AgentScapes—An agent-based framework for designing water efficient residential landscapes

Rhonda Hoenigman, Elizabeth Bradley
Dept. of Computer Science
University of Colorado
{Rhonda.Hoenigman,lizb}@colorado.edu

Nichole Barger
Dept. of Ecol. and Evol. Bio
University of Colorado
nichole.barger@colorado.edu

ABSTRACT

In arid and semi-arid regions, landscaping can reduce the energy use of a home and generate a more pleasing environment for the home's residents. However, water in these regions is a scarce resource, which makes landscaping a tradeoff between conflicting objectives—maximizing the growth on the landscape while minimizing the water use. This paper presents a new system, called AgentScapes, that uses agent-based modelling and distributed optimization to design water-efficient residential landscapes. The agent-based model included in AgentScapes combines the basic ideas of local search and the specifics of how plant communities emerge based on individual plant-plant interactions and responses to resources available on the landscape. Agents in this model are plants with different light and water requirements placed on a simulated landscape. Agents employ a search routine that mimics how plant communities evolve over time to search for locations that maximize growth and minimize water use. In experiments with a range of landscapes and plant agents, AgentScapes consistently produced solutions close to the optimal solutions and outperformed random and greedy search algorithms.

1. INTRODUCTION

Residential irrigation accounts for 40 to 70 percent of household water use in semi-arid and arid regions [15]. This water comes out of reservoirs, many of which are at risk of depletion [4]. There are benefits to irrigated landscapes that offset this water use. Landscaping can reduce the heat index around the home, which decreases air conditioning use and saves energy [7, 28]. Quantifying the costs and benefits of individual landscapes, however, requires establishing the landscape and collecting the relevant statistics over a possibly long period of time [15, 29, 19], which limits the number of studies that can be performed. Finding landscape designs that generate the most benefit–overall growth for the least water use–is not possible using real landscapes given the number of experiments that would need to be performed and the time scale for each experiment. There are heuristics, such as Xeriscaping, which encourage clustering plants by water requirements and planting drought-tolerant species [18]. However, homeowners who want to find the optimal locations for one or more plants on a landscape have no way of testing how each plant will grow in a particular location without putting the plant in the ground and waiting.

This paper presents AgentScapes, an application for designing landscapes optimized for water conservation. AgentScapes uses a distributed, agent-based model, where agents are plants that react to their surroundings. AgentScapes simulates how real plants interact on a landscape–using water based on environmental conditions and water requirements, and growing based on available light and water. Each plant agent resides on a discretized landscape with light and water conditions. A set of equations, derived from botanical literature on real plants, dictate a plant agent's growth at its current location based on the light and water available. Each plant agent's fitness is calculated with an optimization function that includes the agent's growth equations, and a penalty for excessive water use. The optimal conditions for plant agents, based on knowledge from master gardeners, are designed to provide agents with their desired light level and limit the agents' exposure to harsh afternoon sun [33]. In afternoon sun, real plants can shut down to conserve water, which also limits their growth, or, in some cases, use more water to stay cool, depending on the conditions and the plant. Agents respond to unfavorable conditions by migrating to a new location, just as real plant communities migrate over time in response to changing environmental conditions. Through optimizing its own location, each plant agent searches for planting conditions that maximize its growth while minimizing the amount of water it requires. The water-efficient landscape, and the best locations for each plant agent, emerge from the agents' individual actions.

