A Reconfigurable Garden for Studying Plant Behavior

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I. INTRODUCTION

Digital agriculture is a growing field that studies how technology can be used to improve farming practices and optimize food production. This developing field may help to mitigate the negative effects of climate change on global food security [1]. Additionally, the global population is increasing exponentially, straining an already overburdened industry. Developing strategies for farming in environments that have been previously underutilized is one solution to this problem. Robotic assistance of traditional farming practices is another method currently being explored in order to ascertain how emerging technologies can be used to enhance food production.

This project develops a model for a virtual garden with two species of edible plants. The behavior of the plants is derived from experiments with a real-world model; the conditions of the physical experiment are reflected in the simulation. The virtual model also assumes that plants are attached to mobile robotic platforms so that they can self-organize in an optimal position to receive resources. We adopt a multi-agent system with robot-plant-agent (RPA) hybrids that are capable of sensing light and water, and rearranging their position in the environment.

This approach addresses some limitations of industrial farming where crops have limited diversity and placement, as reconfigurable gardens may increase plant survivability and yield. By enabling RPAs to change placement based on their individual needs, the robot-assisted mobility increases the system's autonomy so that less human interference is needed. Mobile RPAs can be used in environments with no pre-existing infrastructure and in terrain that is difficult to navigate. This virtual model can contribute meaningful insights that may assist in the establishment of autonomous farming systems on other celestial bodies, such as Mars or the Moon. This research topic has the potential to produce novel contributions in the field of bio-inspired algorithms, agricultural applications, and provide a deeper understanding of plant behavior in the natural environment.

II. RELATED WORK

Many of the current robotic farming implementations deploy robot gardeners that oversee a plant's health. FarmBot [2], is an open-source, computer-numerical-controlled machine that is commercially available. An aluminum frame is installed over a garden bed with different toolhead options to perform routine gardening tasks, such as watering, seed injection, soil sensing, and weeding. A graphical user interface (GUI) allows users to plan and design custom robot-maintained gardens. While the FarmBot platform is fully functional, the use of a traditional gantry requires users to invest considerable time

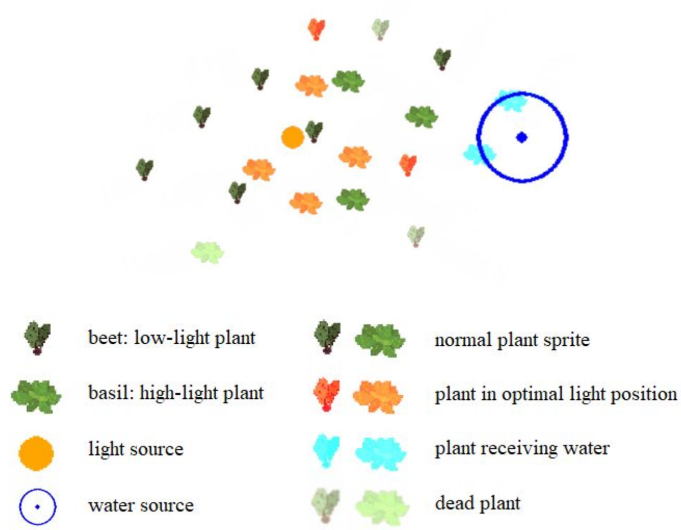

Figure 1. Snapshot of virtual garden and simulation sprites and colors legend.

setting up the system. The overhead structure also limits the growing area of the plants so that they do not interfere with the machinery. Robots that tend to plants automates farming procedures; however, this approach treats plants as stationary entities in the environment, and cannot be re-arranged in response to dynamic environmental conditions. The collective of mobile robot-plant-hybrids discussed in this paper presents a flexible alternative, as plants move in response to the environment, rather than cultivating an environment that is optimal for the plants.

There are several existing robot-plant hybrids that explore the intersection of plant behavior and robotic capabilities. HEXA [3], is a six-legged robot that supports the growth of a succulent plant by performing automated light seeking behavior. The robot also initiates human-robot interaction, as it performs a dance to communicate with the user when the plant needs to be watered. HEXA progresses hybrid behavior models; however, it is designed to operate as a single agent and still relies on human intervention to monitor plant health.

