and real-time view of droplet distribution than traditional methods. Farmers and researchers can use DIH to optimize their spray applications, improving efficiency and reducing environmental risks.

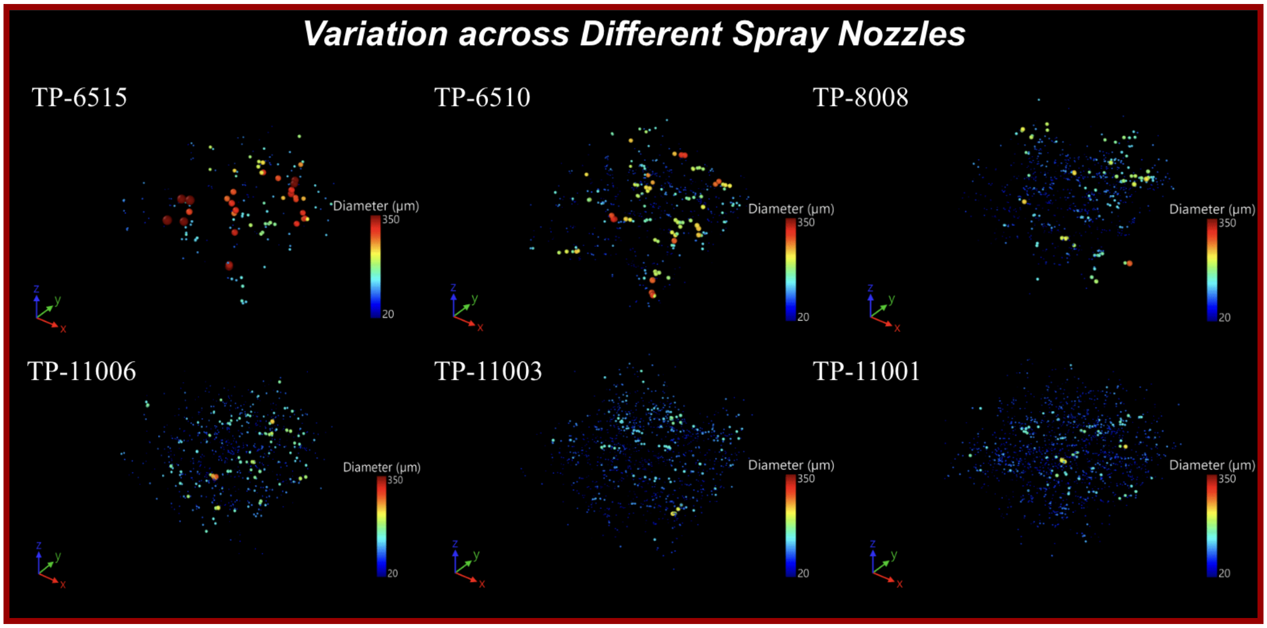

Figure 8: Analysis of Different Pesticide Spray Nozzle Performances

These are additional results from case study 1 analyzing how different spray nozzles perform when it comes to droplet size distribution, giving a clear idea of how each nozzle disperses pesticide spray. Using the Digital Inline Holography (DIH) system, this experiment captured detailed 3D visualizations of the spray patterns produced by six different nozzles: TP-6515, TP-6510, TP-8008, TP-11006, TP-11003, and TP-11001. The DIH system makes it easy to compare nozzle performance by covering the entire size range commonly used in agricultural applications. The results highlight significant variations in droplet sizes and distribution patterns, which is crucial for optimizing pesticide application and minimizing drift.

From the results, it's clear that each nozzle produces a unique spray pattern — just like Figure 7 — with droplet sizes ranging from 20 µm (blue) to 350 µm (red), as shown by the color scales next to each visualization. Some nozzles, like TP-6515 and TP-6510, produce larger droplets, which are indicated by the red and orange colors, meaning they're better for applications where precise targeting and reduced drift are important. On the other hand, nozzles such as TP-11003 and TP-11001 generate much smaller droplets, with a predominance of blue and green colors, suggesting that they are more suitable for applications that require finer misting but could result in higher drift potential.