This work draws on previous research from several disciplines, including computer science, ecology, horticulture, botany, and landscape design to develop the significant components of AgentScapes. The significant components of AgentScapes and how they are used include the following:

- **Plant growth model**–Establishes how plant agents grow under different light and water conditions.
- **Landscape**–Represents light and water conditions at each location and how plant agents interact with each other and their surroundings.
- **Fitness function**–Measures how well a plant agent's growth requirements are being met in its current location.
- **Agent-based search**–Procedure that enables each plant agent to search for its optimal location on the landscape

2. BACKGROUND

Finding the best locations on a landscape for a collection of plants is a combinatorial optimization problem similar to facility layout and location problems in operations research, also known as the quadratic assignment problem in computer science. In all of these, the solution consists of a spatial layout that produces the highest score based on a fitness function, however, there are differences between locating plants and locating facilities in how distance between items contributes to the fitness function. In the facility layout problem, the objective is to arrange the items in a facility to function efficiently and minimize travel distance [11], which makes the distance between items an explicit part of the optimization. On landscapes, plants influence their surroundings, and distance between plants contributes to the degree of influence that plants have on their neighbors, but the significance of the influence depends on the specific plants, and not strictly on their distance. For example, being next to a tree is a good location for a shade plant, but not for a full-sun plant. Another difference between the two problems is the significance of the individual fitness scores. In the facility layout problem, a "bad" score for any item means the item is not an efficient part of the system. In the landscape design problem, the score represents how well a plant is growing in a given location, and a "bad" score means the plant will not grow.

Calculating the optimal solution to combinatorial problems is computationally prohibitive for anything but the smallest problems. Several metaheuristics, such as local search and tabu search, are often used for finding good solutions to facility layout and location problems. However, agent-based approaches to these problems are not common. In one study, agent-based models were used to locate bus stops in a continuous system [20]. Although the model was not formulated as a combinatorial problem, it is the closest algorithmically to the agent-based optimization engineering for AgentScapes. Other studies have applied genetic algorithms to a version of the facility location problem using known well-known datasets from operations research [21, 1]. Additionally, other agent-based models exist where facilities are located based on activity level, and the results are qualitatively compared to real-world examples [2]. There are also models of situated multi-agent systems, where the spatial relationship between agents is an explicit part of their interactions [10, 3].

In plant ecology, agent-based models, also known as individual based models (IBM) [17], have been used extensively to simulate local competition for resources such as sunlight and rainfall, and other plant-plant interations [13, 9]. In many of these models, the degree of interaction is a function of the distance between plants and all interactions are presumed to be negative, representing competition for resources. Several methods have been used to calculate the expected interaction based on a radius around the plant [23, 22, 31, 32, 6, 5]. Other IBM models are grid based [25]. Another approach to modeling spatial interactions that includes distance as well as resource use is ecological field theory (EFT). In EFT models, each plant's influence on light, water, and nutrients is used to calculate an interference potential around the plant [34, 30, 27], which determines seedling establishment and growth of larger plants based on the resources available on the landscape.

The method for modeling plant interactions in AgentScapes combines the ideas in these IBMs. Plant agents are placed on a grid, one plant per cell, and interact with their surrounding cells by modifying the light and water available in those cells. In IBMs, an individual's impact on its surroundings is not modelled explicitly, which makes simulating an environment where two species have a symbiotic relationship, i.e. one generates shade and one grows best in the shade, difficult. However, these are the types of interactions that need to be modeled in AgentScapes. This is accomplished by explicitly representing the resources available in each cell–an approach that is simpler and more natural than the currently available IBMs. Using this approach, the growth rates of a heterogenous set of individuals emerges directly from the resources provided to the individual at its location.

3. PLANT GROWTH MODEL

The growth model in AgentScapes is based on empirical data from real plants and the basic equation for photosynthesis, $6H_2O + light + 6CO_2 \rightarrow C_6H_{12} + 6O_2$, where water and carbon dioxide combine in the presence of light energy to form sugars and oxygen. For AgentScapes, only light and water requirements will be considered, as these are the variable factors on residential landscapes that impact how well a plant grows in a certain location. Nutrients also impact plant growth, but nutrient levels can be modified such that they are not a limiting factor in plant growth. Therefore, they are not being considered here. Light varies due to trees that generate shade, and water varies from uneven irrigation. The light requirements are categorized discretely as shade, partial sun, and full sun, and the water requirements as low, moderate, and water regularly. The growth in different light levels can be described using a growth curve based on field research [14]. The light and water requirements for plant agents in Agent-Scapes are designed to emulate the above-mentioned discrete categories for light and water. Plant agents are divided into three light requirement categories — low, medium, and high — and two water requirement categories, low and high. Each agent includes a set of equations that operationalize how it grows given the light and water available on the landscape in its current location. These equations are used to calculate a plant agent's fitness score in these light and water conditions, based on the agent's light and water requirements. The fitness score is based on the equation for photosynthesis; Figure 1 shows the CO_2 assimilation rates, representing the net photosynthesis or growth, for the low, medium, and high light plant agents under different light conditions.

