Novel Robotic Approach to Irrigation and Agricultural Land Use Efficiency

A. Hoppe[1], E. Jefferson[2], J. Woodruff[1], L. McManus[1], N. Phaklides[3], T. McKenzie[1]
Department of Mechanical Engineering[1], Computer Engineering[2], Electrical Engineering[3]
Embry-Riddle Aeronautical University
Prescott, Arizona, United States
Emails: hoppea@my.erau.edu, jefferse@my.erau.edu, woodruj4@my.erau.edu, mcmanuc1@my.erau.edu, phaklidn@my.erau.edu, mckenzt4@my.erau.edu

***Abstract*—Current industrial agricultural methods often use inefficient watering, fertilizing, and pest control practices, in part because they lack feedback systems. The prototype proposed combines current agricultural sensing and analysis research with a robotic platform to precisely monitor and care for crops. In this paper, we provide a proof of concept with a path to scalability such that the system may be implemented at an industrial scale.**

Keywords*— *Agriculture; Farming; Robotics; Computer Vision; Machine Learning; Automation

I. Introduction

Conventional agricultural methods overcompensate plant and soil needs through wasteful watering practices and excessive application of pesticides and fertilizers, leading to substantial environmental damage [1]. This damage takes on various forms, including pollution via runoff, soil depletion, and the extinction of local pollinators [2]. The Novel Irrigation and Land use Efficiency (NILE) system aims to optimize current agricultural practices with a unique robotic approach to precisely monitor the health of various crops with a reactive response to caring for the plants. This paper describes the design and implementation of a prototype system to serve as proof of concept for this approach.

In recent years there has been an explosion in the number of robotic systems designed to use varying levels of autonomy to approach challenges facing agricultural industries. Concepts like the Greenhouse Partner Robot System [3] seek to augment farmer abilities in the greenhouse through a cooperative approach to automation. Similarly, Agrobot [4] and Vinebot [5] support farmers by providing an autonomous platform upon which sensors can gather information from afar. Both approaches utilize unique methods of locomotion and control but are limited in their scope and ultimately require the intervention of farmers or other systems to directly affect crops.

Some more autonomous systems, such as the Farmbot, tend to plants based on internal determination. This approach can monitor and water plants based on user input and general watering guidelines based on species [6]. Stereoscopic imaging allows the system to find adequate locations to measure moisture content, for which the user can define feedback systems within its web app. Another approach, as taken by AgBotic Inc. and their robotic gantry, allows for significantly increased control over the watering and fertilizing of a field when compared to traditional systems [7]. Unfortunately, it requires significant infrastructure investment in greenhouses and supporting equipment which so far prohibits widescale industrial adoption.

Numerous systems gather and relay sensor data to farmers for interpretation, but comparatively few systems can independently infer plant health from the data. One promising approach utilized machine learning paired with computer vision to scan images of plant leaves, and identify individual plants, as well as distinguish between healthy and diseased crops based solely on physical appearance [8]. Combining this approach with more conventional sensor data, we plan to develop a fully autonomous plant health assessment system that does not need farmer intervention. The goal of this project is to incorporate concepts from these disparate approaches in a fully autonomous system capable of caring for crops from sow to harvest.

II. Proposed System

The proposed robotic system takes inspiration from the ubiquitous center-pivot irrigation design. The NILE prototype consists of a trolley riding on a circularly driven gantry and is intended to operate in a 2-meter diameter raised bed. In the following sections we discuss the mechanical, electrical, and software integration of the system.

A. Mechanical Model

The mechanical model includes three main subassemblies: the gantry, trolly, and end effector.

The gantry rotates about a central post which houses most of the electronic and hydraulic components in two weatherproof enclosures, as shown in Fig. 1. At the top of the post, one enclosure protects various hardware components, including an absolute rotational encoder to determine the angle of the gantry. Although the robot pivots about the central tower, its motion is driven by a rotational drive assembly at the far end of the gantry. This drive assembly consists of a geared DC motor that uses a chain drive to control two large pneumatic wheels. By increasing the moment arm, this configuration significantly decreases the motor torque required to drive of the rotation.

