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Remote control of greenhouse cucumber production with artificial intelligence – results from the first international autonomous challenge

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Abstract

There is a need for remote greenhouse management. As farms become larger, the crop manager has difficulties monitoring all details of the various compartments. Also, finding skilled staff becomes more difficult and distant management of a crop production system requires new sensing technologies. At Wageningen UR Greenhouse Horticulture a competition on 'autonomous greenhouses' has been organized, in which Artificial Intelligence (largely) replaced human skills in greenhouse operation. The purpose was to test in this proof-of-principle the functionality of the approach, while improving production, product quality and resource use efficiency. Five multi-disciplinary international teams participated. A reference compartment was operated by growers. Each team had available a 96 m^2 greenhouse compartment to grow remotely a cucumber crop ('Hi-Power') from August to December 2018. Visiting the compartment was not permitted so all decisions were based on sensor output and observations on crop development and harvest. Compartments were equipped with standard actuators for climate control and fertigation, and some teams installed additional sensors. Teams decided on plant and stem density in advance. They remotely determined the continuously varying control setpoints, using AI algorithms, and provided instructions for leaf and fruit pruning on a weekly basis. Pest and disease management was WUR's responsibility and was no part of the challenge. All AI-algorithms classified light and CO_2 as the most determinant production factors. The winning team, which had invested most in light, scored best on production at the cost of some resource use efficiencies. The winning AI-algorithm also out-performed the reference. Total fresh yield was closely associated with total number of fruits m^{-2}, which is an aggregate of stem density and fruit pruning strategy.

Keywords: artificial intelligence, remote greenhouse management, crop growth and development, cucumber

INTRODUCTION

Greenhouse production systems are well-suited to produce fresh fruits and vegetables, achieving high production levels and resource use efficiencies (e.g., light, nutrients, water). Although the area of greenhouse production is increasing world-wide (Rabobank, 2019), the greenhouse industry encounters difficulties finding enough skilled crop production managers (Brain, 2018). And as farm size increases, monitoring all details of several greenhouse compartments becomes more demanding. A modern high-tech greenhouse is equipped with active control of actuators (e.g., heating, lighting, irrigation) to create a favorable growing climate. A grower determines the climate, irrigation and crop management strategies and defines the setpoints for all climate and irrigation parameters. Actuators are operated based on the setpoints, and sensors give feedback on measured data for the control loop. Process computers control actuators based on the setpoints.

To increase automated control, various dynamic greenhouse climate and crop models have been developed (e.g., López-Cruz et al., 2018) and have been used to automatically

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determine setpoints and advice, or take over decision making by the grower. If models are connected to sensors and actuators, the models can be controlled by automated algorithms (e.g., Elings et al., 2004). Another way to partially take over grower's decision making is to use machine learning algorithms for greenhouse climate control (Martin-Clouaire et al., 1993). However, to our knowledge machine learning has not been used autonomously during a longer period in greenhouse management resulting in yield levels comparable to commercial practice.

To combine the use of modern artificial intelligence (AI) algorithms and greenhouse climate, irrigation, and crop growth control, an international challenge on "autonomous greenhouses" was conducted in 2018 at the research greenhouses of Wageningen University and Research Greenhouse Horticulture in cooperation with five multi-disciplinary international teams. The experiment was set-up with the goal of benchmarking the use of state-of-the-art AI algorithms for cucumber production. Existing commercial greenhouse equipment (actuators), standard sensors for measurement and control, and a standard commercial process computer were combined with the latest AI technology in order to maximize net profit and minimize resource use, while controlling greenhouse crop growing remotely. Cucumber was chosen as demonstration crop, as the effects of changes in settings can be observed in 1 to 2 weeks from harvested fruits. The goal of this paper is to describe the different crop management approaches taken by the teams, the results concerning production and light use efficiency and explain production differences on the basis of underlying physiological processes.

MATERIALS AND METHODS

Experimental set-up

The experiments were conducted in six identical greenhouse compartments that were equipped with standard actuators, also available in commercial high-tech greenhouses: two pipe heating systems, continuous roof ventilation, anti-thrips netting, inside moveable screens, high-pressure-sodium artificial lighting system, a fogging system, and CO_2 supply. Plants were grown in rockwool substrate cubes and placed on rockwool substrate slabs; the plant-substrate system was then located on hanging gutters. Irrigation water and nutrients were supplied with drippers operated by a valve.

Five teams (Sonoma, iGrow, deep_greens, The Croperators, AiCU) could remotely control the actuators based on their own AI algorithm. A sixth greenhouse compartment was controlled by Dutch growers and served as a reference. Team deep_greens is excluded in the analysis in this paper, as there were technical and irrigation problems for some time.