The x-axis on this graph shows the light level (photon flux density) in mmol $m^{-2}s^{-1}$, ranging from 0 (darkness), to 400 (shade), to 2000 (full afternoon sun on a summer day). At each of these light levels, the value on the y-axis shows the CO_2 assimilation in mmol $m^{-2}s^{-1}$ of leaf surface that can be expected for a plant agent with that light requirement at that light level. The CO_2 assimilation increases as the light level increases. Each curve also has a point where the CO_2 assimilation levels off, known as the light saturation point [8]. At this point, additional light does not increase photosynthesis, and actually results in a decrease in net photosynthesis due to other processes necessary for plant survival. The curves in Figure 1 show that full sun plants have a light saturation point that is about three times higher than the light saturation point of shade plants. The curves also show that full sun plants will still grow in shady conditions, however, not as much as they grow in full sun, while shade plants placed in full sun conditions will die.

The other factor affecting plant growth is water. The

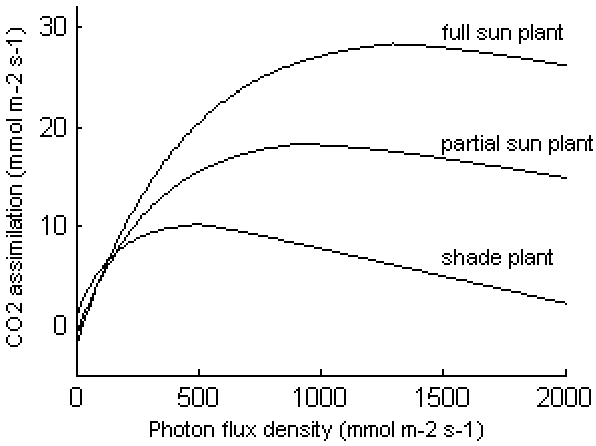

Figure 1: Growth curves for shade, partial sun, and full sun plant agents showing agent growth under different light levels.

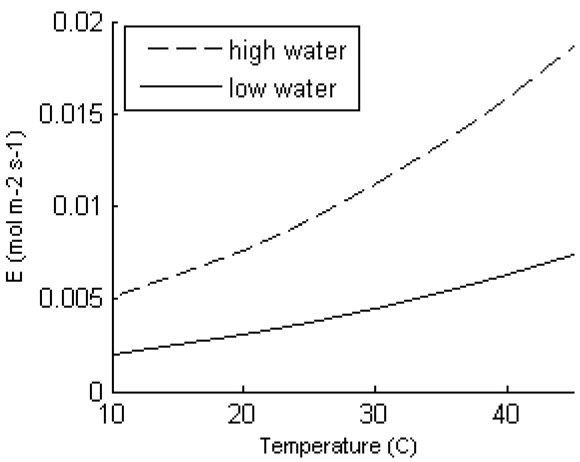

Figure 2: Transpiration curves for low and high water plant agents showing the transpiration rates at different temperatures.

amount of water that a real plant requires is based on the plant's transpiration rate, which varies with temperature, as plants transpire more on a hot day to stay cool [12]. This same approach is applied to plant agents, which use more water in warmer conditions. Plant agents in AgentScapes have low or high water requirements based on actual low and high water plants in the literature [12], as shown in Figure 2.