Breaking it down further, the TP-6515 nozzle shows a good mix of large and medium-sized droplets, with several in the 250-350 µm range. This suggests it would be useful for applications where larger droplets help minimize drift and ensure proper coverage. The TP-6510 nozzle produces a more balanced distribution, with most droplets falling within the 100-250 µm range, making it a great choice for general-purpose spraying with moderate drift control. The TP-8008 nozzle creates a wider spread of droplets, mostly in the 50-200 µm range, making it ideal for fine mist applications over large areas. On the other hand, the TP-11006 nozzle produces predominantly smaller droplets, mostly in the 20-150 µm range, which provide excellent coverage for delicate applications like foliar spraying. According to Patterson (2021), "foliar plant spray involves applying fertilizer directly to a plant's leaves as opposed to putting it in the soil," allowing for quick absorption but requiring careful wind management. The TP-11003 nozzle stands out for producing very small droplets, mostly below 100 µm, making it a great fit for greenhouse applications where ultra-fine misting is needed. Lastly, the TP-11001 nozzle generates the smallest and most dispersed droplets, with most falling within the 20–80 µm range. This makes it less ideal for outdoor spraying due to the high drift potential.

The advantage of using the DIH system for this study is how effortlessly it visualizes nozzle performance, making it easier to see which nozzles provide the best coverage and efficiency for specific tasks. The 3D representations allow for the observation of how droplets disperse and behave under different conditions, helping farmers make informed decisions about which nozzle to use based on their needs. This side-by-side comparison clearly shows the strengths and limitations of each nozzle type, allowing for better planning when it comes to pesticide application.

The results from this nozzle comparison show just how valuable DIH technology is in helping optimize pesticide applications. By providing a detailed and real-time analysis of droplet sizes and dispersion, this technology empowers farmers to choose the right nozzle for their specific needs, whether it's minimizing drift, maximizing coverage, or finding the perfect balance.

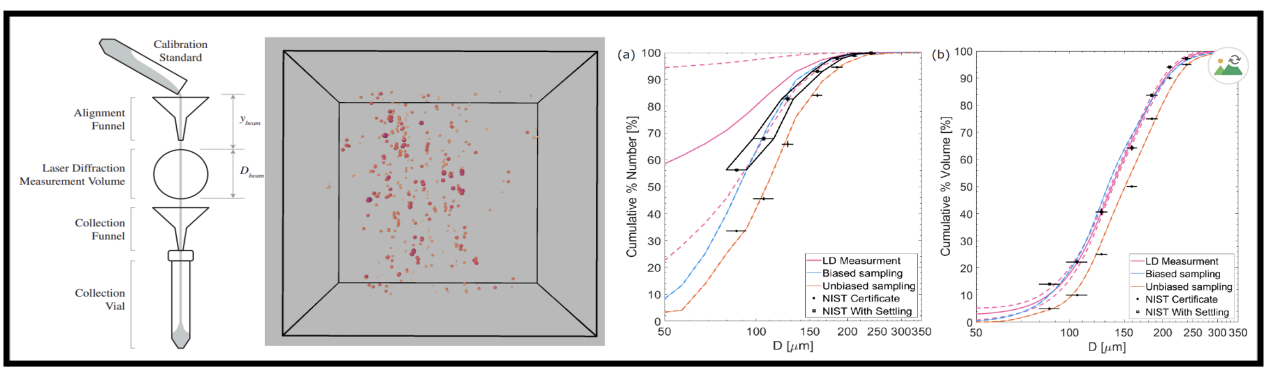

Figure 9: Pesticide Spray Characterization Results Compared to Laser Diffraction System

Above is a figure comparing the results of the Pesticide Spray Characterization case study to the Laser Diffraction (LD) system. The current model efficiently extracts cumulative number and volume distribution from a tiny sample (0.8 seconds for the unbiased sample) of the National Institute of Standards and Technology (NIST) beads. In contrast, the LD system requires a larger sample (~30–40 seconds) to obtain cumulative volume. However, even with multiple pours, extracting the cumulative number distribution is challenging. While LD captures biased cumulative number and volume distributions, DIH can extract both real and biased distributions without multiple pours.

