

# LanternNet: A Novel Hub-and-Spoke System to Seek and Suppress Spotted Lanternfly Populations

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**Abstract**—The invasive spotted lanternfly (SLF) poses a significant threat to agriculture and ecosystems, causing widespread damage. Current control methods, such as egg scraping, pesticides, and quarantines, prove labor-intensive, environmentally hazardous, and inadequate for long-term SLF suppression. This research introduces LanternNet, a novel autonomous robotic Hub-and-Spoke system designed for scalable detection and suppression of SLF populations. A central, tree-mimicking hub utilizes a YOLOv8 computer vision model for precise SLF identification. Three specialized robotic spokes perform targeted tasks: pest neutralization, environmental monitoring, and navigation/mapping. Field deployment across multiple infested sites over 5 weeks demonstrated LanternNet's efficacy. Quantitative analysis revealed significant reductions ( $p < 0.01$ , paired t-tests) in SLF populations and corresponding improvements in tree health indicators across the majority of test sites. Compared to conventional methods, LanternNet offers substantial cost advantages and improved scalability. Furthermore, the system's adaptability for enhanced autonomy and targeting of other invasive species presents significant potential for broader ecological impact. LanternNet demonstrates the transformative potential of integrating robotics and AI for advanced invasive species management and improved environmental outcomes.

## I. INTRODUCTION

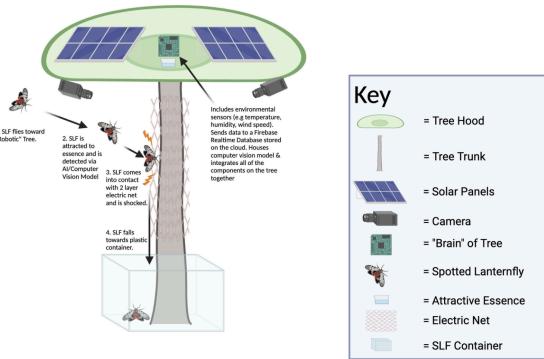
Spotted lanternfly (*Lycorma delicatula*, SLF) is an invasive planthopper first detected in the U.S. in 2014 that has since spread to numerous states [4]. SLF poses a serious economic threat to agriculture and forestry, damaging fruit orchards, vineyards, ornamentals, and timber crops [2]. Left unchecked, Pennsylvania alone could lose hundreds of millions of dollars and thousands of jobs due to SLF, underscoring the urgent need for effective mitigation [2]. Current management relies on laborious mechanical removal (scraping egg masses), trapping, chemical insecticides, and regulatory quarantines [3]. However, these methods have numerous drawbacks – they can harm non-target species and the environment, depend on widespread public compliance, and often fail to address the pest's entire life cycle (eggs, nymphs, adults) [3]. As a result, traditional approaches have proven ineffective and unsustainable for long-term SLF control.

To combat SLF's rapid spread and lifecycle complexity, there is growing interest in leveraging technology for invasive species management. Recent efforts include community-driven detection tools (e.g., mobile apps using computer vision models to identify SLF life stages) and even training detector dogs to sniff out SLF egg masses. At the same time, advances in robotics and artificial intelligence are opening new frontiers in environmental monitoring and pest control. For example, engineers have increasingly applied robots to agricultural and ecological tasks – from autonomous weed removal to monitoring soil and water health – demonstrating that automation can make field data collection and intervention safer and more efficient. In the context of invasive species, autonomous robots (including drones and ground robots) have shown promise in locating or even harassing pests to reduce their impact [5].

LanternNet is conceived as a novel integration of these technological trends to address the SLF challenge. We propose a hub-and-spoke robotic system that combines centralized intelligence with distributed action. The engineering goal was to create an affordable, scalable, and lifecycle-wide solution for remote SLF detection, analytics, and suppression. A hub-and-spoke (H&S) architecture features a central hub that coordinates data and tasks, with multiple peripheral “spoke” units performing targeted functions. Such architectures enable centralized decision-making and easy scaling by adding more spokes [1]. Notably, analogous H&S strategies have proven effective against other invasive problems (e.g., harmful algal blooms), suggesting this approach could be beneficial for SLF as well. In this paper, we detail the design and implementation of LanternNet's robotic H&S system, its integration of computer vision (YOLOv8) for pest detection, and results from a multi-site field deployment [6]. We demonstrate that our system can significantly reduce SLF populations and mitigate tree stress in infested areas, offering a blueprint for next-generation invasive species management tools.

