

Perspective

Real-Time Sensing and Control of Integrative Horticultural Lighting Systems

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Abstract: Optical radiation, including light, plays a crucial role in the structural development of plants through photomorphogenesis and the response to environmental changes. However, plant sensitivity to optical radiation widely varies across species. While research efforts are currently underway to discover the fundamentals of plant physiology, light sources with preprogrammed light settings (light recipes) are offered to clients to expedite plant growth. Since horticultural lighting research is in its infancy, prescribed lighting conditions are not likely to address every plants' needs in terms of the spatial and spectral distribution, intensity, and duration of the light sources. However, it is possible to imagine an intelligent horticultural lighting system that can diagnose plants through sensors, and adjust the light intensity, the spatial and spectral distribution for the specific plant species with active feedback. Such an advanced real-time horticultural lighting system would consist of sensors to detect physiological markers from plants and environmental factors and an artificial intelligence algorithm to adjust the output. While the underlying technology for a real-time optimization system exists, the implementation and training would require further research.

Keywords: solid-state lighting; plant physiology; IoT; big data; machine learning

1. Introduction

The increasing food and energy demand, the need to control CO₂ emission, and the catastrophic effects of climate change are major problems that humankind is facing today. Increasing the efficiency of food production while reducing energy demand requires a multidisciplinary effort encompassing agriculture, engineering, and biological and physical sciences. As part of this multidisciplinary effort, horticultural science focuses on cultivation, plant propagation, plant breeding, crop production, and plant physiology. Horticultural studies concentrate on fruits, vegetables, nuts, and ornamental plants [1], in contrast to agriculture, which contains large-scale crop production and animal husbandry. Plant growth and development depend on a wide range of environmental factors, including temperature, water, humidity, soil, nutrients, and optical radiation (historically and most prominently daylight).

Plants process energy from optical radiation through a biochemical process called photosynthesis. Plants use the converted chemical energy for growth and development. However, the conversion efficiency of natural photosynthesis (i.e., solar energy to biomass) in green plants is surprisingly low, between 4.6% and 6% [2]. This process can be increased by optimizing the lighting to meet the sensitivity curve of photosensitive pigments in plants [3].

The increasing amount of research on the gene and plant level encouraged manufacturers to promote lighting products and specific lighting conditions (also known as light recipes) to deliver positive results. However, the success of generic lighting conditions or products is limited due to the differences in the spectral response of photosensitive receptors such as cryptochromes, phytochromes, phototropin, and zeitlupe [4]. Since the whole plant presents a complex structure in terms of its functions (photosynthesis, photomorphogenesis, and photoperiodism), the generalizability of individual studies

is quite limited. Studies that report nominal “color” categories (e.g., blue, red, far-red) instead of providing the spectral power distribution (SPD) of the light sources prevent the reproducibility of these studies. In addition, there are countless species that have not been studied yet, and certain crops (e.g., lettuce, cannabis) have been studied more often than others, which leads to an unequal distribution of research findings.

While daylight has been the main source of light for millions of years, the generation of light through semiconductor devices (solid-state lighting (SSL)) provides an alternative to daylight and older electric light sources, such as high-pressure sodium (HPS) lamps. SSL devices offer several advantages over traditional electric light sources, such as spectral control, generating a higher light intensity with a low radiant heat output, long lifetime, lower environmental impact over the product lifecycle, and integration into digital systems [5–9]. The reduced cost and increased energy and photometric performance of light-emitting diodes (LEDs) has accelerated their market penetration. LEDs offer another great advantage: connectivity to other electronic systems.

The energy savings resulting from LEDs are due to the increase in the luminous efficacy of radiation (LER) and radiant efficiency compared to older technologies, especially incandescent lamps. SSL devices emit narrowband spectra, which can be maximized where the human visual system is most sensitive. However, human brightness sensitivity (spectral luminous efficacy function) is not similar to plant sensitivity to optical radiation. In addition, the plants’ sensitivity to optical radiation widely varies among species. Therefore, the energy saving comparisons for horticultural systems should utilize radiant efficiency (the ratio of optical power to the input electrical power).