Case Study II Results:

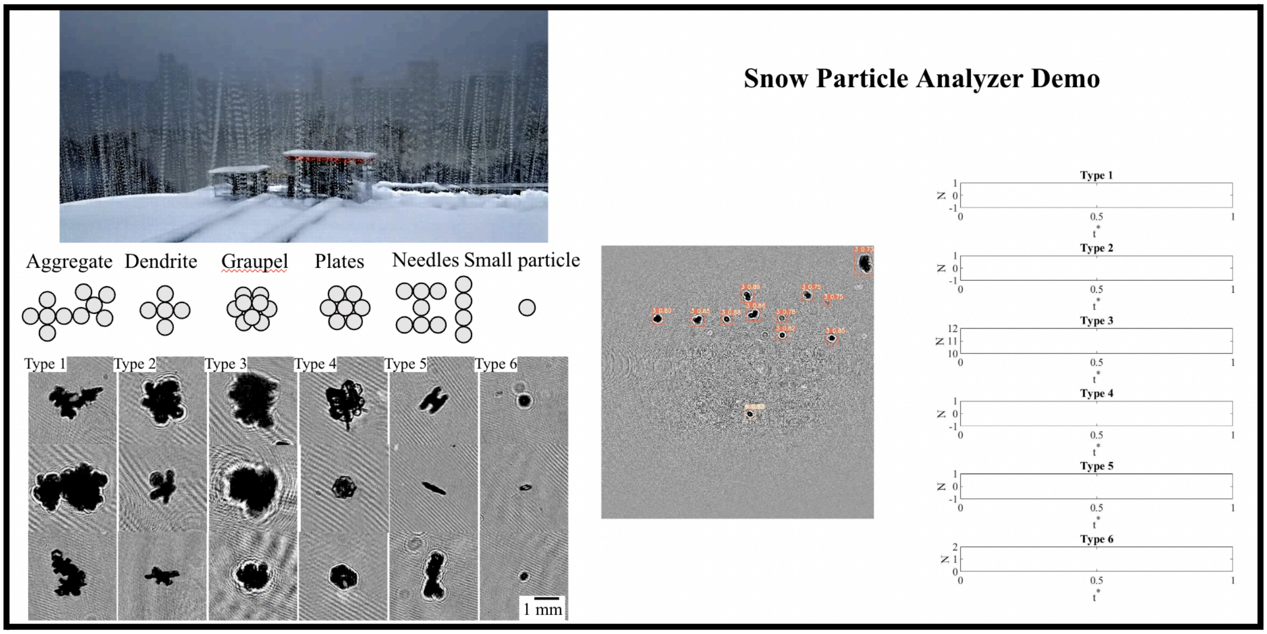

Figure 10: Results from Snow Particle Analyzer Case Study

The results of this case study classify snow particles into six distinct types based on their unique morphological characteristics: Aggregate, Dendrite, Graupel, Plates, Needles, and Small Particles. Each type plays a different role in snowfall dynamics and impacts visibility, accumulation, and overall weather conditions.

Type 1 snowflakes, identified as aggregates, are clusters of smaller snowflakes that have stuck together. These particles are relatively larger and more irregular in shape, which causes them to fall more slowly and significantly contribute to snow accumulation on surfaces. Their irregularity also makes them prone to breaking apart due to wind or physical disturbances.

Type 2 snowflakes, classified as dendrites, exhibit intricate branching patterns. These are the classic "snowflake" shapes commonly depicted in imagery. Due to their complex structure, dendrites fall slowly and tend to accumulate in thick layers, which can significantly increase snow cover. Their light, airy structure makes them highly susceptible to wind drift, reducing visibility during heavy snowfall.

Type 3 snowflakes, representing graupel, are rounded snow pellets formed when supercooled water droplets coat a snowflake, creating a dense, ice-like particle. Graupel tends to fall rapidly due to its higher density and compact shape. These particles are commonly associated with sleet-like conditions and can pose challenges to road safety due to their slippery nature.

Type 4 snowflakes, known as plates, have a flat and thin structure and form in relatively warmer atmospheric conditions. Plates fall moderately fast and settle in an orderly fashion, creating a smooth snow surface. Despite their delicate appearance, they can compact easily, contributing to denser snowpack formations.

Type 5 snowflakes, characterized as needles, are elongated ice crystals that form under specific atmospheric conditions with high humidity. They tend to align in the air as they fall, leading to unique accumulation patterns. Needles can increase snow density and contribute to harder, more packed layers of snow, which can be challenging to remove from roads and pathways.

