Simulation-governed design and tuning of greenhouses for successful bee pollination

Alan Dorin[1*], Adrian Dyer[2], Tim Taylor[1], Zoë Bukovac[1]

[1] Faculty of Information Technology, Monash University, Australia
[2] Bio-Inspired Digital Sensing Lab, RMIT University, Australia
*alan.dorin@monash.edu

Abstract

This paper presents a novel application of agent-based simulation software to tune real greenhouse infrastructure containing flowering seed or vegetable crop plants and their insect pollinators. Greenhouses provide controlled environments for the growth of high-value crops. As global climate and weather become more unpredictable, we are becoming more dependent upon technologically sophisticated greenhouses for reliable crop production. For crop pollination in a greenhouse, although manual or technological alternatives have been explored, pollination by bees is still required in many crops for the best seed yields and food quality. However, the design of greenhouses is driven primarily by the requirements of the plants rather than the pollinators. In light of this, we have designed simulations to explore improvements to greenhouse conditions and layout that benefit the insect pollinators and assist them to pollinate the crop. The software consists of an agent-based model of insect behaviour that is used to predict pollination outcomes under a range of conditions. The best parameters discovered in simulation can be used to adjust real greenhouse layouts. We present a key test case for our method, and discuss future work in which the technique has the potential to be applied in a continuous feedback loop providing predictions of greenhouse re-configurations that can be made by real-time control systems in a modern greenhouse. This is a novel approach linking simulation behaviour to real techno-ecological systems to improve crop and seed yield from valuable greenhouse infrastructure.

Introduction

Our rapidly increasing human population demands more food, and more reliable food production, in a climate that is increasingly unpredictable (Olesen and Bindi 2002, Kjøhl et al. 2011). Greenhouses globally facilitate high crop yields and product quality. These artificial environments facilitate efficient water and fertiliser use, and have low environmental impact. Hence, we are becoming increasingly dependent on large-scale, technological greenhouse facilities for our most valuable crops (Oerke and Dehne 2004).

Within these spaces, bees, especially managed colonies of honeybees (*Apis mellifera*) or bumblebees (*Bombus terrestris*), are key providers of essential pollination services for many food and seed crops. Overall, bees contribute an estimated \$238 billion p.a. to world food production. Currently, 34% of all food is dependent on bees, with the leading pollinator-dependent crops being vegetables and fruits, followed by edible oil crops, stimulants (coffee, cocoa, etc.), nuts and spices (Gallai et al. 2009, Kjøhl, Nielsen et al. 2011).

Surprisingly, greenhouses are not currently designed to suit bee pollinators. Even advanced climate-controlled greenhouses are managed primarily for the sake of crops, usually ignoring all but the most basic needs and behavioural preferences of insect pollinators. Consequently, difficulties arising from greenhouse bee pollination are widely reported and known to reduce the insects' ability to pollinate our high-value crops (Abrol 2012, pp. 353-395). This may result in a reduction in yield, shelf-life and quality of food and seed that is potentially avoidable. However, bee-plant interactions are complex and difficult to predict. It remains an open problem as to how we can design infrastructure to facilitate these interactions for the mutual benefit of the plants, insects, and for the human food producers and consumers dependent on successful pollination.

This paper sets a new agenda for state-of-the-art digitally-connected greenhouses by placing insect pollination as a key component in data-driven horticultural ecosystems. Specifically, we propose to design or configure various aspects of greenhouses around insect pollinator behaviours and preferences, whilst maintaining the requirements for healthy, productive plants.

We tackle this project using techniques developed within the fields of Artificial Life and Ecological Modelling. Specifically, we use agent-based models to simulate insects in specific greenhouse conditions in order to understand, and predict, how real bees will respond in real environments to real flowering crop plants. We then use the predictions to make design decisions for greenhouses that account for insect behaviours and preferences, to enable improved food production. In this paper, we explain how such methods work and provide results for a key test case to illustrate the principle. We discuss extensions to our model that would facilitate the use of our software as a simulation-in-the-loop control system for tuning pollination in greenhouses.

Background

Greenhouse layout and control

In order to produce fertilised seed for sale to commercial growers, a greenhouse is often planted with a male-sterile

"female" plant incapable of producing viable pollen. The only way for these plants to be pollinated then, is for a "male" plant to become a pollen donor. Insects, especially managed hives of bumblebees and honeybees, are common pollen vectors. The greenhouse is planted with male plants from which the bees must collect the pollen (from the flower anthers), and female plants onto which the bees must carry and deposit the pollen (onto the flower stigma). Since only the fertilised female plants will produce viable seed and this seed must not become contaminated with the seed from the male plants (the pollen-bearing line), the male and female plants are commonly arranged in long, parallel, single-sex rows facilitating reliable mass removal of the pollen-bearing plants prior to seed harvest.

Space between plant beds facilitates human and machine movement to maintain the crop, for instance to check plant health, remove weeds, maintain water and nutrient supplies.