Setpoints were sent via a digital interface (LetsGrow.com) to a central climate process computer (IISI, Hoogendoorn, The Netherlands), which then operated the actuators. The composition, EC, and pH of the nutrient solutions were determined by the teams. Standard sensors continuously measured data on outside and inside environment, heating power used, on-off lamp status, CO_2 dosage, screen position, irrigation supply, and amount, EC and pH of the drain. Inside PAR sum, heating energy used, electricity used, CO_2 dosage, and water consumption were calculated. Measured and calculated data were provided to the teams via a digital interface. Both control setpoints and data were exchanged at a 5-min-interval. Some teams placed additional sensors at the start of the experiment.

Cucumbers seedlings 'Hi-Power' (Nunhems/Bayer) were sown on 20 July 2018, in rockwool cubes and were transplanted to the greenhouse compartments on 14 August 2018. The crop was grown in a high-wire growing system. Plant and stem densities had to be chosen by the teams before the start, resulting in values between 2.6 and 3.6 stems m^{-2} (Table 1). First harvest was on 6 September 2018, and the last harvest was scheduled for all teams on 7 December 2018. Based on this last harvest date, the date of topping (removal of head of the crop) had to be chosen by the teams and differed from 19 to 26 November 2018. Crop protection was the responsibility of WUR and was not part of the challenge.

Teams weekly sent instruction for fruit and leaf pruning in the top of the canopy to the greenhouse workers. Fruit pruning strategies ranged from a stable procedure of 50% fruit removal for the whole cropping period to a more variable strategy. With respect to leaf pruning, the majority of the teams decided not to prune or to prune a small fraction of leaves (33%). One team used a deviating strategy of removing 50% of the leaves throughout the whole cropping (Table 1). As a standard procedure applied to all crops, greenhouse workers removed leaves below last harvested fruits, unless instructed differently.

Table 1. A number of experimental details.

Team	Plant density (# m^{-2})	Stem density (# m^{-1})	Date of topping	Fruits retained (fraction)	Leaves retained (fraction)
IGrow	2.6	2.6	20/11	0.5-0.67	0.5-1
Reference	2.5	2.5	9/11	0.5	1
AiCU	1.8	3.6	26/11	0.5-0.67	0.67-1
Sonoma	1.65	3.3	20/11	0.5	1
Croperators	1.6	3.2	19/11	0.33-0.67	0.67-1

Three harvest quality categories were distinguished (A: >375 g and no defects, B: 300-374 g or defects e.g., shape, color, others, C: <300 g per fruit). Harvest data such as fruit number and weight (# m^{-2} and kg m^{-2} per quality category A-C) were measured manually by the workers. Crop related parameters such as stem elongation (cm per week), fruit growth period (d per fruit), leaf formation rate (# per stem per week), and cumulative number of leaves (# per stem) were also measured. Instructions by teams and data measured by workers were exchanged via the digital interface.

Each team developed their own AI algorithms, which varied between supervised, unsupervised, and reinforcement machine learning. In order to use AI techniques, training data are essential. Since training data with a wide variation for the described application are scarce, an artificial training data set was created using the broadly validated dynamic greenhouse climate model KASPRO (De Zwart, 1996) and the cucumber crop model INTKAM (Marcelis, 1994; Marcelis et al., 2009) that was modified for a high-wire cucumber crop. The artificial data set was provided to the teams before the start of the experiment.

The AI-based operation of the different greenhouse compartments by different teams resulted in different cropping, climate, and irrigation strategies, and different yields and resource use efficiencies. In order to properly analyze and compare the different approaches, the above-mentioned combination of greenhouse climate and cucumber simulation models, was used. The combined model assumes adequate supply of water and nutrients and does not simulate the presence and effects of pests and diseases. The KASPRO model computes the greenhouse climate as a function of outside weather conditions and greenhouse climate control settings. The model processes these settings by a control algorithm comparable to the ones used. The model takes full account of the limitations of real greenhouses, which means, for instance, that a CO_2 dosing setpoint of 800 ppm is simply not met in sunny periods when the vents are wide open. The computed greenhouse climate is then fed to INTKAM, which computes the daily gross photosynthesis from the sum of hourly photosynthesis-rates. The hourly values are the result of light-intensity, temperature, CO_2-concentration, and relative air humidity in combination with the dynamically-simulated crop architecture (in particular leaf area index). After subtracting maintenance costs, the daily amount of assimilates is partitioned over the growing organs (roots, stem, leaves, and fruits) on the basis of their relative potential growth rates. Next, dry matter fraction and fresh organ weights are computed, and finally the harvest moment of individual fruits is determined on the basis of, among others, fruit weight.