Elowan [4] is a robot-plant hybrid that explores how sensors can be used to translate bio-electrochemical signals into movement, resulting in light seeking behavior. The project provides valuable insights into the design and implementation of RPAs that can use biological feedback to control the robotic components. Flora robotica [5] also examines the role of emerging technologies in bio-spatial applications. Several aspects of a symbiotic relationship between plants and machines are designed, producing hybrid agents that are capable of sensing and actuation. The result is a distributed system that is mutually beneficial for plants and humans. The health of plants is maintained by machine assistance and in exchange, humans benefit from the architectural structures that are developed, which provide shade, improve air quality, and support restoration from exposure to natural elements. Flora robotica explores how the intersection of plants and machines will co-develop to create meaningful cultural artifacts, but does not address the potential for improved agricultural practices and other productivity-focused applications.

Existing garden simulators focus on human interaction rather than expanding the plant's own behavior and capabilities. The SmartGardenWatering [6] simulation aims to instruct gardeners on ideal watering patterns while Beneš and Cordobá [7] controlled the gardener's actions. Instead of changing the user's behavior, the goal of this work is to develop a model where the RPAs themselves are capable of adaptive behavior, deepening the understanding of how hybrid agents can capitalize on the capabilities of plants and robots. The main contribution of this work is the development of a model of a virtual garden that is guided by observational data collected from plants in the real-world and applied to virtual agents in a digital environment. This model may help to deploy physical, multi-agent RPAs into the environment that function autonomously, and support optimal plant growth. We posit that this model could utilize geographic data and behavior developed from the characteristics of different plant species to establish farming practices in dangerous environments, and improve yield and survivability of traditional farms. A multi-agent approach may reduce the need for high-cost sensors on every agent, as well as increase scalability, which is essential for the industrial agricultural sector.

III. REAL-WORLD PLANT EXPERIMENTS

A. Model Overview

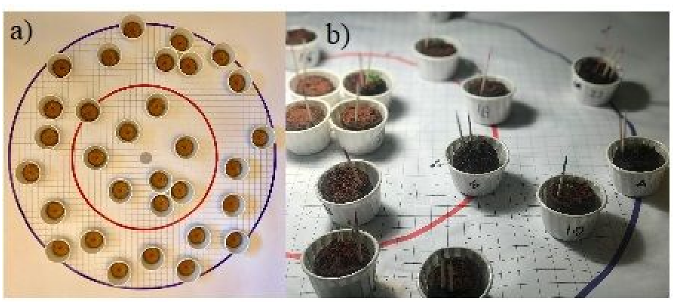

Figure 2. Experimental setup, a) overview of model space b) light gradient.

In order to develop hybrid behavior that accurately represents the environmental needs of edible plant species, several experiments were conducted using real-world plants grown in a controlled environment. Our primary research interest was to observe how the plants responded to different light and water conditions in order to ascertain the optimal conditions for growth and survivability. To determine the effect of *mobile* plant agents, a subset of the experimental plants rotated between different conditions to simulate the movement of the proposed RPAs. An artificial signalling model was developed as a representation of plant communication through airborne signaling systems used by plants in response to environmental stimuli.

Volatile organic compounds (VOCs) are chemical emissions plants use to relay information about their physiological states and environmental conditions[8][9]. Plants use VOCs to communicate the presence of external threats; receiver plants are primed to increase their defense mechanisms. VOC signaling is not only used for plant-plant cooperation, it also produces allelopathic effects, whereby a plant dissuades competing plants from growing in a nearby location. VOCs are also used to repel herbivores and attract pollinators. Fundamentally, VOCs operate as a mediator between plants and other organisms. The study of plant communication through VOC emissions has largely been studied in laboratory settings due to difficulties in measuring airborne chemicals in the field [10]. A bio-inspired algorithm that explores plant behaviors in a virtual garden may provide insights into these biological signaling networks.