Conditions in modern industrial greenhouses may be climate-controlled for humidity, temperature and lighting to minimise the likelihood of pests and diseases such as insects and fungi, whilst providing suitable conditions for plant growth, crop development or fruit and vegetable ripening. Simple greenhouses may have little scope for dynamic control but must nevertheless take heed of these basic requirements for successful horticulture and food production. These conditions are not necessarily suited to the insects, despite the importance of the role they play in food and seed production. For instance, plant rows may be spaced beyond the limited visual range of foraging bees (Dyer et al. 2008) making it difficult for them to act reliably as pollen vectors – they might seldom cross from a row of male plants to a row of females if the space isn't well planned. Simply put, greenhouse-bound bees do not always behave as we would like because greenhouses are currently designed for different criteria.

Pollination and insects.

Ideally, we want bees to be well spread throughout a crop of flowering greenhouse plants, and we want them to be visiting and manipulating flowers in the way required for successful pollination. In cases, such as for tomato crops, where self-pollination is required, we want bumblebees to visit blooming flowers throughout the greenhouse with little need to worry about the visitation order. But where male and female plant organs appear on separate plants and cross-pollination is required, we need bees to visit male flowers to collect pollen on their bodies, and then to visit female flowers to brush it off to facilitate successful pollination. If the order of visitation isn't correct, such that there is no pollen on a bee's body when it visits a female plant, then cross-pollination cannot occur. In light of this need, for seed and food production requiring cross-pollination, male/female planting ratios and layouts have been explored and trialled over many years (e.g. see (Williams and Free 1974) on onion seed production). Industry planting replicates standard layouts to ensure sufficient pollen distribution to the crop that accounts for the specific requirements of each plant, its pollen production and distribution requirements. E.g., see the many requirements of crops surveyed throughout (Delaplane and Mayer 2000). Arrangements must also account for the fact that, in hybrid

seed production (and in fruit orchards), it is the female plants (or "main variety") receiving the pollen that produce the fertilised seed or develops the fruit that generates revenue. E.g., see (Abrol 2012, p.241) on orchard planting patterns. Growers therefore want sufficient male pollen-bearing plants in their farms, but they must offset this space requirement against the need to maximise the number of revenue-generating female plants.

Where suitable insect pollinators are unavailable, labour-intensive manual or expensive technological alternatives have been applied. To give an indication of the extent to which growers have gone in search of bee replacements, tomato pollination attempts include: hand pollination, emasculation, vibration of trellis wires, acoustically forced vibration, air blowers, pulsating air jets, sound waves, air cylinder vibration, plant hormone application, manual pollination with an electric vibrator or "electric bee" (Bell et al. 2006). Bees, however, have coevolved over millions of years with flowering plants and provide significant increases in crop yield, product quality and shelf life in some crops (Klatt et al. 2014). Unfortunately, global bee populations are diminishing due to effects including pesticide use, industrial crop monocultures, Varroa destructor mites and natural habitat loss (Plant-Health-Australia 2018). Managed hives are therefore increasingly valuable to greenhouse growers and it is important to utilise their services effectively.

It is difficult to maintain bees as fully functional pollinators within the confines of a greenhouse; especially when the workspace has not accounted for how bees employ sensory capabilities to find flowers, orientate themselves in the space or navigate to and from their hive. From the bees' perceptual experience, current greenhouses may be likened to a poorly designed supermarket in which they forage. Imagine what it would be like to shop in a human supermarket that was designed solely for the wellbeing of the products without attending to the needs of the customers with regard to climate, navigational aids and easily identifiable food labelling. If all supermarket food was arranged in identical unlabelled aisles, on identical unlabelled shelves, in identical unlabelled boxes, and the space was hot, poorly lit and didn't stock diverse supplies, shopping would be an even more stressful activity. Good visual design suited to the customers' needs is thus a key to success in a modern economy (Clement et al. 2013). Likewise, bees in poorly designed greenhouses easily can, and do, become confused, stressed or lost; reducing food production efficiency (Morandin et al. 2002). Stressed or confused bees may attempt to leave the greenhouse, heading for its upper corners and buzzing there until they die. Or, they may stay in the hive and refuse to forage, or they may forage but then return to the wrong hive. Either way, disorientation isn't good for bees or for food production (Birmingham and Winston 2004).

Agent-based models of insect behaviour.

Bees are complex social organisms with sophisticated behavioural and learning mechanisms and advanced perceptual systems (Dyer et al. 2011). There is no singular, nor simple, solution to managing their interaction within the

complex greenhouse environment. Prediction and management of their behaviour demands complex tools.

The best way to understand insect behaviour under specific environmental conditions is, without doubt, to observe it. Hence, bee behaviour has been observed by naturalists since at least Aristotle (in *Historia Animalum*, c.340 B.C.E), yet, there remains much to discover. Making observations of insect-plant interactions under diverse conditions is prohibitively expensive and labour-intensive. In the case of proposed or predicted environmental change, it may even be impossible to conduct experiments under relevant conditions – they haven't happened yet! How then do we explore current and future greenhouse design to cater for bees? Ideally, for a specific greenhouse with a specific crop and during a specific part of the flowering season, we would like to know which flowers bees have visited and pollinated, which areas of the greenhouse confuse bees, which areas they avoid, and where they congregate. We need to understand the drivers for these insect behaviours to devise mechanisms that encourage bee circulation and enhance pollination.