Type 6 snowflakes, the smallest particles, consist of individual ice crystals that have not yet aggregated into larger formations. These small particles are more prone to remaining airborne for extended periods, affecting visibility but contributing minimally to ground accumulation. They often serve as the foundation for larger snowflake formation under the right conditions.

Each of these snow types presents unique implications for weather forecasting, transportation, and infrastructure management. Understanding their distribution and behavior in real-time helps in making better predictions about snowfall impacts and necessary responses, such as road treatments and public safety measures. DIH does exactly just that.

Case Study III Results:

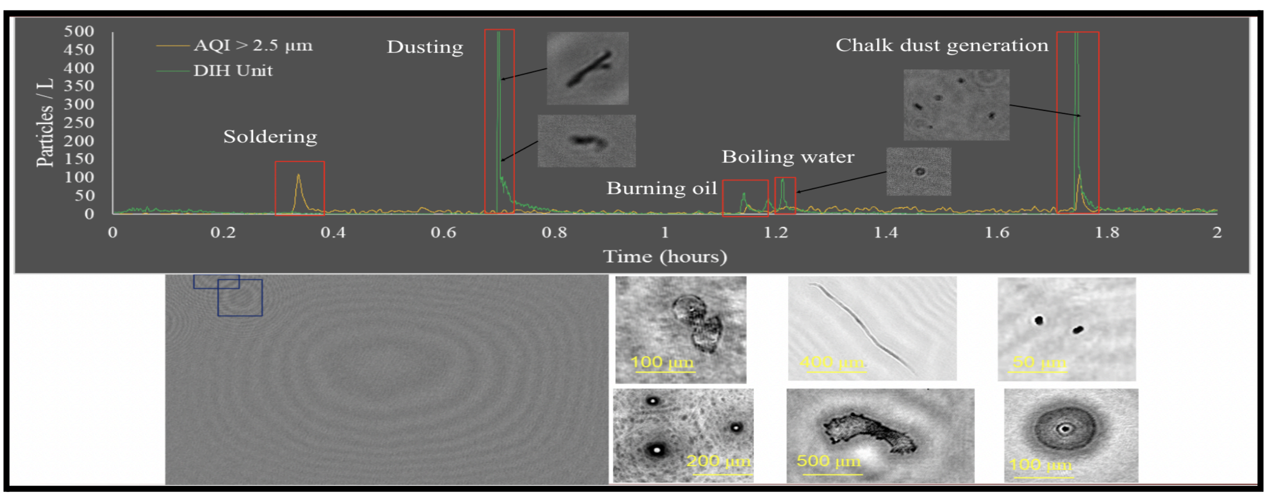

Figure 11: Results from Air-Quality Monitor Case Study

The results from this case study demonstrate how the air quality monitor performed over a two-hour period in a small room where various particulate matter (PM) generation events were conducted. Five key events were introduced at different time points to assess the system's capabilities: soldering, dusting, burning oil, boiling water, and chalk dust generation. The graph in the top section of the figure provides a detailed timeline of how particle levels fluctuated throughout the experiment, with the yellow line representing the readings from the Air Quality Index (AQI) > 2.5 µm sensor and the green line showing data collected by the DIH unit.

From the graph, noticeable spikes in PM levels were observed at specific time points, corresponding to four of the five events: dusting, burning oil, boiling water, and chalk dust generation. The DIH system successfully detected these events, capturing unique particle morphologies that appeared at those times. The insets on the graph provide close-up images of the particles recorded during each event. For example, dusting resulted in elongated particles, while chalk dust generation captured circular clusters. The DIH sensor's ability to capture these detailed shapes confirms its higher sensitivity to larger particles and their distinct structures.

Interestingly, the soldering event was one area where the DIH system fell short. While the AQI 2.5 sensor registered a noticeable spike during the soldering period, indicating the presence of fine PM, the DIH unit failed to capture any significant data. This suggests that the particles generated from soldering were likely too small (less than 1 µm) for the DIH system's detection range, reinforcing the idea that DIH technology is better suited for larger particles rather than ultra-fine ones.

When it came to the burning oil and chalk dust generation events, both the DIH and AQI 2.5 sensors captured significant particle spikes, showing their effectiveness in identifying PM from these sources. However, the DIH unit proved to be much more detailed, providing insights into particle shapes and sizes that the AQI 2.5 could not distinguish. This further highlights how DIH offers a more comprehensive understanding of air quality by not just detecting particles but also analyzing their morphology.