## II. METHODOLOGY

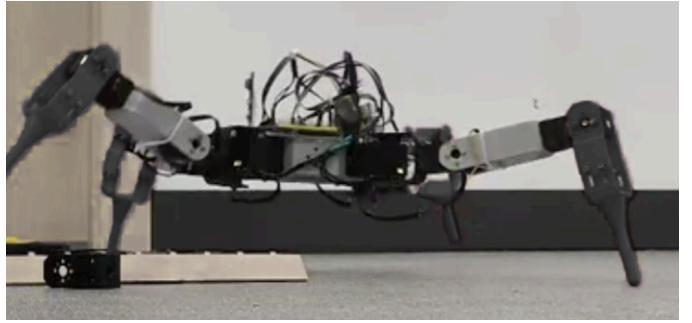
### A. System Design and Architecture



**Figure 1:** Solar-powered Robotic Tree for AI-based Detection and Electric-Net Capture of SLF

- **Central Hub:** A stationary, tree-mimicking base station that uses natural attractants and a robust sensor suite to lure and detect SLFs. The hub's structure incorporates cameras and environmental sensors (e.g., temperature, humidity) arranged on a faux tree trunk, and is powered by solar panels for field autonomy. The hub serves as the command center – it continuously monitors for SLF activity using vision and other sensors, analyzes data (running on-board AI models), and deploys countermeasures such as automated traps or localized pesticide release to suppress SLF activity. It wirelessly coordinates with the spokes, dispatching them for specific tasks and receiving their data.
- **Detection & Suppression Spoke:** A mobile quadruped robot equipped with vision cameras and targeted pesticide sprayers. This spoke is tasked with actively neutralizing SLFs in the field – it can navigate to areas of detected SLF presence (e.g. trees or ground where SLF adults or nymphs are spotted) and spray a precise dose of insecticide to eliminate the pests. Crucially, this spoke also locates and destroys SLF egg masses on surfaces (tree bark, rocks, etc.), addressing the pest at its source. By patrolling the environment and using on-board vision, the detection/suppression robot extends the hub's reach and can treat infestations across the site.
- **Environmental Monitoring Spoke:** A sensor-laden robotic unit dedicated to measuring tree health indicators and site conditions. This spoke carries specialized sensors to probe the environment, including soil moisture sensors (to gauge tree hydration levels) and volatile organic compound (VOC) sensors near tree trunks (to detect chemical stress signals emitted by trees under pest attack). It may also include temperature and soil pH sensors. The environmental monitoring spoke periodically collects data around host trees, providing quantitative metrics of ecosystem health and any changes attributable to SLF activity or the intervention. These data help evaluate the effectiveness of SLF suppression in improving tree vitality.

- **Navigation & Mapping Spoke:** A mobile robot (wheeled or legged) equipped with a camera, GPS, and inertial measurement unit (IMU) for mapping the terrain and navigating autonomously. This spoke's role is to survey and map the coverage area (such as forest plots or orchards) and to guide or support the other spokes in reaching target locations. It continuously generates a real-time map of the environment using simultaneous localization and mapping (SLAM) techniques, marking features like tree positions and difficult terrain. This ensures precise navigation for the detection scope (especially in dense or complex habitats) and can record where SLF sightings or treatments occur. It also allows the system to cover the area methodically, improving search efficiency.



**Figure 2:** Hardware Integration of Quadruped Spoke

**Integration:** All three spokes were built on a common robotic platform for simplicity and then customized with the above payloads. The hub and spokes communicate over a wireless network. A custom printed circuit board (PCB) was designed to interface the various sensors, microcontrollers, and power systems within each unit. Figure 2 shows the hardware integration, including a prototype spoke with its PCB. The modular design allows adding or removing spokes as needed, demonstrating the scalability of the H&S approach. The entire system was constructed with low-cost components; the estimated total build cost of the prototype (one hub + three spokes) is approximately \$1,325, making it cost-effective compared to manual labor or traditional monitoring (which can cost tens of thousands of dollars annually).