The combination of data collection on real insects/flowers and computer simulations has the potential to provide a powerful dual approach to understand bee's pollination performance. The process involves using field observations to parameterise and validate computer models of insect behaviour that are then used to understand the implications of the observations under relevant environmental conditions. For this, we have found agent-based models (ABMs) to be suitable, as explained in detail below. By running thousands of simulated interventions or variations to greenhouse design, and assessing their pollination outcomes, we can predict which interventions to test in the real world to improve food and seed production. Ideally, the test results are then used iteratively to improve simulation parameters and algorithms before repeating the cycle.

ABMs allow us to unravel complexity and predict large-scale dynamic behaviours emergent from many individual interactions. They have been increasingly used for ecological applications since the late 1990s (Grimm 1999). Since insect/plant interactions form just such a complex ecological system, ABMs are among the suitable Artificial Life techniques for our case (Dornhaus et al. 2006). Millions of bee-agents must be simulated in detail as they navigate and forage among individual virtual flowering plants that correspond to specific real greenhouses, or alternatives that may improve efficiency. The technique has already been successfully applied to this context. For example, ABMs have been used to show that the benefits of recruitment by honeybees depends on environmental flower density (Dornhaus, Klügl et al. 2006). ABMs have successfully modelled bee-flower interactions, notably for colour discrimination. These have shown the importance of pollinator diversity for success of colonies in complex environments (Dyer et al. 2014), and why flowers evolved colour signals in Australia (Bukovac et al. 2017). ABMs have also revealed different efficiencies of bumblebees and honeybees that forage in environments of variable floral target and non-target density ratios (Bukovac et al. 2013).

Method

We have developed a number of ABMs of bee foraging behaviour (Dyer et al. 2012, Bukovac, Dorin et al. 2013, Dyer, Dorin et al. 2014, Bukovac, Dorin et al. 2017) that have informed the design of the current experiment. Here our scope is to summarise the relevant details. The design rationale and methods for validating our models of insect behaviour are provided in the cited articles. Short explanations of the algorithms and essential parameters are provided below for reference.

Table 1. Main simulation parameters.

ENVIRONMENT	
Modelled grid cell size	0.35 × 0.35m
Colony size	60 bees
VIRTUAL-BEES	
Flower presence detection accuracy (visual range)	100% from neighbour cell or cell shared with a flower
Flower scent mark recognition accuracy	100% from neighbour cell or cell shared with a flower
Storage capacity	Infinite
Scent mark persistence	Infinite
Flower visit	3 time steps
Complete field of view scan	1 time step
Movement in Moore neighbourhood	1 time step
Carried pollen viability time	25 time steps
SIMULATION	
Duration	500 time steps
Number of replications	100 per test layout

The case-study we describe involves establishing a simulation matching one particular industrial greenhouse layout to which we have previously had access. However, it is not special in any regard. Alternative arrangements might just as well have been modelled. As noted above, different crops have different pollination requirements and industry has therefore settled on standards based on observation for each crop (Delaplane and Mayer 2000). Our model is generic and employs plant spacing and bed configuration parameters for a simple trial. To demonstrate the utility of our method, our goal is to illustrate by test case the generation of a planting arrangement that maximises pollination in the presence of a given pollinator species whose foraging behaviour is explicitly modelled in our ABM. The factor under observation is the absolute number of *female plants successfully pollinated* after a fixed time interval within the space and layout limitations imposed by greenhouse area. Our hypothesis is that the ABM will enable us to establish the relative effectiveness of different planting arrangements for a two-row per bed greenhouse being bee pollinated. We don't specify in advance the ratio of male to female rows/plants in the greenhouse (this is partly what our simulation explores), only total row/plant count.

As explained below, the honeybees' limited visual range causes them to tend to forage along plant beds, crossing only occasionally between adjacent beds. Hence, we expect the best planting arrangement to contain males and females together within forager visual range – the best *bed* layout ought to consist of one male and one female plant row. This, in theory, positions all females as near as possible to a male plant and should maximize pollination. However, this is not

necessarily the best arrangement for the greenhouse overall, when we account for the complex foraging behaviour of the pollinators. So, a good planting solution isn't necessarily the "obvious" case with all beds consisting of male/female rows – if it is possible to have fewer male rows in the greenhouse than one per bed, whilst pollen can still be successfully distributed to the females, then the space freed up by having fewer males can be filled with valuable yield producing, pollinated, female plants. Our simulations assist to unravel the complexity of this situation.

Virtual greenhouse simulation overview.