4. PLANT-LANDSCAPE INTERACTION

The landscape is represented in AgentScapes using a discrete grid, where each cell in the grid is one square foot. This size is the average amount of space needed by summer annuals, the smallest plants considered here. Only one plant can occupy any one cell. Each landscape cell has three parameters: morning light, afternoon light, and water, representing the amount of that resource present in the cell at a given time. The light is divided into morning and afternoon light to simulate the different growing conditions that can exist in a cell at different times of the day.

Plants interact with the landscape by removing water from their own and surrounding cells and by generating shade. In AgentScapes, there is a one-to-one relationship between the size of the plant and the amount of water the plant can access. Plant agents larger than one foot can access water in surrounding cells proportional to their size over one foot. Plant agents one foot or smaller can only use water from their own cell. Water is withdrawn evenly from all cells that an agent can access. Plant agents also shade surrounding cells, again in proportion to the agent's size. Each foot of height over one foot shades one cell in the horizontal direction. The shading is directional, affecting morning and afternoon light in neighboring cells accordingly. For each two feet of height over one foot, the plant also shades one cell in the vertical direction for morning and afternoon light. This shading profile does not entirely reflect real world shading, as cells south of the plant should never be shaded (in the northern hemisphere), but this will be addressed in future work. Seasonal changes in the angle of the sun are also not considered. A primary concern in this work is reducing water use and real plants are most heavily irrigated in the summer. Therefore, only the mid-summer sun angle is implemented. If a cell is shaded, the light in that cell is reduced by 30 percent. If two plants shade the same cell, the 30 percent reduction is applied twice, once to the original value, and then again to the reduced value. The amount of shade generated, the number of cells impacted by shading, and the number of cells from which plant agents can access water are all tunable parameters in the model.

The plant growth model and the landscape conditions are used to simulate a how a plant responds to its environment in the morning and afternoon. There is a difference between the growing conditions provided by morning sun and afternoon sun [33]. That difference is reproduced in AgentScapes by calculating the CO_2 assimilation in the morning and the afternoon, CO_2AM and CO_2PM respectively, using the light saturation curves shown in Figure 1. The CO_2AM and CO_2PM values are then adjusted as a function of the amount of water available on the landscape, which reflects what happens in real plants when the CO_2 assimilation is limited due to insufficient water available to the plant [8]. In real plants, as the water in the soil drops below a certain value, a plant's ability to extract the water drops exponentially, until the plant cannot extract any of the remaining water [8]. Water is necessary for transpiration, and plants that do not have enough water for transpiration will also limit their photosynthesis (CO_2 assimilation). The amount of water available to a plant agent is based on the amount of water on the landscape that the agent can extract. The agent's transpiration rate based on the water available in the morning, $tRate_{AM}$, is used to adjust the CO_2AM such that

$$CO_2AM = CO_2AM * tRate_{AM} \quad (1)$$

The $tRate_{AM}$ is also used to calculate the amount of water to remove from the landscape, simulating its use by the plant agent. The amount of water that an agent transpires in five hours is based on the transpiration curves for plants with different water requirements in Figure 2 and $tRate_{AM}$

$$trans_{AM} = E * (5 * 3600 * h) * tRate_{AM} \quad (2)$$

where h is the size of the plant, and E is water transpired in mol $m^{-2}s^{-1}$. The transpired water is then removed from the landscape, simulating its use by the plant agent, before calculating the afternoon transpiration rate, water use, and CO_2 assimilation

$$trans_{PM} = E * (5 * 3600 * h) * tRate_{PM} \tag{3}$$

$$CO_2PM = CO_2PM * tRate_{PM}. \tag{4}$$

4.1 Calculating agent fitness

The AgentScapes optimization process uses a fitness function to calculate a plant agent's growth and water use in its current location. Under ideal conditions, a plant agent has a maximum amount of CO_2 that it can assimilate, $maxCO_2$, based on its light requirements and Figure 1. This amount is the summation of the CO_2 assimilation at the agent's light saturation point in the morning and the afternoon. The values for CO_2AM and CO_2PM and the plant agent's $maxCO_2$ are used to calculate a plant agent's growth as a percentage of its maximum growth