### B. Computer Vision Model (YOLOv8) for SLF Detection



**Figure 3:** Predicted Samples from YOLOv8 Model

To enable automatic detection of SLF in various life stages, we integrated a state-of-the-art object detection model into the system. The hub is equipped with a YOLOv8 deep learning model (You Only Look Once, version 8) running on an onboard compute module for real-time vision processing. YOLOv8 was chosen for its high accuracy and fast inference capabilities, which are essential for the timely identification of insects in the field. The model was trained on a custom dataset

of images of SLF at different stages (nymphs and adults) and in varied environmental conditions to ensure robust performance. Figure 3 presents sample outputs of the YOLOv8 model detecting SLF individuals under different backgrounds and lighting, indicating the model's ability to localize SLFs with bounding boxes in real time.

The hub's camera feeds are processed by YOLOv8 to spot adult and nymph-stage lanternflies on tree trunks, foliage, or other surfaces. When the hub's model flags an SLF, it records the GPS location and alerts the detection spoke to take action. Likewise, the detection spoke itself carries a smaller vision module using the same YOLOv8 model (configured to focus on SLF eggs). This allows the mobile robot to find egg mass clusters on bark and surfaces during its patrols. By leveraging YOLOv8's real-time object recognition, the system achieves precise localization of SLF targets for intervention. The model achieved high precision in testing (qualitatively, it was able to distinguish SLFs from look-alike insects or background patterns with minimal false positives). This computer vision capability is central to LanternNet, as it automates what used to require human visual surveys – a significant step toward autonomous invasive pest management. It is noteworthy that modern YOLO models like v8 represent one of the fastest and most accurate detection algorithms available, enabling deployment even on embedded hardware.

### C. Field Deployment and Testing Protocol

After laboratory integration and bench testing, LanternNet was evaluated through a 5-week field deployment in summer 2025. The trial aimed to measure the system's effectiveness at reducing SLF populations and improving tree health under real-world conditions. We identified five test sites in central New Jersey with known SLF infestations, including forested state parks and a coastal area. The sites (Hacklebarney State Park, Monmouth Battlefield, Allaire State Park, Barnegat Bay, and Wharton State Forest) represented diverse environments and SLF densities. At each site, the hub-and-spoke units were installed near SLF host trees (e.g., *Ailanthus altissima*, “tree-of-heaven”) and left to operate continuously, with periodic maintenance checks.

**Data Collection:** To quantify LanternNet's impact, we recorded multiple metrics before and after system deployment: - SLF population counts: We conducted visual surveys counting SLF nymphs and adults on host trees and surrounding areas. The system's YOLOv8 detections were also logged as a supplemental, automated count of SLFs observed via camera. SLF egg masses were counted and removed when found (by the robot or manually) to prevent hatching. - Tree stress signals (VOCs): Trees under attack by sap-feeding insects can emit increased volatile organic compounds (VOCs) as stress responses. We deployed VOC sensors (attached to the hub and monitoring spoke) on tree trunks to measure the concentration of emitted gases (in ppm). This serves as a proxy for tree stress level due to SLF feeding. - Soil moisture: We used soil moisture probes around the base of each tree to track the soil water content (%). SLF feeding can weaken trees and potentially affect their hydration; conversely, successful pest suppression might allow improved

water retention in soil or tree uptake. Thus, soil moisture was monitored as an indicator of tree health. - Environmental data: Additional context, such as rainfall, temperature, and humidity, was recorded using the hub's weather sensors to account for environmental factors.