Our simulated greenhouse layout consists of four beds of two plant rows each (fig. 1). Plant rows may be either entirely male pollen-donors, or entirely female plants requiring pollination. The ABM is used to establish the ideal arrangement of male and female rows within beds to maximise pollination after a fixed time interval (500 time steps per run, a value chosen by observation to ensure all flowers are visited). The greenhouse is divided into grid cells labelled as either empty space, or occupied by a single male or female plant. Grid cells represent $35cm^2$ making it possible for a bee to view the centre of one cell from the centre of its neighbours to correspond to the visual range of a honey-bee. The greenhouse is 72x18 cells, rows 60 cells long, inter-bed/wall spacing is 2 cells.
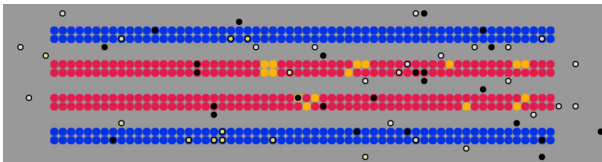

Figure 1. Simulated greenhouse visualisation. Red: un-pollinated female flowers, orange: pollinated females, blue: males. Black circles: bees (Small pale, yellow circles within bees indicate carried pollen. Pale yellow fades to white as pollen is lost. Bees return to black upon losing all pollen).

Virtual bees and virtual plants.

Simulated plants support a single virtual flower to represent the pollination status of the crop at that location. Male flowers can be pollen donors; they commence the simulation with a single pollen grain available for collection (rationale below). Female plants can be pollen recipients; they start the simulation un-pollinated and are pollinated when a grain of pollen is deposited on them by a virtual bee.

Real bee colony sizes vary from a few to many tens of thousands depending on species, but there is variation even within species (e.g. (Michener 1964)). We modelled a colony of 60 foragers initially placed at random on the grid but, in the virtual world, could just as well have chosen any number and obtained the same results by adjusting simulation run length. For this experiment, in order to control the number of tests required in our brute force approach, we do not model hive location; a worthwhile extension that has long been explored in the field (Free 1960). We do model scent-marking of flowers by bees. Honeybees mark flowers with a pheromone while harvesting to signal to others that the flower's nutrition has been depleted (Giurfa and Núñez 1992). In our model, virtual bees (v-bees) mark every visited flower with a scent that persists for the remainder of that simulation run. V-bees can detect this mark on any visible flower and will reject marked flowers for landing. Consequently, each flower is visited only once – virtual male flowers therefore only need to carry a single grain of pollen, and females need only receive one grain for pollination. Scent marks are the only means by which v-bees interact with each other.

Real-world time is not explicitly simulated, so a single time step does not directly imply a particular real timespan. Crop pollination occurs over days and weeks, but we need only to assess how pollen disperses in a short period. Consequently, we limit the simulation outcome to the worst-case scenario; if each plant were visited only once, which planting arrangement results in the best pollination? A persistent scent mark allows us to gain the desired pollen distribution snapshot.

V-bee decision-making is governed by the algorithm illustrated (fig. 2) and its parameters (tab. 1). Each v-bee flight is a sequence of randomized straight-line movements; a line's orientation is selected from a uniform random distribution, its length is drawn from a Cauchy distribution as honeybee searching is consistent with Lévy flights, and their flight path lengths follow a Lévy-stable distribution / Cauchy distribution (Reynolds and Rhodes 2009). In one simulation time-step, a v-bee moves in its Moore neighbourhood (the 8 cells surrounding its current location). If it can see an unvisited flower it moves towards it. In the absence of a target, a v-bee acquires a random angle, and random path length drawn from the Cauchy distribution as just noted, calculates the corresponding destination grid cell, and moves one grid step along the rasterized path that approximates a straight line to the destination. In subsequent turns, the v-bee continues towards the destination in this way, only stopping if it sees an unvisited flower, runs into the greenhouse wall, or reaches its destination cell. At the destination, if it finds no unvisited flowers, a v-bee repeats the movement process. Hence, v-bee movement is guided by both simulated vision and biologically plausible random movements.