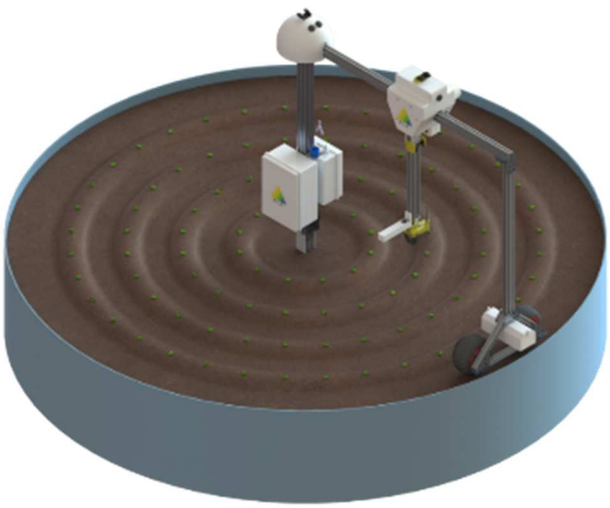

Figure 1. NILE design render

The gantry assembly supports the most mechanically complex component of the NILE system: the trolley assembly, shown in Fig. 2. The trolley manages the radial and vertical translation of the system in addition to housing the electronic hardware required to drive the end effector. Radial translation is achieved by three high-friction roller wheels that ride within the tracks of the gantry's aluminum extrusion. One wheel is driven by a geared DC motor while the other two wheels stabilize the assembly and determine the location of the trolley via encoders attached to the drive shafts. Vertical translation is accomplished via an ultra-precision lead screw driven by a high-torque stepper motor. As the lead screw drives the end effector mounting shaft, the shaft rides on bearings slotted into the aluminum extrusion.

Finally, the end effector assembly (see Fig. 3), for which the entire system was designed to support, includes the sensors, High Voltage Elimination Circuit (HVEC), and water/fertilizer nozzle. To make determinations on soil quality, both a capacitive moisture sensor and a thermal probe are used. In addition, the HVEC system, discussed in the following section, allows NILE to destroy all weeds in the growing zone with high-voltage electric arcs. Furthermore, a nozzle integrated into the underside of the support structure delivers water and fertilizer to the growing zone. Not pictured is the stereoscopic camera which will be utilized for computer vision and machine learning.

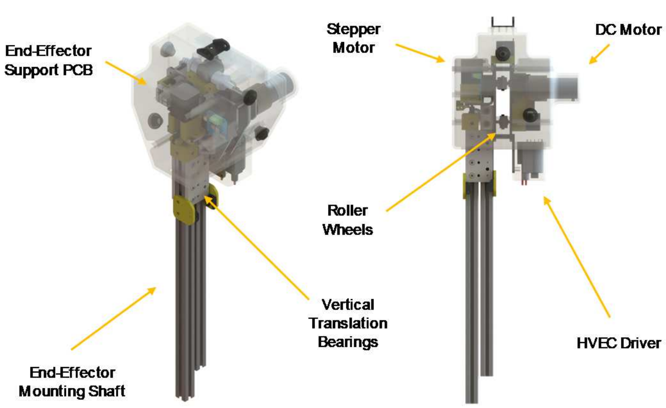

Figure 2. Trolly mechanical design

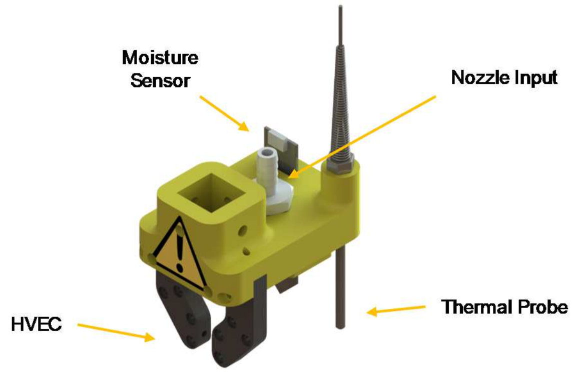

Figure 3. End effector mechanical design

B. *Electrical Model*

To ensure maximum compatibility, the robotic system will operate on North American standard 120VAC power routed into a 24V, 25A DC power supply. While an industrial system would require significantly more power, this configuration is more than adequate to drive all components on the prototype robot. Power is distributed across the system through three voltage levels: 5, 12, and 24 volts. The 5V rail is used to power microprocessors and sensors, the 12V rail is used to power the fluid solenoids and the rotational drive motor, and the 24V rail is used to power the trolley motors and the HVEC. An overview of the electrical system is shown in Fig. 4.