Plant mortality is an important factor in the creation of an ecological simulator. Hawkes provides a review of 61 models involving plant mortality algorithms to provide a state-of-the-art analysis of such algorithms, as well as some suggestions on how the models may be improved [11]. Our virtual garden also incorporates a plant mortality algorithm as an important metric to evaluate the success of the modeled behavior in response to the virtual resources. Minimizing plant mortality is vital in agricultural settings that must produce large crop yields to be profitable.

B. Methods

Two edible plant species were selected for the real-world plant experiment, a high light plant (HLP) and a low light plant (LLP). Beets were selected because they thrive in low-light conditions (LLC); basil requires high light conditions (HLC) and emits high levels of VOCs [12]. A total of 24 plants were included in the experiment, with 12 of each plant type. Seeds of both plant types were planted in starter seed pellets, which help to ensure that all plants were deposited in soil with comparable density and nutritional content. The pellets were placed in small dixie cups to prevent water spillage.

The model space was comprised of two concentric circles printed on paper board to delineate HLC from LLC. The interior of the circles was filled with a half inch grid to assist in determining and tracking the plants' location on the board. A 60 W grow light bulb was positioned to produce a gradient of light, with the highest lighting conditions centered on the board. Four lighting conditions were recorded using a light meter, and defined by the number of lumens reaching the board in a given location: low-light (LL;0-300 lm), medium-low-light (MLL; 300-600 lm), medium-high-light (MHL; 600-900 lm), and high-light (HL; 900-2000 lm). Two water conditions were tested, a subset of the plants in each lighting condition were assigned to receive water every day or every other day. Each plant was marked with its plant type and assigned light and water conditions. Plants that rotated between two lighting conditions (R) were moved every day; both locations were marked on the board so that they were placed in the same spot at each rotation. Figure 2 shows the experimental setup.

Two pilot tests were conducted prior to the experiment, which helped determine the final experimental conditions. Observations were recorded daily, including the day the seed first sprouted above the soil level and mortality. The experiment was completed on day ten, and a digital caliper was used to measure the height of the remaining plants. For plants that died before day ten, the height was measured on the day that it died and left in the model space for the remainder of the experiment.

Figure 3. *HLP growth in LL, MHL and HL conditions.*

C. Results

Seventeen of the plants in the experiment (n =24), were still alive at completion; eleven of the HLP (n =12) and six of the LLP (n =12). The mean height of the HLP (x = 4.24 in) was substantially lower than the LLP (x = 0.793 in). This was caused by natural differences in the growth rate between the two plant species. For LLPs, the best growing conditions, defined by the tallest plants, were rotating between LL-MHL (1.98 in), MLL- HL (1.68 in) with water every day, and LL with water every other day (1.68 in). For HLPs, the best conditions were HL with water every day (0.63 in), and rotating between MLL-HL with water every other day (0.57 in). Mean height of both plants types in each condition demonstrated that the LLPs grew tallest when rotating between lighting conditions and in the LLC; HLPs grew tallest in the HL and MHL conditions (Figure 4).

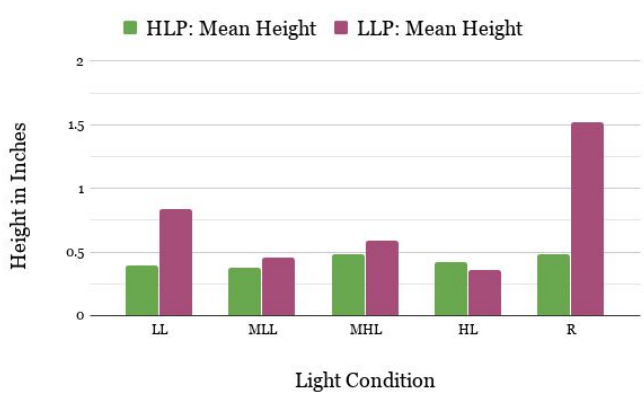

Figure 4. Mean height of plants type by lighting condition

The effect of water in different lighting conditions was also observed (see Table 1). For LLP in the HLC no plants that received water every other day survived; conversely none of the LLPs in the LLC with water every day survived due to mold. LLPs in the rotating conditions grew considerably taller with water every day (x = 1.81 in) than with water every other day (x = 0.95 in). For HLPs, none of the plants survived in the HLC with water every other day; HLPs in the LLC had similar mean heights in both water conditions. Interestingly, for HLPs that rotated positions, the mean height was greater with water every other day (x = 0.42 in) than water every day (x = 0.35 in).