$$growth = \frac{CO_2AM + CO_2PM}{maxCO_2 * 2} \tag{5}$$

A plant agent's water use is related to air temperature and the agent's size–the same factors that drive water use in real plants. AgentScapes represents temperature by correlating darkness with an average summer low temperature an average summer high temperature with full sun. Using this approach, as light increases, so does temperature, resulting in an agent using more water. However, beyond the light saturation point, there is no additional growth benefit for the additional water use. The agent is transpiring at a higher rate simply to stay cool. This is an undesirable condition for plant agents. A penalty term is added to the growth score to penalize water use beyond the light saturation point

$$penalty = \alpha * (maxH - h) * (\frac{mL + aL - 2 * lS}{2 * lS}) \tag{6}$$

where mL is morning light, aL is afternoon light, α and $maxH$ are parameters of the model, h is the size of the plant, and lS is the plant-specific light saturation point. The penalty term is applied as a summation of the degree above the light saturation point in the morning and afternoon, and is only applied when the lighting conditions are above this point. When the plant agent is in light conditions at its light saturation point, the penalty is zero. The penalty is also minimized for agents above a certain size, as these agents generate shade on the landscape and have access to deeper sources of groundwater and require less irrigation. The $maxH$ parameter is used to adjust the penalty term's size dependency. The final fitness score includes the growth and penalty terms

$$fitness = growth - penalty \tag{7}$$

The growth score has a maximum value of one, and the penalty term can only reduce the final fitness score.

5. AGENT-BASED SEARCH ALGORITHM

AgentScapes uses a distributed, agent-based search algorithm to find the best location on the landscape for each plant agent as determined by the fitness function. Each agent reacts to its conditions through local search techniques and random jumps. There is no communication between the agents. The search algorithm proceeds as shown in Algorithm 1. First, the initial morning and afternoon light

Algorithm 1 Agent-based search algorithm

```
repeat
  for all agents do
    Calculate fitness score for plant agent.
    if score > threshold then
      Leave the plant alone
    else
      if plantMoves < movesAllowed then
        Search locally for better plant location
        if local search successful then
          Plant moves to new location.
        else
          Random unoccupied location selected for the
          plant.
        end if
        increment plantMoves
      end if
    end if
  end for
until scores > threshold for all plants or no more moves
allowed
If a solution is found for all plants above the threshold,
increase threshold to plant agent's fitness score and repeat
the algorithm.
```

and water on the landscape are set for each cell based on the shade that plant agents generate. A fitness score is calculated for each agent at its current location, which shows how well a plant agent will grow in that location over a predetermined number of days. Each day, water is removed from the landscape based the plant agent's water requirements and the light/temperature conditions on the landscape. In certain locations, plant agents will run out of water before the end of the growth period due to environmental conditions, competition with nearby plants, or their own water requirement type. These agents are candidates to search for a better location on the landscape to improve their fitness score.

A threshold value for the fitness score establishes acceptable conditions for growth. Plant agents with an average daily fitness score above that threshold at the end of the growth period can grow in their current location, while plants below the threshold need to search for a new location. Plant agents first search locally in a pre-determined range. If a better spot is found, the plant agent's location is reset to this better location. If that better cell is already occupied by another agent, the two agents "compete" for the location by placing each plant in turn in that location and calculating the fitness score for the agent. The agent with the highest fitness score at that location gets the spot, and the other agent gets a new, random unoccupied location. If the plant agent does not find a better location during the local search, the plant agent is assigned to a new random location. After all agents have been processed, the search restarts with the new set of locations. All parameters for the landscape are recalculated, and the growth period starts over. There is a restriction on the number of new locations that an agent can try. This guarantees that an agent will not search forever for growing conditions that do not exist on the landscape. The search algorithm stops when all plant agents on the landscape have a fitness function above the threshold or no additional searching is permitted.