At the core of the system, two computers work in tandem to ensure robust operation. A NVIDIA Jetson Nano serves as the System Determination Computer (SDC) and handles data processing, command sequencing, computer vision, machine learning, and server hosting. The SDC interfaces over USB with the Hardware Microcontroller (HWM) which amalgamates all sensor data and controls the actuators based on commands from the SDC. This data is collected through two PCBs which interface to all the system's sensors and motors, routing information back to the HWM (and thus, the SDC). An overview of this dataflow process can be seen in Fig. 5.

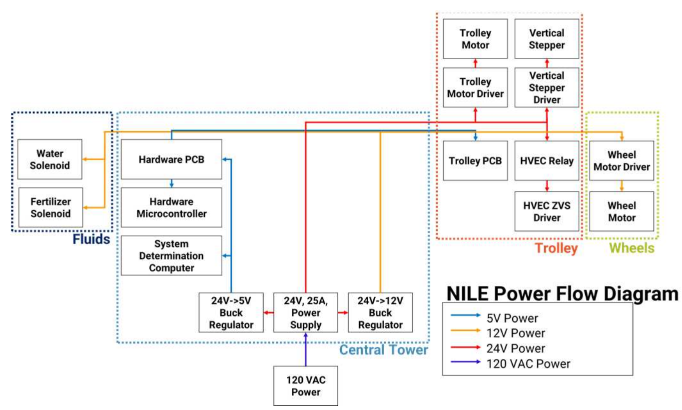

Figure 4. Power flow diagram

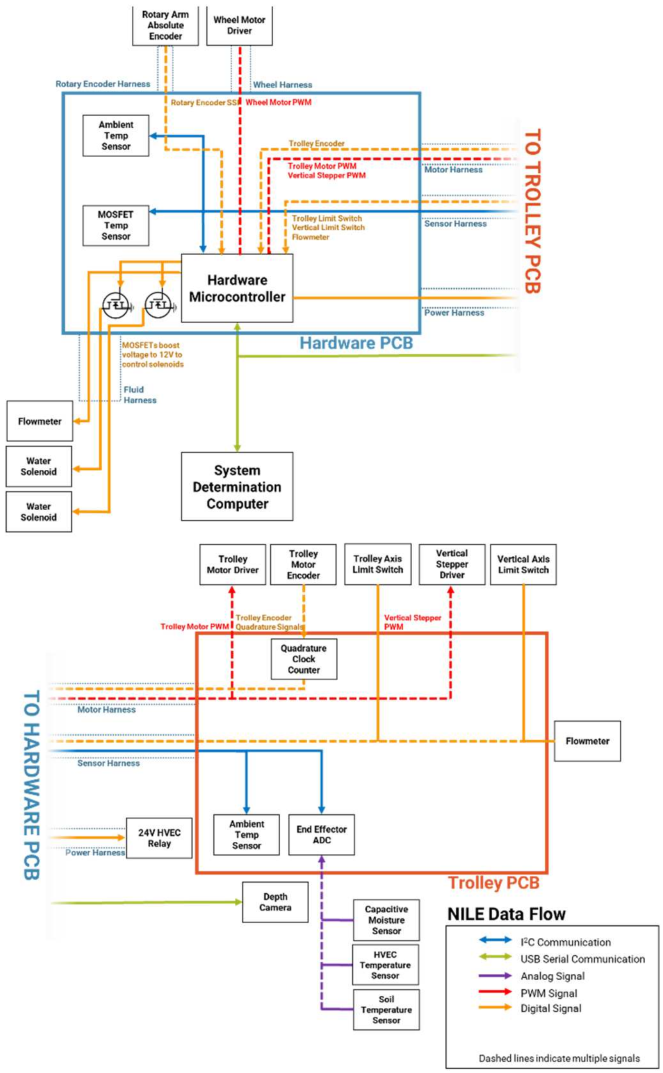

Figure 5. Data flow diagram

As demonstrated in [9], electrical arcs are highly effective in eliminating undesired plants by destroying their xylem tubes and thus eliminating the weeds' ability to draw water and nutrition from the soil. Our HVEC system utilizes a Zero-Voltage Switching (ZVS) Driver with a flyback transformer to generate a targeted arc of 60kV at the end effector of the robot. This is used in conjunction with images of the growing zone and a machine learning algorithm, discussed in the following section, to discriminate between desired and undesired plants.