Physiological analysis

The of different control strategies in the final production could be determined with these models. First, the combined model was used to calculate yield of each of the compartments, while using the actually applied crop density, fruit and leaf pruning strategy, and the realized lighting and climate (temperature and CO_2) setpoints in that compartment as model inputs. The calculated fresh yield was compared with the realized yield in the same greenhouse compartment to validate the models. Then, for each greenhouse compartment, model calculations were carried out applying the cropping strategy of other teams to predict the changes in yield while maintaining the original lighting and climate strategy. In another step, original cropping and CO_2 strategies were applied in combination with the lighting strategy of the other teams, and original cropping and lighting strategies were applied in combination with the CO_2 strategy of the other teams. Interactions of cropping, lighting, and climate strategies were not calculated. The simulations of the swapping strategies represent the yield retrieved prior to topping, to eliminate the effect of early topping dates selected by some of the teams. Further details are given in Hemming et al. (2019).

RESULTS

The combined KASPRO-INTKAM simulation model adequately simulated crop growth and development, when stem density and fruit and leaf removal were made model input (Table 2). We focus on presentation of simulated results to ensure a fair analysis.

Table 2. Simulated values of seasonal gross assimilation, maintenance respiration, crop growth, dry matter partitioning to the fruits, and dry and fresh fruit weight (the latter also for realized values).

Team	Gross ass. (g CO_2 m^{-2})	Maint. resp. (g CH_2O m^{-2})	Crop growth (g m^{-2})	Dry matter part. (-)	Dry fruit weight (kg m^{-2})	Fresh fruit weight (kg m^{-2})	Fresh fruit weight (kg m^{-2})
	Simulated						Realized
IGrow	4378	521	1880	0.554	1.140	36.0	34.3
Reference	4376	515	1868	0.550	1.120	34.5	34.6
AiCU	4086	446	1800	0.533	0.995	32.0	29.5
Sonoma	5003	598	2162	0.557	1.286	41.1	38.7
Croperators	4785	524	2101	0.537	1.233	37.9	35.4

Team Sonoma achieved highest seasonal gross assimilation with 5003 g m^{-2}, followed by team Croperators and IGrow, while the Reference growers obtained a seasonal gross assimilation of 4376 g m^{-2} (Table 2). Team AiCU obtained lowest seasonal gross assimilation of 4086 g m^{-2}. Differences in temperature and organ weights caused differences in maintenance rate, with team Sonoma also here being the highest and team AiCU being the lowest with 598 and 446 g CH_2O, respectively, during the cultivation season. The combined effects of gross assimilation and maintenance respiration results in net CH_2O production, which, after correction for growth respiration leads to total crop growth rate. This showed again a similar ranking as for gross assimilation. There were some small differences in dry matter partitioning to the fruits, which had an overall average value of 54.6% (this is on the basis of total weight, including root weight). The overall effect was that team Sonoma achieved highest fresh production with 41.1 kg m^{-2}, followed by teams Croperators and IGrow, while Reference growers obtained a fresh production of 34.5 kg m^{-2}. Team AiCU obtained lowest fresh production of 32.0 kg m^{-2}.

Marcelis (1994) related development rate to air temperature and radiation, however, in a recent research on the same cultivar 'Hi-Power', Elings and Janse (2020) related development rate to air temperature alone. A higher air temperature leads to a higher development rate and more nodes per stem. Node number varied between 99 and 106 per stem (Table 3). In combination with number of stems per plant and number of plants m^{-2}, this resulted in 260 to 356 nodes m^{-2} on a seasonal basis. Each team had its own fruit removal strategy, and each crop suffered from some abortion, indicating that the carrying capacity of the crop was not enough to bring all fruits to maturity. In other words: more fruit removal should have been applied given the growing conditions. As a result, the number of harvested fruits of team Sonoma was highest with 97 fruits m^{-2} during the season. The number of fruits m^{-2} is closely related to the cumulative harvest, as fruits were harvested at approximately the same weight. This decision was taken by the greenhouse staff, and the teams had no say in this. The relation between the number of fruits maintained and the number of aborted fruits is given in Figure 1. In general, the more fruits are maintained, the more fruits abort, unless the right amounts of light and CO_2 are given. This are wasted resources that go at the cost of final production.