Pollen carryover is the amount of time any pollen deposited on a bee's body during a flower visit remains on its body available for pollinating a flower (Thomson and Plowright 1980). Modelling the mechanical complexity of pollination is beyond the scope of this case study. Our experimental goal lies only in establishing relative differences in pollination extent between planting arrangements. So, as long as our carryover value is plausible, it won't impact relative differences between plant arrangements – this was confirmed by testing. We model pollen carryover as a simple timer whereby after 25 time steps pollen collected from a flower on the body of a v-bee is lost. In the real world, this may be due to insect grooming, loss during flight, or whilst moving through flower and plant components.
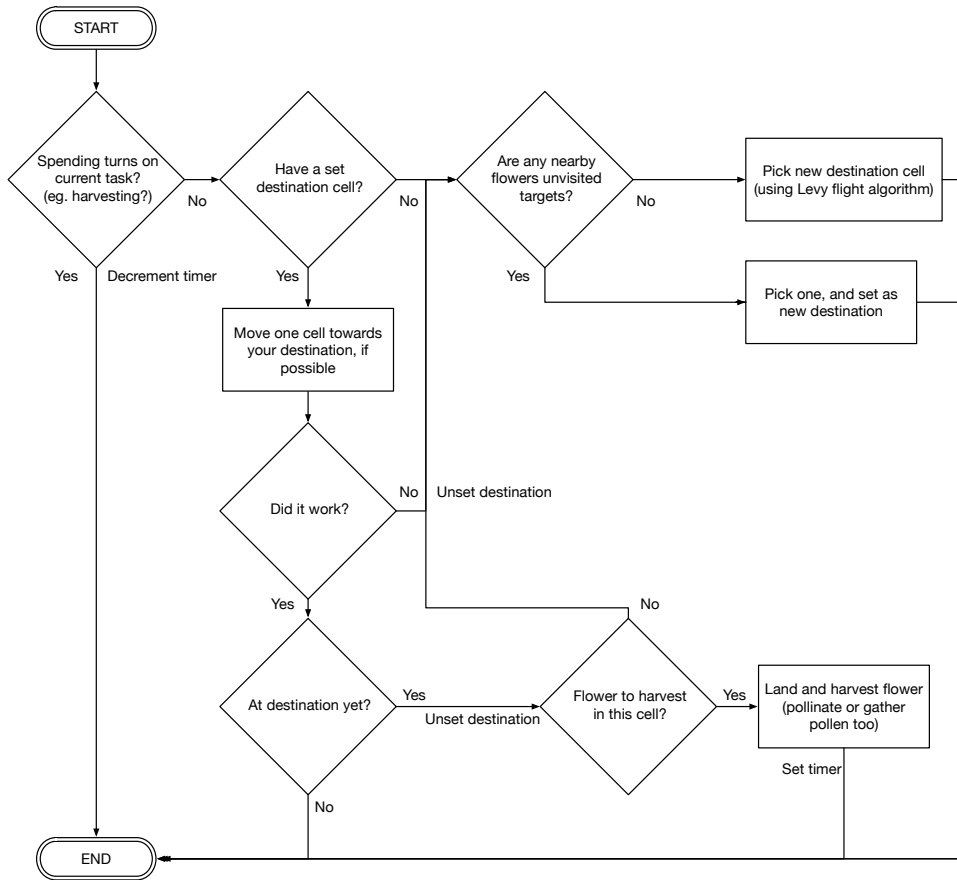
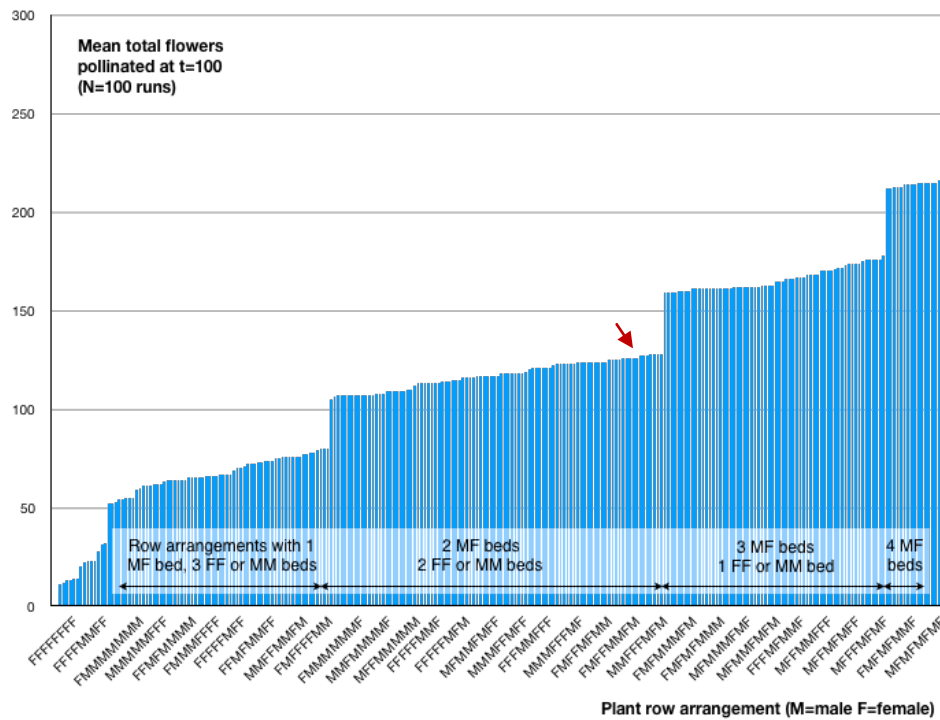Figure 2. Virtual bee decision-making algorithm.

Figure 3. Mean total flowers pollinated out of 480 at t=500 (N=100 runs) for each plant row arrangement. Row configurations sorted in order of increasing pollination count. For legibility, only sample planting arrangements are labelled, although all data is plotted. Red arrow marks sample industrial greenhouse planting arrangement encountered in practice.

Results and Discussion.

The ABM results are illustrated in fig. 3. The x-axis shows planting arrangements sorted in increasing order of numbers of pollinated female plants. The y-axis marks the number (out of a possible maximum total of 480 females – the case with all rows fully planted with female plants) that were pollinated. For legibility, only some sample planting arrangements are explicitly labelled, although all data is plotted on the bar graph.