Light Conditions	**LLP Growth in inches**		**HLP Growth in inches**	**(0 = did not sprout)**
	Water Every 1 Day	Water Every 2 Days	Water Every 1 Day	Water Every 2 Day
Rotating	1.81	0.95	0.35	0.42
LL	0	1.68	0.385	0.36
MLL	0.23	0.57	0.42	0.54
MHL	0	1.18	0.46	0.38
HL	0.71	0	0.63	0.34

Table 1. Mean height of plants: lighting by water condition.

D. Discussion

Observational data from the plant experiment was essential in the formation of the virtual garden, as it ensured that the behaviors modeled in the simulation were grounded in accurate representations of actual plant behavior within a similar environment. Both plant types thrived in the rotating light conditions, providing evidence that reconfigurable gardens may help to increase crop yield and survivability. Furthermore, since the HLPs grew tallest in the HLC (Figure 3), and LLPs also grew quite tall in the LLC, second only to the rotating condition, it is reasonable to assume that plants will benefit when rearranging themselves into a position with the optimal light quality. Both of these observations were translated into algorithmic behavior of the RPAs that move through different light conditions, and seek a place in optimal light according to plant type. Another important observation was the importance of suitable water conditions. Too much water in LLC conditions led to mold in the soil causing the plant to die. Too little water in the HLC also killed the plants as they quickly became dehydrated without constant moisture. This was incorporated into the model through the RPA water resource behavior, whereby agents seek water but cannot stay in the position to receive water for too long. In this way, plants obtain the resource, but quickly return to their optimal light conditions in order to prevent mold from forming and drowning the plants.

IV. MODEL AND TECHNICAL DETAILS

A. Model Overview

We incorporate three agent behaviors into our model: a water resource, a light resource, and VOC communication. The first two are natural resources plants seek and act as attractors while VOCs act as repellers and convey a plant's stress level. Figure 1 shows the different sprites and colors used to represent the agents and resources. Agents are initialized as either a low-light or high-light, represented by beet and basil, respectively. The two plant types are defined as high light and low light plants (see Section IV.D). Agents have health and stress properties that determine survival and influence the system, discussed in detail in Sections IV.B and IV.E, respectively. During simulation, an agent's movements are governed by a resource goal and inter-plant communication. Agent's select one resource to seek and cannot switch goals for a set amount of time. A plant moves along either the vector between it and its goal or between it and an agent emitting VOCs. Our simulator is written in Python and utilizes the pygame library.

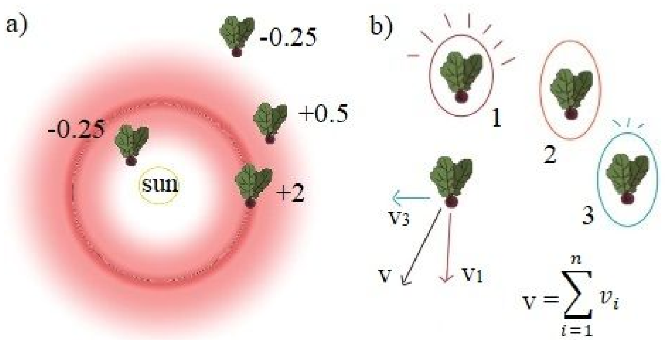

Figure 5. Agent Behaviors. a) The optimal sun value is a radius (dark red) where agent's gain the most health. The amount of health gained decreases with distance in either direction, eventually becoming a constant decrement. b) Agent's with more stress (more lines in this figure) have a stronger repulsive force. An agent's velocity is the summation of contributions from all other agents. Note: images are not accurate to simulation's final appearance.