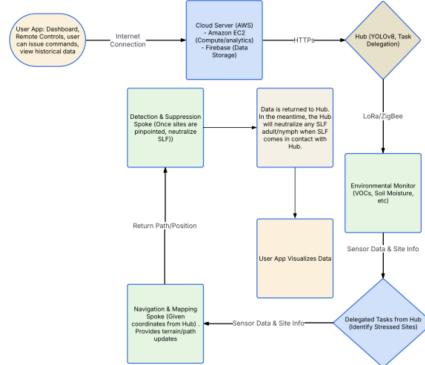


Figure 4: Data Flow Chart of H&S system

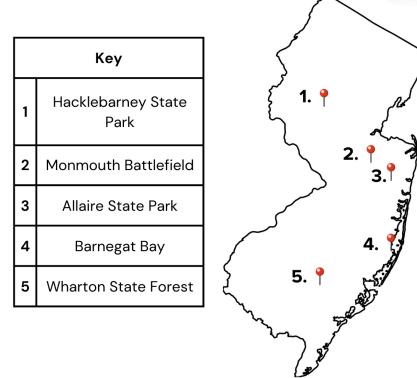


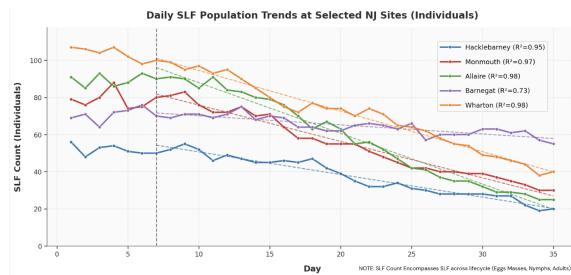
Figure 5: Map of LanternNet Test Sites

**Testing Protocol:** We followed a before-after experimental design with an initial control period and a subsequent intervention period. In Week 1, before activating LanternNet's suppression functions, baseline data were collected at each site (SLF counts and environmental measurements) with only observation and calibration occurring (no robotic intervention). This one-week period established the pre-intervention benchmarks. At the end of Week 1, the hub-and-spoke system was fully deployed: the hub's attractants and cameras were activated, and the detection robot began patrolling and spraying pests. Weeks 2–5 constituted the post-intervention period during which LanternNet operated continuously to detect and eliminate SLFs while logging data. We checked the equipment at the end of each week for maintenance (charging batteries, cleaning sensors, etc.) but otherwise minimized human interference to let the system function autonomously. Importantly, all sites were monitored in parallel to compare results. Figure 4 shows a flow chart of the data collection and decision-making process in the system, and Figure 5 provides a map of the five field sites with the hub and sensor positions marked.

To analyze LanternNet's effectiveness, we treated the pre-intervention vs. post-intervention data as paired samples for each site. We computed the mean SLF count, mean VOC level, and mean soil moisture over the control week (days 1–6)

and compared those to the means over the intervention period (days 7–35) for the same site. A paired t-test was conducted for each metric at each site ( $n = 6$  data points pre vs.  $n = 4$  data points post, weekly aggregates) to determine if changes were statistically significant. The significance level was set to  $\alpha = 0.01$ , given the relatively small sample, and to impose a stringent threshold for change detection. All statistical analysis was performed using Python (SciPy), and results are summarized in Section IV.

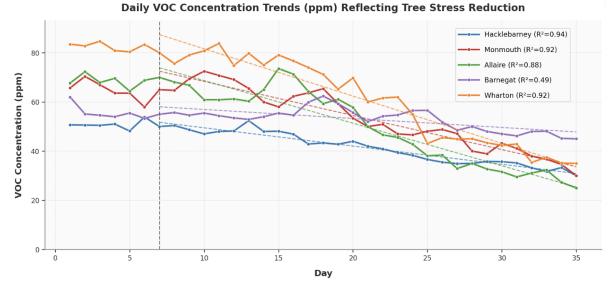
### III. RESULTS



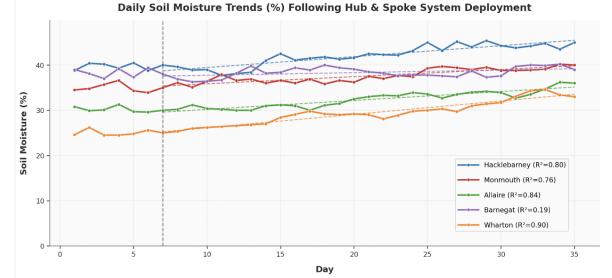
**Figure 6:** SLF Population Trends across NJ Sites