Table 3. Simulated values of some crop characters that describe fruit dynamics.

Team	Average air temperature (°C)	Nodes (# m^{-2})	Nodes (# stem^{-1})	Aborted fruits (# m^{-2})	Harvested fruit (# m^{-2})	Average fresh fruit weight (g)
IGrow	23.06	106	276	42	85.8	420
Reference	22.63	104	260	15	81.25	424
AiCU	21.61	99	356	54	81	396
Sonoma	22.99	105	347	28	97.35	422
Croperators	22.17	102	326	16	91.2	416

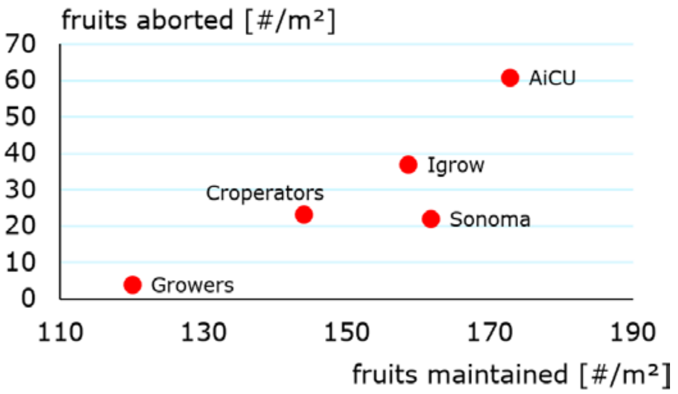

Figure 1. The number of aborted fruits related to the number of maintained fruits. Source: Hemming et al. (2019).

The causes of production differences are summarized in Figure 2. The crop management and CO_2 strategies of team AiCU were most effective The high number of fruits showed less abortion under different conditions, and the CO_2 levels of AiCU were 2nd highest (in spite of what the smoothed data in Figure 8 of Hemming et al. (2019) suggest). The lighting strategy of team Sonoma was most effective., and proved to be the most dominating effect. Application of the crop management strategy of team AiCU to the crops of teams Igrow, Reference growers, Sonoma and Croperators caused a fresh yield increase of 3, 10, 1 and 3%, respectively. The 10% yield increase for Reference growers was largely explained by the higher stem density (3.6 vs. 2.5 stems m^{-2}) and higher number of harvested fruits (90 vs. 81 fruits m^{-2}). For team Igrow, which also had a relatively low stem density (2.6 stems^{-2}), this effect was counterbalanced by the reduced fruit weight (420 vs. 404 g). Application of the CO_2 management strategy of team AiCU to the crops of teams Igrow, Reference growers, Sonoma and Croperators caused a fresh yield increase of 2, 1, 2 and 0%, respectively. The CO_2 effect therefore was much smaller than the effects of crop management and lighting. Although we did not analyze this in-depth, it is obvious that the effects of light dominated the growth and production. Application of the lighting strategy of team Sonoma to the crops of teams Igrow, Reference growers and AiCU resulted in substantial higher productions. Only for team Croperators the simulated production was lower, as their seasonal light sum was higher than that of team Sonoma.