The threshold value is a system parameter, and there are implications for setting the value high or low. Setting the value too low means the plant agents may stop searching too soon for suitable locations. If the value is set too high, the system may never converge to a solution. To solve this problem, a dynamic threshold is introduced. In this approach, the threshold is initially set low for all agents, then increased to the agent's fitness score for each agent when the search finds a solution above the threshold. This process is repeated until one or more agents does not have a score above its threshold. The search returns the last successful configuration where all agents were at or above their threshold.

6. EXPERIMENTS

Experiments were designed to explore AgentScapes' ability to find good solutions to the optimization problem. Several landscapes sizes were used—6x10, 5x9, 4x8, 4x7, 3x6, and 3x5. The landscape sizes were the number of cells that make up the landscape grid. Each cell represented 1 sq. ft., and had a parameter for morning and afternoon light and water. The light values on the landscapes ranged from morning shade (200 mmol $m^{-2}s^{-1}$) to full afternoon sun (2000 mmol $m^{-2}s^{-1}$). The water on the landscapes was initialized to represent recently irrigated soils in many areas in the U.S. Southwest. Plant agents grew for five days. The five-day growth period without water is too long to support high-water plant agents in full-sun conditions, which limits the locations on the landscape where these agents can grow.

Each experiment for a landscape size included 100 simulations, where a simulation used a different, randomly generated collection of five plant agents. Each plant agent had randomly generated light and water requirements selected from the light and water categories in Figure 1 and Figure 2, and a size between one inch and six feet, also randomly generated. The same plant collections were used for all landscape sizes. For example, experiment one on the 6x10 landscape used the same five plants as experiment one on the 3x5 landscape. Each simulation included 20 trials, where the initial location of each plant agent was the only change in each trial, with all other parameters held constant. In each trial, the initial locations were generated randomly and Algorithm 1 was applied using these starting locations. Plant agents were each allowed 10 moves. Agents could search two cells in all directions to identify better growing conditions, before making a random jump. The highest score for all trials in a simulation was returned as the score for that simulation. The solution for the simulation represented the best locations for the five plant agents in that simulation.

The optimal solutions for each simulation were calculated using an exhaustive search of the state space. Random search and greedy search algorithms were also applied for each simulation. In the random search, random locations were selected for each plant agent and the fitness score was calculated for the simulation using those locations. There were 100 random trials, where a trial was defined by a set of random locations. The highest score out of the 100 trials was returned as the score for that simulation. In greedy search, plant agents were placed one at a time on the landscape at the location that produced the highest fitness score for that agent. Once all plant agents were on the landscape, the fitness score for the arrangement was re-calculated.

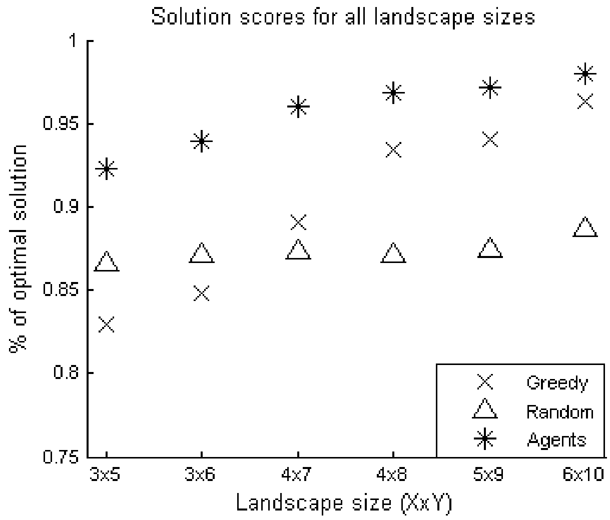

Figure 3: Fitness scores for agent, random, and greedy search algorithms. Scores reported as a percentage of the optimal scores.