It is clear that studying plants’ response to optical radiation requires a complex system approach. Although the Internet of things (IoT) and big data approaches have been previously used to analyze data on agriculture [10,11], a real-time autonomous horticultural system has not been previously conceptualized. To address the challenges in meeting horticultural lighting systems, here a connected lighting system is described that detects environmental and plant-related factors and adjusts the amount and spectrum of the light output in real time using machine learning techniques, thus improving the quality and quantity of the yield.

The spectral optimization of the light source can be utilized by mixing multicolor SSL devices, such as LEDs [12] and lasers [13]. It should be noted that the term “lighting” is used nominally here. Since plants respond to infrared [14] and ultraviolet radiation [15], “optical radiation” would be the technically accurate term.

The advanced real-time lighting system requires initial conditions and progressively updates its output while tracking the plant response in real time, as shown in Figure 1. The initial conditions can be loaded to the system (training artificial intelligence) through datasets based on previous research findings. However, the described real-time optimization system does not require a constant initial feed from the users. Artificial intelligence (AI) techniques (e.g., evolutionary computation) ensure minimal user intervention and the continual improvement of the output using metaheuristic methods. A metaheuristic is an algorithm designed to seek, generate, or identify a feasible and satisfactory solution to an optimization problem. Users can define target parameters (e.g., improve crop quality and energy efficiency, reduce light pollution) for the real-time horticultural lighting system. The optimization of the lighting system can be adjusted to meet plants’ varying needs at different stages of growth. For example, a plant in the flowering stage may require different spectrum and intensity compared to the ripening stage. Plant growth can be measured by comparing the fresh vs. dry weight, calculating the root mass measurement (e.g., grid intersect technique) and root-shoot ratio, or through visual observation. The performance assessments can be done by comparing the growth with a baseline scenario. The real-time optimization system can also perform adaptive and predictive plant behavior analytics beyond sustaining the energy efficiency and accuracy of plant morphology descriptors.