On the other hand, the AQI 2.5 sensor struggled with dusting and boiling water, failing to capture meaningful data during these events. This is where the DIH system outperformed, successfully detecting and classifying particles from these sources, showing its strength in recognizing a wider range of particle sizes and shapes.

At the bottom of the figure, several close-up particle images highlight the diverse range of PM detected during the experiment. The particles are labeled with their sizes, ranging from 50 µm to 500 µm, showcasing the system's ability to capture a broad spectrum of particles with distinct shapes and textures. Expanding on what was previously mentioned in the methods section, the lensless DIH sensor played a crucial role in imaging these particles in a sample volume of 3 mL, capturing intricate details without the need for traditional optical components. The onboard GPU processor utilized deep learning algorithms to classify, count, and measure particle sizes in real-time, ensuring that the system could handle a rate of 26 L/min, making it highly efficient for continuous monitoring.

The 100 µm and 200 µm particles appear as clusters, generated during the chalk dust event, where fine particles dispersed into the air in a uniform pattern. The 500 µm particle, on the other hand, exhibits an irregular shape, which originated from the burning oil event where larger droplets and debris were introduced into the air. Additionally, the 400 µm particle appears elongated, linked to dusting activities, while the 50 µm particle represents smaller dispersed contaminants from the boiling water event.

These detailed particle images further validate the efficacy of the DIH system in providing real-time understandings of air quality by not only counting particles but also identifying their unique features, based on their size and shape, making it an invaluable tool for comprehensive environmental monitoring.

The DIH system proved exceptional sensitivity to larger PM, effectively capturing particles from four out of the five events and providing detailed morphological data. However, it did miss the smallest particles from the soldering event, which were successfully detected by the AQI 2.5 sensor. These results highlight the complementary strengths of both sensors — DIH excels in identifying larger particles and their characteristics, while traditional AQI sensors remain useful for detecting finer PM.

Case Study IV Results:

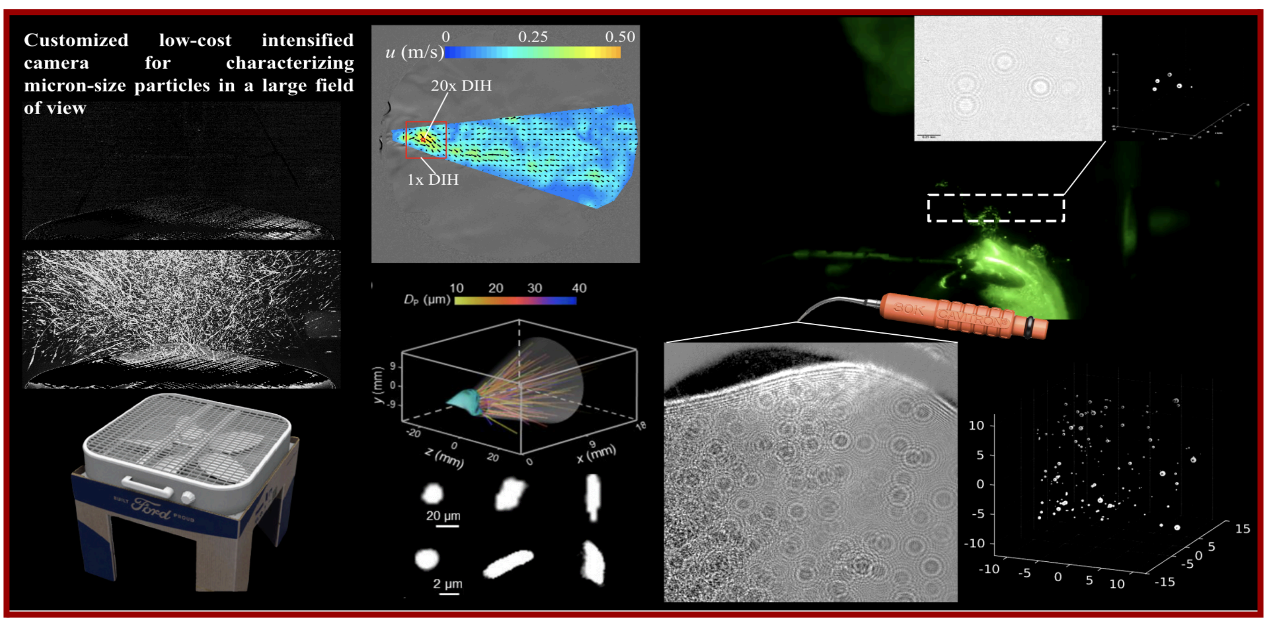

Figure 12: Results from Respiratory Aerosol Analysis Case Study

The results from this respiratory aerosol analysis case study provide an intricate understanding of how aerosols behave during breathing and speaking. The experiment was conducted on Ramakrishna Tammana to test the setup using a miniature CCD camera to capture micron-sized particles across a wide field of view. The DIH system was able to detect particles as small as 2 µm, which is super impressive because conventional systems usually struggle with such tiny aerosols, especially during normal breathing when the yield is naturally low.

The results show how aerosols disperse in different airflow patterns. The middle left section displays Schlieren imaging results, capturing the airflow from breathing. The bottom left section includes a homemade fan setup, used to create a controlled airflow environment for better visualization and measurement. The colorful visualization in the center, labeled with "1x DIH" and "20x DIH," implies the velocity distribution of the aerosols, with the color scale indicating speeds from 0 to 0.50 meters per second. This indicates that closer to the source, the aerosol particles move faster, and as they spread out, their speed gradually decreases.

The color gradient from yellow to blue in the particle size distribution graph indicates that particle sizes range from 10 to 40 µm, with most of them clustering around the lower end, meaning smaller particles dominate in normal breathing. The magnified holographic images at the bottom further confirm this, with clearly resolved particles as small as 2 µm and some larger ones around 20 µm.

On the bottom right, the graph highlights how DIH was used to reconstruct aerosol particles in 3D, showing their positions and sizes. The 3D scatter plot maps the particle positions in a spatial field and shows their distribution over a small area. This gives a clear view of how aerosols spread in a real-world scenario, helping to understand potential transmission risks in different environments.

These results show that the system worked well in capturing and analyzing respiratory aerosols with high precision. The combination of Schlieren imaging and DIH provided a complete picture of how particles move and spread during breathing, which is super helpful in improving things like mask designs and ventilation systems. Testing this setup on a human subject further demonstrates its viability and accessibility for real-life applications.

Case Study V Results:

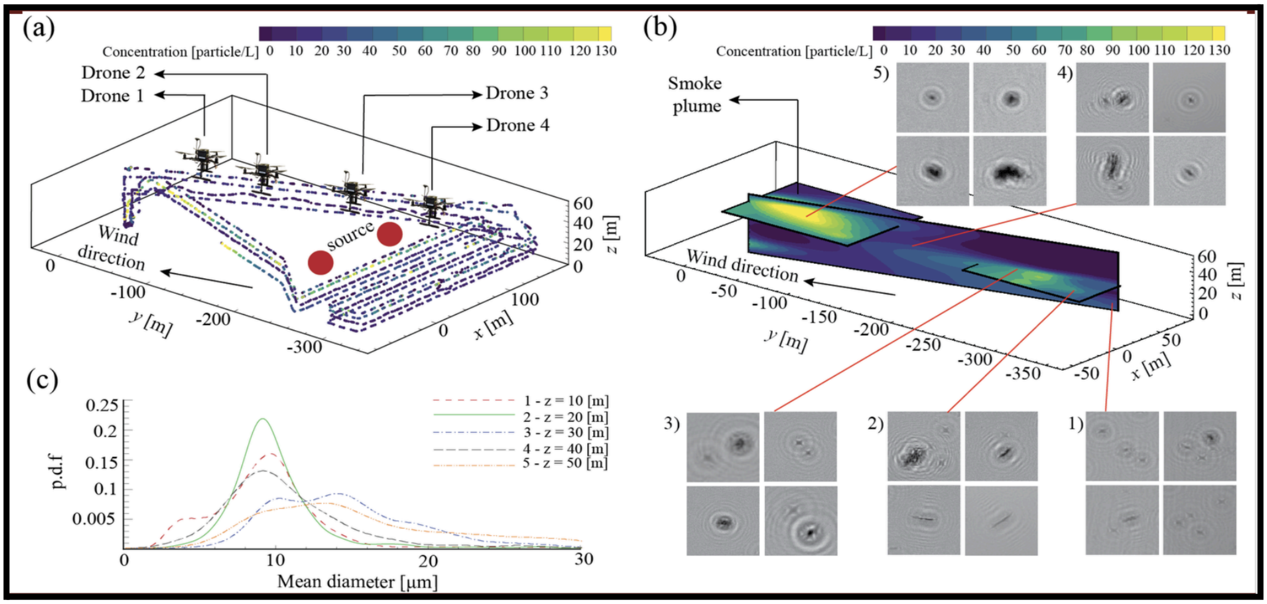

Figure 13: Results from Autonomous Drone for Aerosol Samplings Case Study

The results from the Drone Swarm for aerosol samples showcase how a network of drones was used to detect and analyze airborne particle concentrations in a real-world setting at Cedar Creek, MN. The deployment involved four drones, strategically positioned to capture data as particles dispersed from a designated source due to wind. In diagram (a), you can see the layout of the deployment with the particle source marked by red dots and the drones positioned at different locations to track the dispersion pattern. The color-coded path lines represent the concentration of particles in particles per liter, with values ranging from 0 to 130, indicated by the scale at the top. Higher concentrations are shown in yellow and green, while lower concentrations appear in darker shades of blue and purple. This visualization helped to understand how particles travel and disperse in the environment, providing valuable insights for pollution tracking and airborne contaminant studies.

Diagram (b) provides a closer look at how the smoke plume spreads, showing the particle concentration levels across different distances and heights. The plume is shown in a 3D representation, with the highest concentrations observed closer to the source and gradually decreasing as the particles move further downwind. The arrows indicate the wind direction, pushing the plume from left to right, influencing particle distribution across the area. Surrounding the diagram are several close-up images of detected particles at various measurement points (labeled 1 to 5). These holographic reconstructions provided detailed views of individual particles, highlighting their varying shapes and sizes, which can give insights into their sources and potential impacts.

Diagram (c) presents a probability density function (p.d.f.) plot, which breaks down the distribution of particle sizes measured at different altitudes (z-values of 10, 20, 30, 40, and 50 meters). Each line represents a different altitude, showing how the particle sizes vary with height. The peak of the green curve (z = 30 m) indicates that most particles at that altitude had an average diameter of around 10 micrometers, whereas the red line (z = 10 m) suggests a broader range of particle sizes, with some larger particles present closer to the ground. This analysis helped determine how particles settle and disperse at different heights.

Overall, the results indicate that the drone swarm successfully mapped particle dispersion patterns at Cedar Creek, showing how DIH technology can provide real-time, high-resolution data on airborne particles. This information is incredibly useful for applications like air quality monitoring, wildfire smoke tracking, and agricultural studies to further understand how pollutants or spores spread through the air. The findings from this deployment prove that drone-based aerosol detection can be a powerful tool for tracking environmental pollutants with great precision and efficiency.

6. CONCLUSIONS & DISCUSSION

The results from all five case studies demonstrate that the comprehensive Digital Inline Holography (DIH) system developed for this research is effective across a wide range of real-world applications. Whether analyzing pesticide sprays, studying snow particles, monitoring air quality, assessing respiratory aerosols, or utilizing drones for environmental sampling, the DIH system consistently provided accurate and high-resolution results.

A key takeaway from this research is that DIH technology offers a versatile and reliable solution for characterizing particles in diverse environments — an area where traditional methods, such as laser diffraction, often encounter challenges, particularly with irregularly shaped or larger particles, and sometimes extremely small particles. The system's capability to capture and analyze particles in real-time, enhanced by machine learning algorithms, presents significant potential for improving agricultural efficiency, public health monitoring, and environmental assessments.

The findings confirm that DIH technology can be a valuable tool for both farmers and industry professionals. The successful integration of drones further expands its potential, enabling remote and large-scale data collection that can revolutionize air quality monitoring and agricultural practices. This is a significant step forward in safeguarding the future against deadly viruses.

Future work will focus on refining and expanding the system's applications to new areas, such as healthcare and industrial pollution monitoring. Another goal for the future is expanding on tracking and analyzing microbiological particles. The research establishes a solid foundation for continued innovation and further advancements in decoding aerosol particles.

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