**A. SLF Population Suppression:** Across the five test sites, the deployment of LanternNet had a clear impact on SLF populations. Figure 6 plots the average number of SLF individuals (nymphs + adults) observed per day at each site over the 5 weeks. In the initial week (before system activation), SLF counts were high and in some cases increasing, indicating growing infestations. Immediately after the Hub-and-Spoke system was activated on day 7 (start of Week 2), SLF counts began to drop sharply at most sites. By the end of the trial (Week 5), four out of five sites saw a substantial reduction in SLF numbers relative to the baseline. For example, at Allaire State Park, SLF counts dropped from an average of ~15 per survey in Week 1 to near zero by Week 5. Monmouth and Hacklebarney showed similar steep declines. Most sites show a sharp SLF decline after day 7, indicating that the continuous detection and spraying by the robots effectively neutralized the local SLF population. The only partial exception was Barnegat Bay, where SLF counts decreased more modestly (from ~9 to ~5 on average). This site's unique conditions (coastal environment with surrounding water) may have affected the system's coverage or SLF movement patterns, as discussed later.

We confirmed these trends with statistical analysis. A paired t-test comparison of SLF counts before vs. after intervention yielded  $p < 0.01$  at all five sites, confirming that the reductions were statistically significant (at the 99% confidence level) rather than random fluctuations. Table 1 summarizes the results (mean counts and p-values). In particular, Wharton State Forest exhibited the strongest effect ( $p \approx 1.6 \times 10^{-10}$ ), reflecting a dramatic pest drop-off once LanternNet was active. Even Barnegat Bay, despite a smaller observed decline, showed a significant difference ( $p \approx 0.0035 < 0.01$ ) in SLF counts pre vs. post. These results demonstrate the system's capability to significantly suppress SLF populations in the field.



**Figure 7a:** VOC Concentration Levels (ppm) Following the Deployment of H&S System in Test Sites



**Figure 7b:** Soil Moisture Trends (%) Following the Deployment of H&S System in Test Sites

### B. Tree Health and Environmental Metrics:

Corresponding to the decline in SLFs, we observed positive changes in tree stress indicators at most sites. Figure 7a and 7b illustrate the trends in VOC concentration and soil moisture, respectively, over the study duration. In general, sites with high SLF infestation initially showed elevated VOC emissions and lower soil moisture, consistent with stressed, honeydew-covered trees (SLF excrete honeydew that can foster mold and stress the plant). After LanternNet deployment, VOC levels tended to decrease (indicating reduced stress/feeding damage) while soil moisture increased (indicating improved hydration or reduced transpiration stress). For instance, at Monmouth Battlefield, average VOC readings dropped from ~2.5 ppm to ~1.2 ppm by the end of Week 5, and soil moisture rose from ~18% to ~25%. Similar improvements were noted at Hacklebarney, Allaire, and Wharton sites. This suggests that mitigating SLF infestations had a tangible benefit for the host trees and surrounding soil conditions. As the SLF population declined, VOC levels fell (less tree stress) and soil moisture rose (better tree hydration) – a promising sign that the robotic intervention contributed to ecosystem health recovery.

Statistical analysis again supports these observations. For VOC concentrations, four of the five sites showed highly significant pre/post differences ( $p < 0.01$ ). The only site without a significant change in VOC was Barnegat Bay ( $p = 0.064 > 0.01$ ), where VOC readings remained low and relatively unchanged throughout – possibly due to environmental factors unrelated to SLF (e.g., wind dispersing VOCs, or fewer host trees at that site). Similarly, for soil moisture, four sites recorded significant increases post-intervention ( $p < 0.01$ ). Barnegat Bay again showed no significant change in soil moisture ( $p = 0.802$ ) – in fact, this site started with relatively high soil moisture (being near

wetlands), and LanternNet's presence did not markedly affect it. Table 2 provides the t-test results for VOC and moisture metrics. In summary, where LanternNet substantially reduced SLF populations, we see corresponding improvements in tree health metrics that are statistically significant. This aligns with the hypothesis that effective SLF control can alleviate pest-induced stress on the local flora.