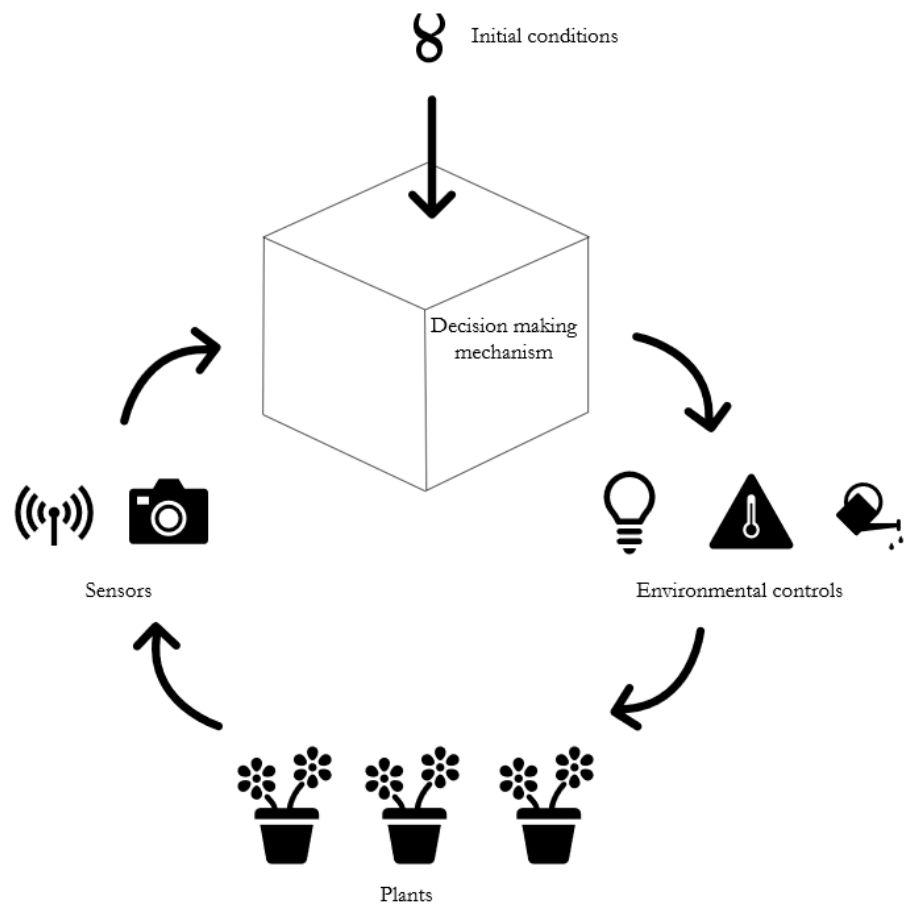


Figure 1. A real-time ambient intelligent horticultural system can ensure plant growth and development by controlling the environmental conditions, such as optical radiation, temperature, and moisture, without human intervention. Sensors can be used to identify the plant morphology, vital signs, and crop quality.

Adding technological features to an existing system often adds costs and complexity. Sensors, intellectual property related to the machine learning algorithms, and spectrally tunable lighting systems are the main costs of a real-time adaptive lighting system. However, the adaptive horticultural system can provide a return on investment through the increased efficiency of the light output (reduced energy consumed by lighting), reduced water consumption (recycling water by condensing vapor in the air-conditioning system and returning it to the root zone), increased efficiency of produce production (reduced product growth time), and reduced use of pharmaceuticals. Despite the initial technical challenges and costs that are innate to any automated system, an integrative horticultural system can increase the energy efficiency and product quality, and enable re-engineering plants with increased nutrition values. It should be noted that water will likely be a scarce resource in the future, and optimizing the use of natural sources to improve the quality of produce should be the primary optimization goal for any sustainable system.

2. Precision Agriculture

Precision agriculture (PA) is the management of spatial and temporal variability in fields using information and communication technologies [16]. PA can help to improve the quality and quantity of the produce by using advanced techniques, such as remote sensing [17], mobile robots [18], and GPS [19]. The quality management of the crops is a major component of PA, which requires site-specific technologies and strategies [20]. These site-specific technologies require tailor-made solutions using sensors and cameras.

The sensing and control of horticultural systems are key components of the successful adoption of new technologies. For example, wireless sensors are more frequently used in agriculture and food industries for environmental monitoring and precision agriculture [21]. Similarly, imaging systems that use CCT cameras have been proposed to detect defection on the surface of the produce [22] and classify fruits and vegetables [23]. Plant species can be identified using digital equipment with an up to 94% accuracy [24,25].

In the control area, advanced methods, such as evolutionary computation algorithms, can be used to tune the output of a system. For example, multi-objective genetic algorithms have been previously used in horticultural research to regulate a crop area's temperature distribution, carbon dioxide concentration, energy consumption [26,27], pot-growth substrate mixture [28], resource use and net profit [29], energy savings [30]; reduce over-segmentation [31]; and ensure a return on investment [32]. Techniques used in the sensing and control of PA systems can also be adapted to light optimization systems.

3. Light Optimization

Adaptive real-time sensing and controls in lighting are not widely investigated, although several architectural lighting applications have been previously proposed. Studies show that light source SPDs can be optimized to increase the energy efficiency and color quality of light sources [33], reduce damage to artwork [34], and synchronize the non-visual (melanopic) response to optical radiation [35]. These proposals can be deconstructed, similar to horticultural systems, where a sensing device (e.g., charge-coupled device (CCD) camera) and control mechanism (e.g., computational algorithm) are deployed to optimize the light output. Sensing devices have been previously used to estimate the spectral power distribution of light sources [36] and the spectral reflectance function of objects [37] in architectural spaces.