B. Mortality Algorithm

Our measure of success for this model is the number of plants that are able to survive in the system. Thus, a method of determining how the plants would die is required. From our research, there are many different types of plant mortality algorithms implemented in previous research projects [5]. Our algorithm classifies as a stochastic, abiotic, resource based algorithm since the plants solely die with increased likelihood if they have lower quantities of resources.

Plants have three internal quantities that are checked at every time step to see if they die or not: *Health, Sun_Health*, and *Water_Health*. Sun_Health and Water_Health are both numbers in [0 , 70], while Health is a number in [0 , 140]. Sun_Health and Water_Health are defined by the history of the simulation, while Health is strictly the summation of Sun_Health and Water_Health. Each agent generates a random number at every timestep between 0 and 100. If this roll is greater than the current Health of the agent, that agent dies. Otherwise they can continue living in the system. In short, the higher an agent's health is, the lower their chance of dying. The Sun_Health and Water_Health have upper bounds greater than 50 to give agents a benefit to absorbing a larger amount of a resource than required. For example, a plant that has been watered a significant amount recently does not need more water in the near future. This will become more clear in Sections IV.C and IV.D.

Once an agent dies, it is ignored by the other agents currently in the system and cannot move or interact. For simplicity's sake, dead agents only exist graphically on the simulation screen.

C. Water Resource

Water is a point source with a binary, fixed health gain or decrement. Only agents within a certain radius of the water source's center, (see Figure 6) will increase their health by 2. Agents that are outside this circle will lose 0.25 health. The amount of health gained/lost was chosen based on qualitative observations of our simulation runs so that the agents lived long enough to interact with other agents or reach their resource goal.

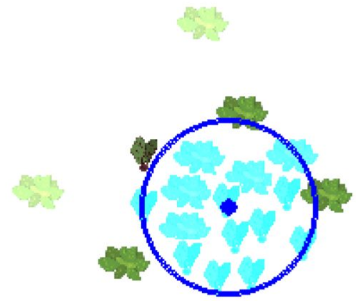

Figure 6. Agents surrounding a water source.

D. Light Resource

Health gained/lost from the light resource follows a continuous function. Figure 5a illustrates the health gain function. Each plant type is specified an optimal sun value corresponding to the distance away from the light source where an agent gains the most health. As the agent moves farther away from its optimal value, the health gained will decrease, approaching a constant negative value. Movements toward and away from the light source are treated equivalently.

The equation used to determine the amount of Sun_Health gained is: $\Delta health = (p+q)e^{-(b*dist^2)} - q$, where p is the maximum amount of health gained at an agent's optimal sun value, b is an exponential decay constant, *dist* is the distance of an agent from its optimal value, and q is the maximum health lost when an agent is far away from the optimal. P and q were chosen to be 2 and 0.25, respectively, to match the values used to change the agent's water health.

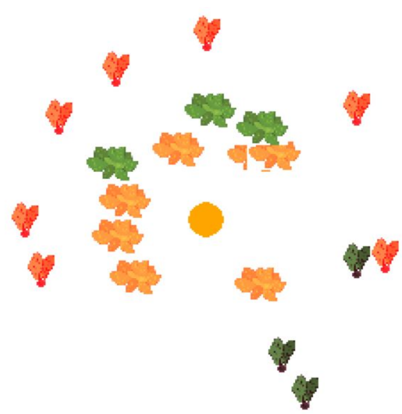

Figure 7. Agents surrounding a light source.

Emission of VOCs is the only method, other than direct collision, by which plant agents can communicate. It is modeled as a repulsive force between plant agents whose effect on a given plant, *a*, is the weighted vector sum of VOC forces between every other agent and itself. Figure 5b provides a graphical explanation of this. This sum is then normalized to a velocity parameter, *v,* which is the max velocity that the agent can physically move (and that it moves toward throughout the entire simulation). The magnitude of the VOC repulsion felt on an agent *a* by just one other agent *b* is proportional to plant *b*'s stress parameter scaled exponentially by the distance between the two and the emittance parameter. The force is along the vector between *a* and *b*, pointing towards *a*. The total effect on *a*'s velocity by all agents is thus:

$$\Delta \vec{vel}_a = \frac{v}{\left\| \vec{C_a} \right\|} * \vec{C_a}$$

$$\vec{C_a} = \sum_{i=\{agents\} | i \neq a} \left(\| voc_{i \to a} \| \, \hat{e}_{i \to a} \right)$$

$$\| voc_{b \to a} \| = stress_b * e^{-\frac{dist^2_{b \to a}}{(emittance_b * stress_b))}}$$