C. *Software Model*

To tend to plants within the growing zone, the system implements a waypoint positioning algorithm. At regular time intervals, the SDC inspects the plant bed by navigating the end effector to predetermined locations that have been calculated to encompass the entire soil bed. Upon reaching a waypoint, the SDC captures an image from a stereoscopic camera and performs other sensing and plant care operations. When not active, the system remains in a computational sleep state. A flowchart illustrating this process can be seen in Fig. 6.

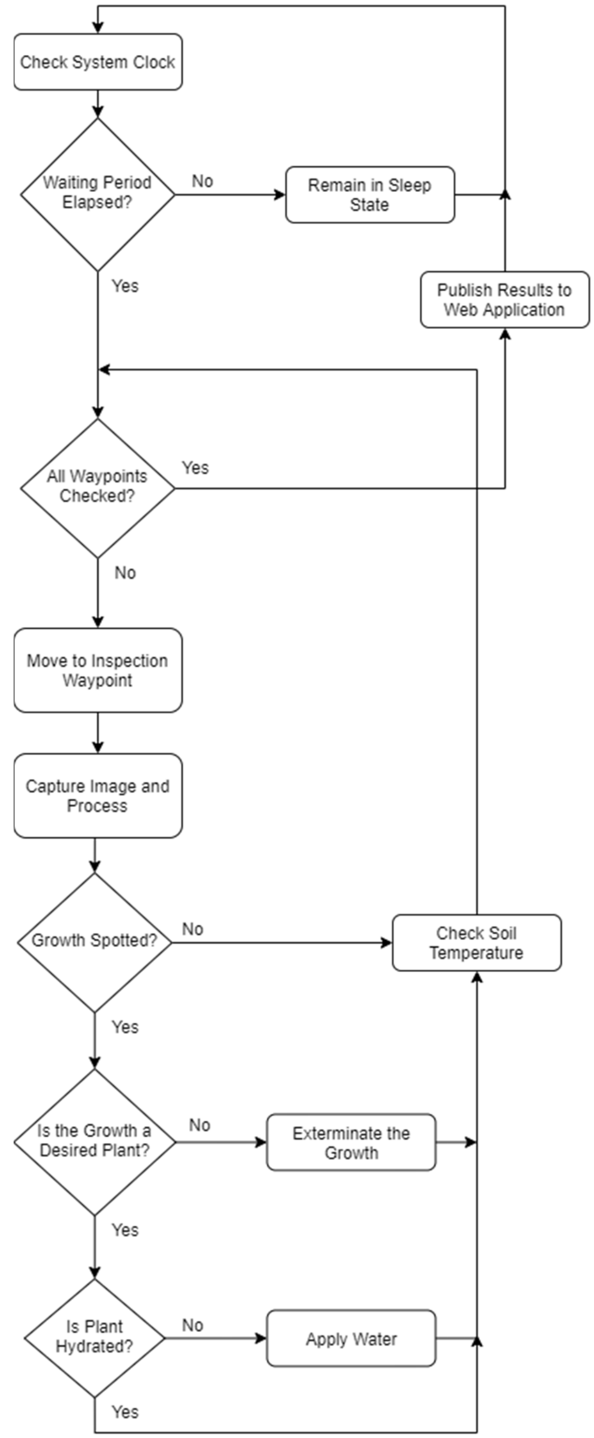

Figure 6. Software flowchart

Upon capturing a still image from the camera video feed, the system applies a machine learning image classifier that makes use of a Convolutional Neural Network to identify specific objects within the image. After locating plants and potential weeds, the system uses a Python script to process the image and isolate Regions of Interest (ROI) that either contain crops needing to be analyzed, or weeds needing to be exterminated.