Evolutionary optimization algorithms can control the light output to address user-defined functions, such as reducing damage to artwork by optical radiation. However, target parameters in an optimization problem can be conflicting. For example, light enables human vision, but it also causes damage to light-sensitive artwork through photochemical action [38]. To address the visibility-damage dilemma, multi-objective genetic algorithms have been employed to find the optimal light conditions in terms of optical damage, energy efficiency, and color quality [39]. Visual assessments were also conducted to ensure that the visual quality of objects under optimized lighting conditions is acceptable [40]. Although it is more challenging than spectral optimization, the spatial optimization of lighting has also been performed for artwork conservation using machine vision algorithms [41]. These advanced light optimization systems consider the objective specific parameters (e.g., the appearance of objects, energy efficiency, damage to the artwork), and the mathematical models used in the algorithms are all based on the human visual response to optical radiation.

4. Light Optimization for Horticulture

Advanced light control methods can be applied to areas beyond architecture, such as optimizing lighting for roadways, in product and lighting design processes, in modeling circadian impacts, and for plant growth [42,43]. Early research on the role of electric lighting on plant growth was conducted using commercially available light sources which were not varied in terms of spectral power distribution [44,45]. High-intensity discharge lamps (e.g., metal halide, high-pressure sodium) have been widely used in horticultural applications. However, SSL devices offer a higher luminous efficacy, longer life, and spatial and spectral control over the output. Multi-colored LEDs emit narrowband spectra, which allows the fine-tuning of the light source spectrum compared to older technologies, as shown in Figure 2.

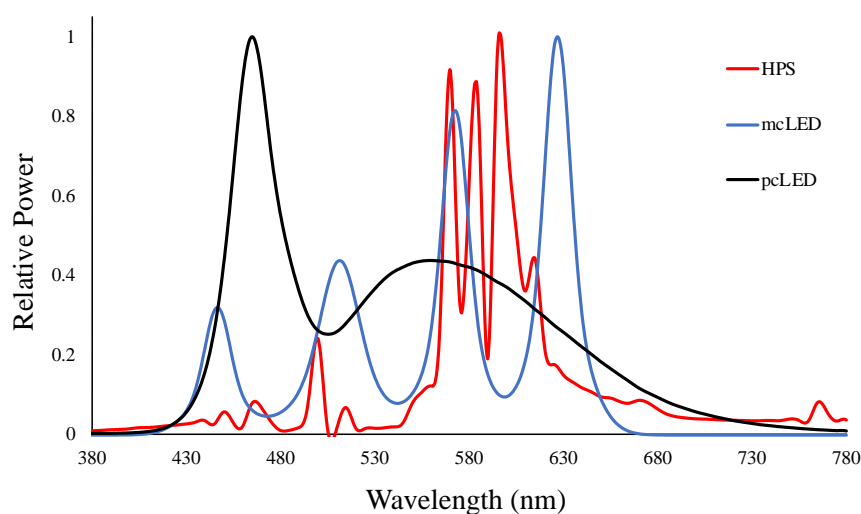


Figure 2. High-pressure sodium (HPS, red line) lamps are widely used in horticulture as grow lamps. LEDs offer a wide range of spectral power distributions. Two of the most widely used LED types are multi-colored LED (mcLED, blue line) and phosphor-coated LED (pcLED, black line).

More recent research was conducted by National Aeronautics and Space Administration (NASA) to explore the possibility of developing lighting systems for space stations [46]. The following studies showed that LEDs can increase the efficiency of photosynthesis and photomorphogenesis [47–49] and control disease development [50]. However, research in this field indicates that the complexity of the plant physiology requires a multi-objective optimization approach where plant growth can be ensured by optimizing the lighting [6,44] without sacrificing energy goals [51] or visual quality [52]. Although it has been argued that a broadband spectrum is required for the visual monitoring of crops [53], visual assessments showed that fruits and vegetables can appear natural and attractive to observers under optimized lighting conditions [54]. On the other hand, adding more complex conflicting parameters, such as the detection of plant stress with spectral reflectance through remote sensing, may require broadband spectrum emission as opposed to the narrowband emission provided by LEDs [55].