As can be seen, the success of a greenhouse arrangement is proportional to the number of beds with dual-sex male/female (MF) row planting. The sets of arrangements with 1, 2, 3 and 4 MF beds are marked for clarity on the figure and create visibly stepped performance increases. All runs ran to saturation by simulation termination at t=500 (i.e. all flowers were visited, but not all females were necessarily pollinated). Planting beds with neighbouring male and female plants in a 1:1 ratio maximized the total number of pollinated females in the greenhouse. We noted above that this was the intuitive best arrangement for individual *beds*, but within the limitations of our simulation, this also appears to be the best layout for the entire greenhouse. For the reasons noted above, this isn't necessarily what we would expect. So, why isn't it more effective to reduce the number of males and replace them with more yield-producing females? Our simulation seems to indicate that the bees' inability to see between beds severely impacts their ability to carry pollen from one bed to another. Hence, each bed requires its own source of pollen – a row of males in each bed – to facilitate effective pollination. In a real greenhouse, multi-day foraging by bees may overcome this deficit to an extent. However, within the limitations of our model, we suggest that a better arrangement for all beds for increased overall yield is MF planting.

As noted, industry planting arrangements vary and there may be disagreement about best-practice (e.g. (Williams and Free 1974) and references within). Anecdotally, the reasons for this may be obscure although they may simply be related to lack of information, the variability of crop growing conditions, variation in the crops themselves, and in their pollinators. Crop pollination is a very complex interaction. In many cases, farmers utilize the services of several sets of fresh hives, as well as many days or weeks of repeated foraging, for pollination. Their aim is to allow time for satisfactory pollination and realise a net increase in crop yield. The number of bees and timing required then becomes another factor of relevance for growers (Abrol 2012, p.243) and (Delaplane and Mayer 2000). Likewise, the spacing between plants has long been considered important (Crane and Mather 1943).

Trivially, our model can be adjusted to accommodate multi-day pollination by increasing the number of virtual days over which pollination runs, removing scent marks after an appropriate decay time, increasing the number of pollen grains collected, carried and deposited by bees, and altering the number of grains that must be deposited on a plant for pollination. However, this extension has not been explored in the current paper. The simple version of the model presented here nevertheless demonstrates the utility of our ABM-based approach for choosing the plant layout within the limitations imposed by the pre-determined greenhouse configuration under study.

Future work

The potential applications of this ABM-based approach are extensive. So, our paper now explores opportunities for the future in which complex greenhouse infrastructure is dynamically adjusted to account for insect pollinators.

The control of simple systems such as for heating a small home requires only a simple device – a thermostat that turns on or off a heater may suffice. Often, the relationship between the desired outcome, a particular house ambient temperature setting, and the required alteration of heater parameters is obvious. At the other extreme, the requirements for control systems of commercial greenhouses can be extremely complex. Such infrastructure ought to account for the dynamic requirements of developing plants, ripening fruit/vegetables, pollinating insects and human growers, whilst keeping at bay unwanted insect pests and fungi, and whilst the structure remains exposed to changes in the external environment. To tackle this, we propose a general framework for addressing the complexity of the issue: simulation-determined layout and control for data-driven greenhouses. This infrastructure we term a *techno-ecological system* (TES).

A modern greenhouse equipped with sensors coupled to automated control systems encompasses strongly coupled interactions between the organisms it contains and the technological infrastructure. A basic greenhouse might have control systems akin to those of a simple house that adjust the temperature and humidity inside based on sensor data. What is missing however is any technique for environmental control that suits the dynamic behavioural repertoire of insect pollinators. The complexity and dynamics of insect/plant interactions positions this task beyond the capability of directly coupled sensors and actuators. As shown above, simulations can inform us in making decisions on greenhouse layout that assist pollination by bees. But the system described above is "set and forget" in the sense that once a greenhouse is configured it must be (more or less) left alone in this regard. An alternative is to place the simulation into a feedback loop as part of greenhouse control. The simulate-perturb-sense cycle is necessary because the needs of colonies of managed bees are dynamic. They change over the course of a day, over the course of a season, and between seasons. Greenhouses, plants and bees are not "set and forget" systems for which a single set of observations is effective in dictating ideal conditions. Hence, a real-time method to tune greenhouse conditions in response to the complex dynamical interaction of flowering crops and bees is desirable. The difficult process of control system design for complex models or physical robots provides a potential source of inspiration for the design of complex greenhouse controllers. For example, Terzopoulos et al. (1994) present a method applied fully in-simulation to allow virtual fish to learn effective use of their own actuators. Sims' use of evolutionary computation to evolve "virtual (blocky) creature" body forms and controllers in simulation is well known also (Sims 1994). Lipson extended the application of the principle by evolving robot forms and controllers for

3D printing, thereby bringing the results of the simulated world into physical form (Lipson and Pollack 2000).