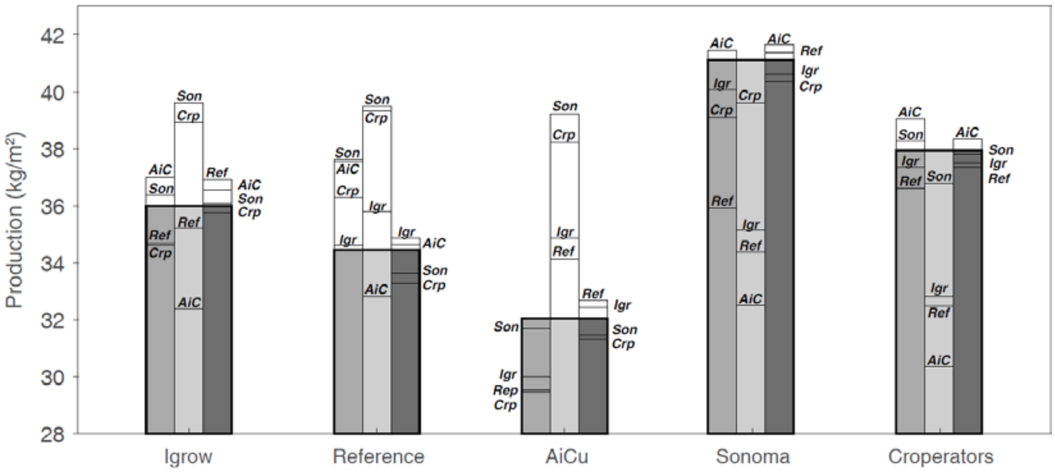

Figure 2. Simulated production per team (greyscale bars), and production using the cropping (1st bar), lighting (2nd bar), or CO_2 (3rd bar) strategy of each of the other teams. Solid lines within the greyscale bars indicate lower production than realized by the team, whereas the top colorless bars represent higher predicted production. E.g., team iGrow realized a yield of approximately 36 kg m^{-2}; with the lighting strategy of Sonoma (but same climate and cropping strategy) it could have realized approximately 40 kg m^{-2}, while with the lighting strategy of AiCU, yield would have been approximately 33 kg m^{-2}. Source: Hemming et al. (2019).

Light use efficiency, defined as the weight of dry or fresh fruit weight produced per quantity of light above the crop, was highest for Sonoma growers, who achieved high yields because of the use of a relatively large amount of assimilation light (Table 4). In contrast, lower use of light resulted in lower yields and lower LUE. This illustrates the fact that in a high-tech environment, resources are most efficiently used if high input levels result in high yields.

Table 4. Simulated and realized values of light use efficiency.

Team	LUE simulated dry harvest (g mol^{-1})	LUE simulated fresh harvest (g mol^{-1})	LUE realized fresh harvest (g mol^{-1})
IGrow	0.703	22.21	21.17
Reference	0.690	21.23	21.32
AiCU	0.640	20.62	18.98
Sonoma	0.715	22.88	21.53
Croperators	0.677	20.83	19.43

DISCUSSION

Crop photosynthesis is determined by the amount of intercepted photosynthetically active radiation, which is the energy source, and the level of air CO_2 concentration, which is the carbon source (Farquhar et al., 1980). Both factors interact (Qian et al., 2012), with minor roles for temperature and air humidity under normal conditions. Teams that maximized light and CO_2, achieved highest production. Under the experimental conditions, the effect of light dominated the effect of CO_2. Teams iGrow, AiCu and Reference growers would have reached higher yields under the supplemental lighting used of teams Sonoma or Croperators, while team Sonoma would have reached only slighter higher yields at higher CO_2 dosages. This does not mean, however, that under other climate and crop management conditions, the situation would have been the same. Other outside weather conditions will for example influence the ventilation regime and consequently air CO_2 concentration.

Analysis of underlying physiological processes (Table 2) shows that the combined effects of light and CO_2 on gross assimilation dominate, and that effects on maintenance respiration, which are dominated by temperature, play a minor role. Dry matter partitioning, which follows from potential fruit growth rate relative to potential crop growth rate, varied only a little and neither influenced the ranking of the teams.

In the Netherlands, cucumber fruits are harvested at approximately 400 g. This implies that maximizing the number of fruits is important to achieve high yields. The mechanisms for this (apart from creating conducive growing conditions) are: variation in plant density and stems plant^{-1}, leaf removal to ensure the optimum leaf area to intercept light (Elings and Janse, 2020), and fruit removal to ensure that just enough fruits develop. Development of too few fruits will obviously result in relatively low yields, while development of too many fruits will result in fruit abortion due to the lack of assimilates to sustain growth of all fruits (Marcelis, 1993) and loss of assimilates that already have been invested in these fruits. Moreover, fruit abortion normally goes along with un-even distribution of fruits over stem height, causing further yield reduction and variation of production over time. In this experiment, none of the teams succeeded in completely avoiding abortion (Table 3). The winning team, Sonoma, combined a relatively high number of fruits maintained with a relatively low number of aborted fruits, resulting in the highest number of harvested fruits. This was combined with the 2nd highest average fruit weight.

Greenhouse production is the result of complex interactions between physical, chemical, and biological processes (van Straten et al., 2000). Crop response to environmental conditions can vary from seconds (e.g., photosynthesis) to weeks (e.g., harvest), which makes optimization of the environmental conditions difficult. Growers base their decisions on their intimate knowledge of crop performance in response to the environment, and if possible on market demands. Optimal control strategies can assist growers in this. Optimal control refers to a control strategy that maximizes a goal function (van Straten et al., 2000). Dynamic modeling can play an important role in determination of the set points and crop management practices. This was demonstrated in the experiment described here, in which 5 teams that did not have physical access to the greenhouse successfully managed cucumber crops, utilizing different AI algorithms.

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Supplementary materials

Data collected in this research is available on https://doi.org/10.4121/uuid:e4987a7b-04dd-4c89-9b18-883aad30ba9a.

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