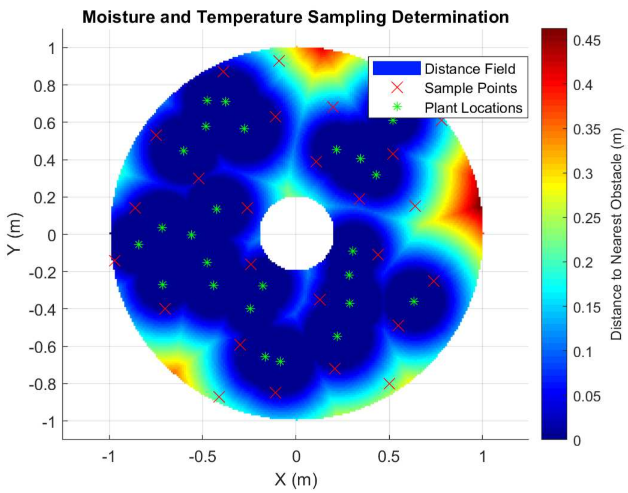

Figure 7. Distance-based soil sampling algorithm

To rate plant health and confirm the presence of weeds, a process called feature extraction is employed using rudimentary computer vision techniques. This feature extraction consists of four major steps: Gaussian blurring, RGB-to-HSV conversion, color masking, and contour detection. The result of this algorithm is a verdict on specific crop health such as hydrated, wilted, or diseased, in addition to a confidence score for suspected weeds.

The waypoints are spaced such that a collage of images taken at each location produces a complete representation of the growing zone. This image collage informs the system as to where the end effector and its probes can be inserted into the soil without damaging vegetation. By computing the distance to any plant growth, safe areas where the end-effector can sample without disturbing the plants are found. The algorithm then uses a Monte-Carlo approach to place sample points as close to the plants as possible while maximizing sensor coverage. By doing this, the system will prioritize sampling data-rich areas with plants rather than areas with just soil. A simulation of this algorithm operating on an arbitrary distribution of plants is shown in Fig. 7.

III. Implementation and Results

As of this writing, the full system as proposed is under construction, with expected completion by late-spring 2022. However, modeling and testing of various subsystems has already begun. The following sections will describe the control system development, HVEC implementation, and computer vision implementation.

A. Modeling and Controller Development

Simulation development began by deriving the forward and inverse kinematic equations from the mechanical model. This was a straightforward process except for the rotational link. As the rotational drive wheels and angle of the gantry are not independent, a constraint equation was derived by assuming no slip. The kinematic and the constraint equations were then implemented as MATLAB functions to return either the task space or joint space coordinates.

Figure 8. HVEC Operation

Development of the open-loop dynamic simulation began by deriving the system's equations of motion. These were implemented in matrix form as the system mass matrix, vector of Coriolis, centripetal forces, and generalized gravitational forces. In addition, the joint limits were applied by using virtual springs to model collisions. All these equations were then combined to model the system as a vector of generalized forces acting upon each linkage.

For the closed-loop dynamic simulation, the desired task space coordinates of the system are the initial input. The input is then converted to desired joint space coordinates using the inverse kinematic functions. The converted coordinates are fed into the control rule which outputs the generalized forces required to achieve the desired position. A Proportional Integral Derivative (PID) control rule was developed because the low desired speed made fast response times unnecessary. Thus, we were able to tune the control system in the virtual environment by adjusting PID gains to achieve acceptable rise time, overshoot, and steady state error.

B. HVEC Implementation

During testing, the HVEC driver proved to be incredibly effective in eliminating undesired plants. Using a 12V source voltage, it could produce a 2 cm length arc, equating to about 60kV (assuming air's breakdown voltage of around 30kV/cm). Early testing, depicted in Fig. 8, shows promising results; because the arc destroys the xylem [9], this process ensures the weed will not grow back.