We propose, however, to adopt a means of dynamic control similar to that of Bongard et al. (2006) who created robots that incorporate real-world performance feedback into their control systems. Firstly, as described above, we take data from the behaviour of a real, complex techno-ecological system into a simulation to explore the impact of perturbing that system. Secondly, we suggest in the future to introduce an iterative feedback loop that applies the proposed perturbations to the real world and monitors the results, before once more feeding newly sensed data back into the simulation to continuously improve the model, and to generate new perturbations responding to the dynamic state of the physical system.

A variety of sensor data would need to be collected on environmental conditions in the greenhouse to achieve our goal. However, sensors, sensor-networks and multi-spectral imaging have been used in precision agriculture to monitor the environment, lighting and plant condition, and to adjust greenhouse conditions such as temperature and humidity, drip-irrigation and nutrients directly in response to crop needs since 2003 (Ruiz-Garcia et al. 2009) so the inclusion of such technology in greenhouses isn't rare. Sensor data on insect speed, direction of travel and location, and on floral visits and idle-time of bees throughout the flowering crops is also required. Recently "bees with backpacks" have become a viable option with the potential to be applied to this end (Engelke et al. 2016).

Data collected on the greenhouse environment and its insect occupants can be fed into an ABM of bee greenhouse activity as the "current system state". From this, a set of alternative greenhouse configurations would be generated to be explored, for example, by an Evolutionary Algorithm (EA). The best configuration the EA generates is the one resulting in even and robust pollination. Each simulation run within the EA is an attempt to predict the ideal "future state" of the greenhouse and the conditions that lead to it. Hence, the parameters of the best run must be fed back into the physical greenhouse controllers to attempt to drive the real situation towards this state. The simulate-perturb-sense cycle repeats as long as the greenhouse requires pollination and at a rate that must be governed by the systems under control, since, not all infrastructure can, or should, be updated rapidly – the need of bees, crops and (human) growers for different types of environmental stability must be taken into account.

Each member of the evolving population in the EA is then an ABM of bees pollinating flowers laid out in accordance with the greenhouse configuration and parameters. These test cases can be generated based on standard EA mutation and crossover operators. Bee behavioural parameters are fixed in accordance with existing tested and validated models whilst greenhouse parameters are varied as part of the EA digital genome. Some samples for the kinds of parameters to be included are already given above as the basic elements of our ABMs above (Tab. 1).

Conclusion.

The test case we have explored, how to plant male and female plants for cross-pollination in a pre-determined bed set up, is an important consideration that has long been an essential aspect of greenhouse layout. Our ABM takes account of essential honeybee foraging behaviours including Lévy flights, scent marking, and limited vision, to test possible planting configurations exhaustively. It settles on an arrangement with dual MF rows in each bed as most effective for pollination – the more beds like this, the more female plants were successfully pollinated in the model. Whilst some of the cited literature reports testing on a variety of planting arrangements, much more fieldwork would be required to ascertain the accuracy of the model's prediction for different crops and different bee species – the simulation however gives a starting point that matches a common setup found in the literature.

We also present a proposal for future research where models like ours might be employed as part of a continuous feedback loop to assist in greenhouse control. Such simulation-in-the-loop control is, potentially, a way to monitor and respond to the complex dynamics of plant-pollinator interactions under the variable environment of the greenhouse. This seems to be a likely way to think beyond simple reactive control systems in order to govern the performance of complex techno-ecological systems for the benefit of human food production.

References.

Abrol, D. P. (2012). Pollination Biology: Biodiversity Conservation and Agricultural Production, Springer.

Bell, M. C., R. N. Spooner-Hart and A. M. Haigh (2006). Pollination of Greenhouse Tomatoes by the Australian Bluebanded Bee Amegilla (Zonamegilla) holmesi (Hymenoptera: Apidae). *Journal of Economic Entomology* 99(2): 437-442.

Birmingham, A. L. and M. L. Winston (2004). Orientation and drifting behaviour of bumblebees (Hymenoptera: Apidae) in commercial tomato greenhouses. *Canadian Journal Of Zoology* 82(1): 52-59.

Bongard, J., V. Zykov and H. Lipson (2006). Resilient Machines Through Continuous Self-Modeling. *Science* 314(5802): 1118-1121.

Bukovac, Z., A. Dorin and A. G. Dyer (2013). A-Bees See: A Simulation to Assess Social Bee Visual Attention During Complex Search Tasks. *12th Euro. Conf. on Artificial Life (ECAL 2013)*, Taormina, Italy, MIT Press.

Bukovac, Z., A. Dorin, V. Finke, M. Shrestha, J. Garcia, A. Avarguès-Weber, B. M., S. J. and D. A.G. (2017). Assessing the ecological significance of bee visual detection and colour discrimination on the evolution of flower colours". *Evolutionary Ecology* 31(2): 153–172.

Clement, J., T. Kristensen and K. Grønhaug (2013). Understanding consumers' in-store visual perception: The influence of package design features on visual attention. *Journal of Retailing and Consumer Services* 20(2): 234-239.