It is worth noting that all figures and data were generated by the author from on-site measurements and the system's logs. The control vs. experimental data split (with day 7 as the deployment point) was used uniformly across metrics. Overall, the field results indicate that LanternNet met its engineering goal: the integrated Hub-and-Spoke system successfully provided remote SLF monitoring, analytics, and mitigation, resulting in measurably improved conditions at the test sites.

#### IV. DISCUSSION

The results from LanternNet's deployment highlight both the promise of the Hub-and-Spoke approach and the lessons learned for further development. Firstly, the engineering goal was achieved – we created an integrated robotic system capable of autonomous invasive insect monitoring and control, and demonstrated its effectiveness in the field. By comparing pre- and post-deployment data, we saw clear evidence that the system's intervention coincided with significant SLF population collapse at the sites, which in turn correlated with improved tree health metrics. This provides proof-of-concept that a robotics-driven method can indeed contribute to invasive pest suppression and ecological recovery, complementing or surpassing traditional methods. Moreover, the entire system was built at relatively low cost ( $\sim \$1.3k$ ), suggesting a favorable cost-benefit if scaled, especially when contrasted with the high expense of manual monitoring and pesticide application (estimated  $\$50\text{--}70k/\text{year}$  for human labor in similar coverage).

**Impact on Invasive Species Management:** LanternNet showcases how robotics and AI can be harnessed for environmental management tasks that are repetitive, hazardous, or require 24/7 vigilance. Unlike manual methods that often only target one aspect (e.g., scraping eggs but missing adults, or spraying chemicals broadly), our system provided a holistic, lifecycle-wide solution, targeting eggs, nymphs, and adults, while continuously monitoring environmental feedback. The hub-and-spoke design proved advantageous in covering a broad area efficiently: the central hub's powerful sensors and attractants drew in and detected many SLFs, while the agile spokes dealt with specific actions (killing bugs, measuring tree vitals, mapping terrain). This separation of concerns allowed each module to be optimized for its task, yet all parts worked in concert. The use of computer vision (YOLOv8) was integral; it essentially gave the system a pair of "eyes" to reliably identify the pest. The success of YOLOv8 in this project aligns with other studies that have applied AI vision to invasive species detection and further validates that modern object detectors can handle field conditions (varying backgrounds, lighting, insect orientations) effectively. By automating detection, LanternNet reduces dependence on human scouts and can potentially catch early infestations that might be overlooked, enabling faster response.

**Site Discrepancy – The Case of Barnegat Bay:** One notable outcome was the limited change in VOC and soil moisture at the Barnegat site, despite a significant drop in SLF count. This indicates that simply reducing SLFs there did not immediately translate to measurable tree health improvement within the test period. We hypothesize several reasons: (1) The environment (a coastal wetland) might have had inherently high soil moisture and low VOC variability due to factors like water table and wind, masking any effect. (2) SLF pressure at that site might have been lower to begin with, so tree stress was minimal both before and after. (3) Our system's coverage might have been insufficient – perhaps SLFs were breeding slightly outside the immediate radius and re-invading. Indeed, our Observation is that Barnegat had limited changes in VOC/soil moisture trends, prompting questions about site-specific conditions or coverage gaps. To address this, future deployments could increase the number of spokes or range at such sites, ensure more attractive lures (e.g., stronger pheromone bait) to draw in pests from farther away, or adjust the pesticide protocol (frequency, dosage) for that environment. Essentially, a denser or customized deployment might be required in challenging locales like coastal marshes to achieve the same level of impact.