Stress is accumulated purely by a plant's inability to retrieve whichever resource it is actively seeking. The value of stress increases at the same rate that a plant's health decreases. For instance, should a plant be in need of water, but unable to reach the resource, its health reduces by 0.25. At the same time, its stress is increased by 0.25, pushing agents away. Emittance is set as an intrinsic property of the plant, and is initialized at plant creation.

V. SIMULATIONS

A. Water Radius

Our first simulation focused on the effects that the radius size of the water source had on the agents. Placing 10 of each agent type in the space with the water source at the same position as the light source, we altered the radius of the water source from 10 to 50 units. For each radius, we set a timer for 60 seconds to signal when the simulation was complete. If an agent died, we reset this timer. The results are shown in Figure 8 below.

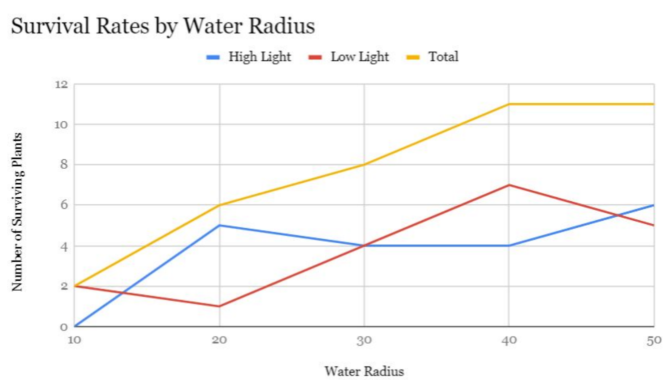

Figure 8. Survival rates by water radius.

B. Water to Sun Distance

Our next simulation examined the effect of the distance between the water source and the light source. Once again, populating the space with 10 of each agent, we observed the agents in the system. Fixing the radius of the water source to 40 units (one of the radii with the highest survival rate from the previous simulation), we began moving the water source away from the light source in increments of 25 units. Using the same timer and completion criteria (no agents died in the last minute), we computed the time for the system to reach its carrying capacity. The results are found in Figures 9 and 10.

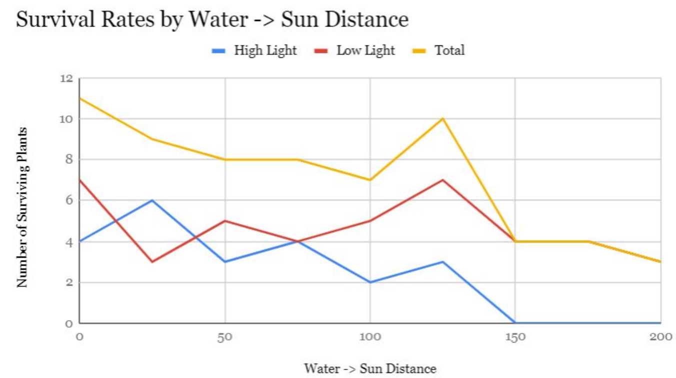

Figure 9. Survival rates by water radius.

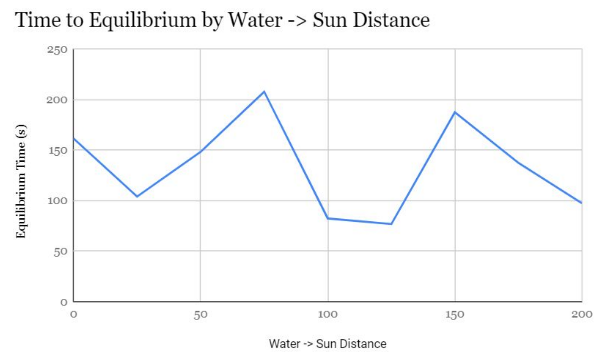

Figure 10. Survival rates by water radius.