7. RESULTS

AgentScapes produced solutions with fitness scores close to the optimal fitness scores and outperformed the solutions produced through random and greedy search. Figure 3 shows the results for all search algorithms for all landscape sizes. The x-axis is the size of the landscape and the y-axis represents the % of optimal for all 100 simulations. The agent search performed the best on the 6x10 landscape with scores around 97 percent of optimal. On this landscape, greedy search produced solutions close to the agent solutions. On the smaller landscapes, 3x5 and 3x6, agent search still performed well at 92 percent of optimal, while greedy search was about 10 percent worse. The difference in the agent and greedy algorithms on the smaller landscapes is likely due to more interaction between the plants. A plant placed on the landscape after other plants during greedy search is more likely to lower the scores of the existing plants with this smaller landscape due to competition for light and water resources. On the 6x10 landscape, five plants represented only eight percent of the landscape space. The same five plants was 33 percent on the 3x5 landscape. Random results were consistent across all landscapes at around 86 percent.

8. CONCLUSION

This paper presents the initial work for AgentScapes, an application that uses agent-based modeling to design water efficient residential landscapes. Future work for this project will involve further analysis of the search algorithm and how different plant arrangements impact the emergent conditions on the landscape. For example, a full sun plant placed in afternoon sun of 2000 mmol $m^{-2}s^{-1}$ will reduce the light in surrounding cells by a higher percentage than the same plant in afternoon sun of 1000 mmol $m^{-2}s^{-1}$. In these two scenarios, the plant agent's location not only generates different growing conditions for other plants, but also has a different impact on the mean light level on the landscape. The emergent behavior will be explored through modifications in the existing fitness function, as well as additional rules for the plant agents.

9. REFERENCES

[1] O. Alp and E. Erkut. An efficient genetic algorithm for the p-median problem. *Annals of Operations Research*, 122:21–42, 2003.

[2] T. Arentz and H. Timmermans. A multi-agent activity-based model of facility location choice and use. *disP*, 170(3):33–44, 2007.

[3] S. Bandini, S. Manzoni, and C. Simone. Dealing with space in multi-agent systems: A model for situated MAS. *Proceedings of AAMAS02*, 2002.

[4] T. Barnett and D. Pierce. When will Lake Mead go dry? *Water Resources Research*, 44:W03201, doi:10.1029/2007WR006704, 2008.

[5] S. Bauer, U. Berger, H. Hildenbrandt, and V. Grimm. Cyclic dynamics in simulated plant populations. *Proceedings of the Royal Society of London B*, 269:2443–2450, 2002.

[6] U. Berger and H. Hildenbrandt. A new approach to spatially explicit modelling of forest dynamics: spacing, aging and neighborhood competition of mangrove trees. *Ecological Modelling*, 132:287–302, 2000.

[7] A. Bernatzky. The contribution of trees and green spaces to a town climate. *Energy Build.*, 5:1–10, 1982.

[8] M. Crawley, editor. *Plant Ecology*. Blackwell Scientific Publications, Oxford, 1997.

[9] D. DeAngelis and L. Gross, editors. *Individual-based models and approaches in ecology: populations, communities, and ecosystems*. Chapman and Hall, New York, 1992.

[10] J. Ferber and J. Muller. Influences and reaction: A model of situated multiagent systems. *Proceedings of ICMAS96*, 1996.

[11] R. Francis and J. White. *Facility Layout and Location: An Analytical Approach*. Prentice-Hall, Englewood Cliffs, New Jersey, 1974.

[12] P. V. Gardingen and J. Grace. Plants and wind. *Advances in Botanical Research*, 18:192–254, 1991.

[13] V. Grimm and S. Railsback. *Individual-based modeling and ecology*. Princeton University Press, Princeton, New Jersey, 2005.