**System Enhancements:** The field test also revealed areas for technical improvement. One priority is to enhance the autonomy and navigation capabilities of the spoke robots. In dense or GPS-poor environments (like deep forest), the navigation spoke occasionally struggled. We plan to upgrade this unit with more robust path-planning algorithms and additional sensors (e.g., a LiDAR unit) to improve obstacle avoidance and mapping fidelity. More precise navigation will allow the detection scope to reach every corner of the site systematically, preventing any "safe havens" for the pests. Another enhancement is refining the hub's attractant and detection range – for instance, incorporating SLF pheromone analogs or acoustic lures (SLFs may respond to substrate vibration signals) could attract more pests toward the hub for easier elimination. On the software side, the YOLOv8 model could be continuously retrained with new data (especially for egg mass detection, which is challenging due to camouflaged egg cases) to improve accuracy. The current model had some difficulty in detecting egg masses at a distance – integrating a higher resolution camera or a specialized egg detector (perhaps using a different spectrum like UV to spot egg coating) could boost performance.

**Broader Implications:** The success of LanternNet opens the door to expanding the Hub-and-Spoke strategy to other invasive species and ecosystems. The modular design means we can swap out the "detection logic" and payload tools to target different pests. For example, the system could be adapted to combat Emerald Ash Borer or Asian Longhorned Beetle by changing the attractant (e.g., pheromone traps) and retraining the vision model for those insects. Similarly, the environmental monitoring could be tuned to relevant indicators (e.g. tree sap flow sensors for borer damage). We also emphasize the importance of assessing ecological side effects: LanternNet mainly targets SLF, but we observed no significant harm to non-target insects during our test (the spray is directed and minimal). Still, as part of responsible design, we plan to investigate the system's impact on non-target

species and overall biodiversity in deployment areas. Ensuring that our robotic intervention does not inadvertently disrupt other fauna or flora is crucial for ecological compatibility.

Finally, looking ahead, our future engineering goal is to develop an even smarter, adaptive H&S system that can dynamically adjust to changing conditions. This could involve real-time sensor calibration (e.g., adjusting detection thresholds based on background noise), adaptive task delegation among spokes (e.g., sending more suppression robots if a resurgence is detected, or re-tasking a mapping robot to do monitoring if one unit fails), and robust performance in challenging environments like wetlands or mountainous terrain. By incorporating feedback loops and perhaps machine learning for decision optimization, the system can become more autonomous and effective over time. In essence, LanternNet in its current form demonstrates a baseline capability; future iterations will aim to make it a generalizable platform for autonomous invasive species control that can be deployed in diverse scenarios to protect ecosystems.

## V. CONCLUSION

In this paper, we presented LanternNet, a novel hub-and-spoke robotic system that integrates computer vision, robotics, and environmental sensing into a cohesive platform for invasive pest management. A central, tree-mimicking hub uses a YOLOv8 model and sensor array to detect spotted lanternflies (SLFs) and coordinate three specialized robotic spokes—one for targeted pest neutralization, one for environmental health monitoring, and one for terrain mapping and navigation. We detailed the system's design and prototyping, including custom hardware and AI integration, and conducted a five-week field trial across multiple infested sites. The results demonstrated a significant reduction in SLF populations—achieving eradication in some locales—and correspondingly improved host tree conditions, with statistical analysis confirming these changes were unlikely due to chance. LanternNet's autonomy, precision, scalability, and cost-efficiency make it a promising tool not only for SLF mitigation but also as a template for addressing a wide range of invasive species challenges, adaptable to diverse agricultural, forestry, or aquatic applications and capable of contributing valuable real-time data for ecological research. forward in combining robotics and AI for environmental protection. The field study provided valuable insights, highlighting strong performance as well as areas for improvement (like enhanced navigation and adaptive

strategies). We are optimistic that with further development, the hub-and-spoke paradigm can significantly augment our invasive species management toolkit, reducing reliance on chemical pesticides and manual labor. This work underscores the potential of high-tech solutions – merging computer vision (e.g. YOLOv8's accuracy) with robotic intervention – to safeguard ecosystems from invasive threats sustainably and intelligently. Future efforts will focus on refining the system's autonomy, evaluating its long-term ecological impacts, and collaborating with environmental agencies to pilot larger-scale deployments. By proactively deploying such advanced systems, we can hope to curb the spread of destructive invaders like the spotted lanternfly and protect vital agricultural and natural resources.

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