Crane, M. B. and K. Mather (1943). The natural cross-pollination of crop plants with particular reference to the radish. *Annals of Applied Biology* 30(4): 301-308.

Delaplane, K. S. and D. F. Mayer (2000). Crop pollination by bees. Oxon, UK, CABI Publishing.

Dornhaus, A., F. Klügl, C. Oechslein, F. Puppe and L. Chittka (2006). Benefits of recruitment in honey bees: effects of ecology and colony size in an individual-based model. *Behavioural Ecology* 17(336-344).

Dyer, A. G., A. Dorin, V. Reinhardt, J. E. Garcia and M. G. P. Rosa (2014). Bee reverse-learning behavior and intra-colony differences: simulations based on behavioral experiments reveal benefits of diversity. *Ecological Modelling* 277: 119-131.

Dyer, A. G., A. Dorin, V. Reinhardt and M. G. P. Rosa (2012). Colour reverse learning and animal personalities: the advantage of behavioural diversity assessed with agent-based simulations. *Nature Precedings*(March): 20.

Dyer, A. G., A. C. Paulk and D. H. Reser (2011). Colour processing in complex environments: insights from the visual system of bees. *Proceedings of the Royal Society B* 278(1707): 952–959.

Dyer, A. G., J. Spaethe and S. Prack (2008). Comparative psychophysics of bumblebee and honeybee colour discrimination and object detection. *Journal of Computational Physiology A* 194: 614-627.

Engelke, U., P. Marendy, F. Susanto, R. Williams, S. Mahbub, H. Nguyen and P. d. Souza (2016). A Visual Analytics Framework to Study Honey Bee Behaviour. *2016 IEEE 18th International Conference on High Performance Computing and Communications; IEEE 14th International Conference on Smart City; IEEE 2nd International Conference on Data Science and Systems*, Sydney, Australia, IEEE Computer Society.

Free, J. B. (1960). The Pollination of Fruit Trees. *Bee World* 41(7): 169.

Gallai, N., J. M. Salles, J. Settele and B. E. Vaissiere (2009). Economic valuation of the vulnerability of world agriculture confronted with pollinator decline. *Ecological Economics* 68: 810-821.

Giurfa, M. and J. A. Núñez (1992). Honeybees mark with scent and reject recently visited flowers. *Oecologia* 89(1): 113-117.

Grimm, V. (1999). Ten years of individual-based modelling in ecology: what have we learned and what could we learn in the future? *Ecological Modelling* 115: 129-148.

Kjøhl, M., A. Nielsen and N. C. Stenseth (2011). Potential Effects of Climate Change on Crop Pollination. Rome, Food and Agricultural Organization.

Klatt, B. K., A. Holzschuh, C. Westphal, Y. Clough, I. Smit, E. Pawelzik and T. Tscharntke (2014). Bee pollination improves crop quality, shelf life and commercial value. *Proceedings of the Royal Society B* 281(1775): 20132440.

Lipson, H. and J. B. Pollack (2000). Automatic design and manufacture of robotic lifeforms. *Nature* 406: 974–978.

Michener, C. D. (1964). Reproductive efficiency in relation to colony size in hymenopterous societies. *Insectes Sociaux* 11(4): 317-342.

Morandin, L. A., T. M. Laverty, R. J. Gegar and P. G. Kevan (2002). Effect of greenhouse polyethelene covering on activity level and photoresponse of bumble bees. *The Canadian Entomologist* 134(4): 539-549.

Oerke, E.-C. and H.-W. Dehne (2004). Safeguarding production—losses in major crops and the role of crop protection. *Crop Protection* 23(4): 275-285.

Olesen, J. E. and M. Bindi (2002). Consequences of climate change for European agricultural productivity, land use and policy. *European Journal of Agronomy* 16(4): 239-262.

Plant-Health-Australia. (2018). "BeeAware." Retrieved 1 April, 2018, from http://beeaware.org.au/.

Reynolds, A. and C. Rhodes (2009). The Levy flight paradigm: random search patterns and mechanisms. *Ecology* 90(4): 877–887.

Ruiz-Garcia, L., L. Lunadei, P. Barreiro and J. I. Robla (2009). A Review of Wireless Sensor Technologies and Applications in Agriculture and Food Industry: State of the Art and Current Trends. *Sensors* 9: 4728-4750.

Sims, K. (1994). Evolving virtual creatures. *SIGGRAPH '94 Proceedings of the 21st annual conference on computer graphics and interactive techniques*, Orlando, USA, ACM Press.

Terzopoulos, D., X. Tu and R. Grzeszczuk (1994). Artificial fishes: Autonomous locomotion, perception, behavior, and learning in a simulated physical world. *Artificial Life* 1(4): 327-351.

Thomson, J. D. and R. Plowright (1980). Pollen carryover, nectar rewards, and pollinator behavior with special reference to Diervilla lonicera. *Oecologia* 74(1): 68–74.

Williams, I. H. and J. B. Free (1974). The Pollination of Onion (Allium cepa L.) to Produce Hybrid Seed. *British Ecological Society* 11(2): 409-417.