C. Computer Vision and Machine Learning

Classification of plants and objects within an image begins with a high-level machine learning pipeline. Before any pre-processing is applied, the raw RGB image is fed into a pre-trained Convolutional Neural Network (CNN) that iterates through square segments of the image, performing mathematical convolutions of the pixel grid at each step. Since crops and common weeds have very similar visual appearances when first sprouting, distinguishing them at this early stage could prove difficult. Consequently, this CNN has been trained on a dataset of 400 images of our desired crop at a mature stage and another 400 of generic plant sprouts. By applying this algorithm to an input image, the CNN can locate features that match those of either the crop or sprouts. Any greenery within the image not identified as crop or sprout can be conclusively labelled either a weed or an inorganic entity.

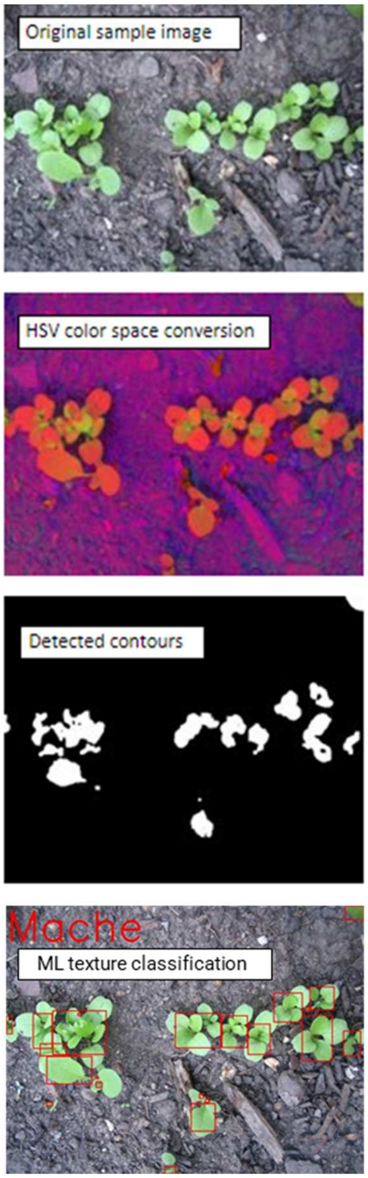

Figure 9. Computer vision and machine learning implimentation

To distinguish weeds from foreign objects, we make use of the four-step image processing algorithm mentioned in the Software Model section. Fig. 9 displays the intermediate output of each step of this process. In the first stage, Gaussian blurring is performed on the original image to reduce data noise and eliminate exceedingly small contours within the picture.

In the second stage, the image format is transferred from Red-Green-Blue to Hue-Saturation-Value (HSV) representation to allow the vision system to identify colors in the presence of shadows and varied lighting conditions.

In the third stage, a color mask is applied with parameters that have been determined heuristically to isolate leafy green hues. The result of masking is a binary image containing only black and white, where white segments correspond to colors within the desired range. The binary image is passed into the fourth stage of the algorithm which groups the blobs into individual objects called contours. These contours define the regions where potential plant or foreign objects have been identified and are ready for classification.

Distinguishing plant material from inorganic items is accomplished through texture analysis. Using the Python Sci-Kit-learn library [11], a mathematical model for leafy plant textures was generated with a Local Binary Pattern (LBP) descriptor. This texture designator searches for small-scale pixel patterns within a grayscale image and saves a generalized model of a particular category of texture. Much like a neural network, the LBP must be trained on a set of labelled images to recognize the trend for a given texture. In the image processing script, the algorithm applies this texture model to each contour detected and generates a classification prediction. The final stage of Fig. 9 shows all the leaves detected using purely the texture model.

In future implementations, this texture-based approach for locating plants will also be applied to analyze the overall health of desired crops. An approach using a Random Forest classifier has been demonstrated to diagnose plant health issues with a 70% accuracy with only 160 training images [12].