[14] G. Harvey. Photosynthetic performance of isolated leaf cells from sun and shade plants. *Carnegie Inst. Washington Yearbook*, 79:161–164, 1979.

[15] R. S. Hilaire, M. Arnold, D. Wilkerson, D. Devitt, B. Hurd, B. Lesikar, V. Lohr, C. Martin, G. Mcdonald, R. Morris, D. Pittenger, D. Shaw, and D. Zoldoske. Efficient water use in residential urban landscapes. *HortScience*, 43(7):2081–2092, 2008.

[16] R. Hunt. *Plant growth curves–The functional approach to plant growth analysis*. University Park Press, Baltimore, Maryland, 1982.

[17] M. Huston, D. DeAngelis, and W. Post. New computer models unify ecological theory. *BioScience*, 38(10):682–691, 1988.

[18] J. Knopf. *The Xeriscape flower gardener: A waterwise guide for the Rocky Mountain region*. Johnson Book, Boulder, Colorado, 1991.

[19] C. Martin and L. Stabler. Plant gas exchange and water status in urban desert landscapes. *Journal of Arid Environments*, 51:235–254, 2002.

[20] S. Moujahed, O. Simonin, and A. Koukam. Location problems optimization by a self-organizing multiagent approach. *Multiagent and Grid Systems*, 5(1):59–74, 2009.

[21] S. Otto and G. Kokai. Decentralized evolutionary optimization approach to the p-median problem. *LNCS*, 4974:659–668, 2008.

[22] S. Pacala and J. Silander. Neighborhood models of plant population dynamics. I. single species models of annuals. *American Naturalist*, 125:385–411, 1985.

[23] H. Pretzsch, P. Biber, and J. Dursky. The single tree-based stand simulator SILVA: construction, application, and evaluation. *Forest Ecology and Management*, 162:3–21, 2002.

[24] P. Prusinkiewicz. Modeling plant growth and development. *Current Opinion in Plant Biology*, 7:79–83, 2004.

[25] C. Rademacher, C. Neuert, V. G. C. Wissel, and V. Grimm. Reconstructing spatiotemporal dynamics of central european beech forests: The rule-based model BEFORE. *Forest Ecology and Management*, 194:349–368, 2004.

[26] J. Reynolds and B. Acock. Predicting the response of plants to increasing carbon dioxide: a critique of plant growth models. *Ecological Modelling*, 29:107–129, 1985.

[27] P. Sharpe, J. Walker, L. Penridge, H.-I. Wu, and E. Rykiel. Spatial considerations in physiological models of tree growth. *Tree Physiology*, 2:403–421, 1986.

[28] L. Shashua-Bar, D. Pearlmutter, and E. Erell. The cooling efficiency of urban landscape strategies in a hot dry climate. *Landscape and Urban Planning*, 92:179–186, 2009.

[29] L. Stabler and C. Martin. Irrigation regimens differentially affect growth and water use efficiency of two southwest landscape plants. *J. Environ. Hort.*, 18(2):66–70, 2000.

[30] J. Walker, P. Sharpe, L. Penridge, and H.-I. Wu. Ecological field theory: the concept and field tests. *Vegetatio*, 83:81–95, 1989.

[31] J. Weiner. A neighborhood model of annual-plant interference. *Ecology*, 63(5):1237–1241, 1982.

[32] J. Weiner, P. Stoll, H. Muller-Landau, and A. Jasentuliyana. The effects of density, spatial pattern, and competitive symmetry on size variation in simulated plant populations. *The American Naturalist*, 158(4):438–450, 2001.

[33] D. Whiting, M. Roll, and L. Vickerman. *Plant growth factors: Light – Garden Notes 142*. Colorado State University Cooperative Extension, 2007.

[34] H.-I. Wu, P. Sharpe, J. Walker, and L. Penridge. Ecological field theory: a spatial analysis of resource interference among plants. *Ecological Modelling*, 29:215–243, 1985.