VI. DISCUSSION

In the water radius experiment, it was expected that the high-light agents (HLA) would be more likely to survive since the low light agents (LLA) would have to pass through a ring of HLA to get to the water source (due to the HLAs' optimal distance from the light being 50 units); however, this was not supported. At a radius of 20 units, the LLAs were able to push their way into the water source due to their high stress level and resulting VOC levels. After being watered, they would remain stressed as they were too close to the light source, and thus would push the HLAs away from both the light and water source. The HLAs were then unable to quickly gain enough stress to push back into the center, producing a higher mortality rate. This resulted in the LLAs outnumbering the HLAs 5:1. This ratio was more comparable in the higher water radius experiments, as all agents were able to more easily gain access to water.

The second experiment yielded multiple interesting findings. While the total survival rate was highest when the water source was placed on the light source, a local maxima was found when the water source was 125 units away from the light source. This seems to be due to the radius of the water source being placed in such a way that the LLAs were able to obtain both light and water at the same time. This lead to their collective VOC values being very low, making them more compliant to the HLAs needs for water. For the same reason, the system converged quickly to its carrying capacity at distances of 100 and 125 units. While these distances appear to be local minima in terms of time to reach a carrying capacity, distances of 75 and 150 seem to be local maxima. This supports the idea that the best location for a water source to be placed would be in this location if the center of the system is unavailable. Additionally, low stress agents of the same type tend to move in clusters as their needs grow and are satisfied at roughly the same rate, leading them to not push each other away. After a distance of 125 units the survival rate of the system dropped significantly, with no HLAs surviving. This is because the radius of the water source no longer overlapped either type of agent's desired light location. This resulted in HLAs being starved of water as the LLAs were able to fill up on water more frequently.

VII. CONCLUSION AND FUTURE WORK

Our paper focuses on a self-organizing, multi-agent system, with mobile robot-plant agents that arrange themselves according to their optimal resource requirements. Real-world plant experiments directed the design of a computational model, which investigated emergent agent behavior in a series of simulation tests. Three agent behaviors were included in the model: light-seeking to represent plant's phototropic behavior in natural settings, water seeking behavior enabling plants to receive proper hydration, and artificial VOC communication signals, used to mimic allelopathic plant behavior. We have studied how these behaviors direct agent behavior independently and incorporated into a single model. We found that these agent models enable us to consider hybrid behaviors that combine natural and technological entities, which capitalize on the capabilities of both plants and robots. This work contributes to the field of bio-inspired algorithms, which has largely focused on insects and animals rather than botanical entities.

For future work, the first goal is to improve the accuracy of our model. For example, we could find additional reference models for VOCs and plant mortality, to better tune the parameters in order to match the statistics seen in Section III. Conducting more experiments on the configuration of multiple and/or moving resources would also provide useful information when organizing a garden. Secondly, it would be beneficial to implement the RPAs with hardware. Using real plants and robots would mitigate our worries of model inaccuracies since the physical plants would directly inform the behavior regarding water and light preferences. Modeling more complex resource seeking behavior would also help to ensure that computational model accurately reflected real-world conditions. For example, plants in HLC seek water at a faster rate than plants in LLC in order to prevent mortality from plants drying out. Agent behaviors could also be tuned by plant species type, with the ultimate goal of creating a large dataset of different plant species behaviors.

Lastly, adding growth to our simulation would make the model more accurate as plants change in shape and size throughout their life. Plants grow at faster rates based on the amount of resources they obtain. The current model treats agents as static; however, plants are dynamic in their needs and their impact on neighboring agents. This relates to our initial motivation, the agriculture sector. Implementing growth behavior would enable us to differentiate between models where plants barely survive, from ones where they thrive. A farm may favor a few, healthier or bigger plants over several smaller ones. Additionally, this could lead to the implementation of harvesting within the model, where plants are removed from the system and collected into a repository upon reaching a desired size. This would enable us to reason about agricultural yield, and predict optimal patterns of organization.

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