IV. Conclusion

As of early-spring 2022, the NILE team has begun fabrication and implementation of the mechatronic and machine learning systems as modeled and described in section 2. Extensive testing of the prototype system is due to begin mid-spring 2022 which will involve validating sensor collection data, positional accuracy of the end-effector, and machine learning classification accuracy, as well as fine-tuning the closed-loop controller. All test results and other system developments will be uploaded to nile-erau.github.io.

The NILE robotic system was developed with scalability and sustainability in mind. We envision the commercial implementation of this system as an evolution of center pivot irrigation with modular gantry sections combined to cover entire fields with dedicated trolleys for each module. This configuration would result in minimal trolly down time; full field rotations, for the average center pivot installation in the United States, take between 14 and 20 hours by which time plants require rewatering [13]. Thus, after completing one rotation, the system would immediately begin the next cycle. This is significantly more efficient than a comparable mobile system because any downtime from recharging and/or refilling is eliminated. This also reduces manufacturing and environmental costs by eliminating batteries, water tanks, and other storage methods necessary for mobile systems.

In conclusion, the NILE robotic system utilizes sensors and machine learning to precisely monitor and care for crops in a holistic manner, unlike any present-day industrial solutions. This unique robotic approach to farming can provide completely individualized and autonomous care for each plant, which is significantly more sustainable than watering, fertilizing, and spraying an entire field. If expanded and implemented in a large-scale farming operation, the NILE system could greatly reduce water consumption and pollution from runoff while maximizing crop yield.

ACKNOWLEDGMENT

This project was researched and developed with technical assistance from Dr. Douglas Isenberg and communications assistance from Dr. Amelia Chesley. Their contributions were invaluable in the development of the NILE system and this paper.

REFERENCES

[1] K. Smarsly, "Agricultural ecosystem monitoring based on autonomous sensor systems," 2013 Second International Conference on Agro-Geoinformatics (Agro-Geoinformatics), 2013, pp. 402-407, doi: 10.1109/Argo-Geoinformatics.2013.6621952.

[2] G. Merrington, D. Nfa, R. Parkinson, M. Redman, L. Winder, 2014. Agricultural Pollution. London: CRC Press.

[3] H. Durmus, E. O. Gunes, M. Krc, and B. B. Ustundag, "The design of general purpose autonomous agricultural mobile-robot: Agrobot," in Agro-Geoinformatics (Agro-geoinformatics), 2015 Fourth International Conference on, July 2015, pp. 49–53.

[4] K. Kashiwazaki, Y. Sugahara, J. Iwasaki, K. Kosuge, S. Kumazawa, and T. Yamashita, "Greenhouse partner robot system," in Robotics (ISR),2010 41st International Symposium on and 2010 6th German Conference on Robotics (ROBOTIK), June 2010, pp. 1–8.

[5] J. Tardaguila, "The vinerobot project," http://www.vinerobot.eu/, 2014, accessed=2021-11-16.

[6] "FarmBot | Open-Source CNC Farming," FarmBot. https://farm.bot/, accessed=2021-10-1.

[7] J. P. Gaus, "Robotic Gantry Bridge For Farming," US Patent 9,622,398 B2, 18 Apr., 2017.

[8] K. Mahajan, P. Darunte, B Borase, R. Bodake, "Agricultural Robot for Plant Health Detection", International Journal of Engineering Applied Sciences and Technology, 2019, pp 177-181, vol 4, issue 3, ISSN No 2455-2143.

[9] A. Mizuno, T. Tenma and N. Yamano, "Destruction of weeds by pulsed high voltage discharges," Conference Record of the 1990 IEEE Industry Applications Society Annual Meeting, 1990, pp. 720-727 vol.1, doi: 10.1109/IAS.1990.152264.

[10] N. Hodges, "Mache Sprouts", flickr.com/photos/nhodges/2758309821/, accessed=2022-1-14

[11] "Scikit Learn | Machine Learning in Python", https://scikit-learn.org/stable/index.html, accessed=2022-1-14

[12] S. Ramesh et al., " Plant Disease Detection Using Machine Learning," 2018 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C), 2018, pp. 41-45, doi: 10.1109/ICDI3C.2018.0001

[13] SR. G. Evans, "Center Pivot Irrigation," United States Department of Agriculture, July 2001.