The performance of a connected lighting system varies depending on the input and output parameters. A connected lighting system controlling the frequency and pulse widths found that low frequencies (0.1 Hz, 1 Hz, 10 Hz) result in higher quantum efficiency in photosystem II (a protein complex that provides the initial reaction of photosynthesis) compared to higher frequencies (50 kHz and 100 kHz) [56]. The dynamic dimming and optimization of light output for photosynthetic photon flux density (PPFD) and light uniformity resulted in energy savings, with a similar fresh weight of the plants on average [57]. These findings indicate that the success of the optimization procedure depends on the identification of the problem as well as the configuration of the optimization parameters. For a broad review of automation in agriculture, readers can refer to Jha and colleagues [58].

5. Challenges and Future

A real-time lighting system would detect plant physiological markers (e.g., bio mass, gas exchange) as well as environmental factors using sensing technologies, and the output would be adjusted in real-time through artificial intelligence. The initial conditions required for the system would be based on previous research findings on plant physiology (gene expression and holistic plant response). The complexity of the plant response to lighting conditions may bring challenges to the system in the initial steps. Since the initial conditions can cause evolutionary algorithms to prematurely converge to local maxima or minima, the underlying dataset that feeds into the system plays an important role. However, a real-time optimization system has the advantage of delivering the precise

amount of spectral distribution, intensity, and duration of optical radiation tailored to the plants' development stages.

The accuracy and precision of user-defined parameters are expected to influence the success of the lighting system described here. Widely used metrics can be limited in describing the impact of optical radiation on plants. For example, photosynthetically active radiation (PAR) covers the spectral range between 400 nm and 700 nm, which is not entirely accurate due to the discovery of the new chlorophyll photoreceptor (*chlorophyll f*), with an absorption sensitivity peaking around 750 nm [6]. PAR also ignores the wavelength sensitivity (weighting is not applied). Since the success of evolutionary algorithms depends on the accurate parameter definition, it is vital to establish accurate quantities that characterize the impact of optical radiation on plant physiology.

The research directions that are essential to the realization of the real-time integrated horticultural lighting system that uses AI are:

- the identification of physiological markers,
- database generation,
- the development of the processing model and constraints,
- testing sensor sensitivity and accuracy,
- designing and testing feedback loops,
- validation.

The identification of plant physiological markers (membrane injury, leaf greening, gas exchange, water potential [59]) is the focus of agricultural studies. Generating a database of the required parameters requires a collaborative effort between several parties, included but not limited to data scientists and agricultural biotechnologists. The development of the optimization model and constraints is a mid-stage research effort, which is dependent on the previous research phases. However, an optimization system can be developed without obtaining a full picture of the plant physiology. As the real-time adaptive system is likely to improve itself through machine learning, it can likely guide future research interests through data generated from the earlier trials.

Testing sensor sensitivity and accuracy is another key aspect of the overall success of the system, and it should be an effort undertaken parallel to the conceptual development of the optimization system. Optical and network engineering solutions will likely focus on sensor precision, accuracy, and energy trade-offs through simulation, physical modeling, and validation. The algorithm design for real-time computing will require developing hardware and software for data acquisition, processing, and inference. The feedback loops provided by data acquisition systems will feed into the central algorithm to optimize the output. Different machine learning algorithms (e.g., supervised, unsupervised, self-learning, feature learning) have to be assessed against the previously identified optimization parameters (i.e., energy efficiency, plant biomarkers). Finally, the adaptive lighting system should be tested in the field for validation. The results from independent groups can be compared and analyzed to identify future research directions.

The role of AI in tackling the current and future problems in agriculture is tremendous. As the world's population continues to grow, the land available for farming is becoming scarce. Utilizing less land and increasing the productivity (more produce per cost per time) requires automated systems that yield healthier crops; better growth conditions; monitor environmental conditions; and collect, organize, and analyze data to help farmers. AI-based technologies, such as precision agriculture, have already made an impact on various tasks, included but not limited to detecting plant diseases and pests, regulating environmental conditions, and reducing energy consumption and resource use. AI can also contribute to increasing net profit, therefore providing a quicker return on investment.

Real-time monitoring and adjusting the light output through AI can combine all the benefits into a single system. The described real-time horticultural lighting system has the potential to improve the accuracy and precision of horticultural systems by promoting growth, manipulating plant morphology, and improving nutrient quality. While the conceptual and technological aspects of the system are

currently available [60,61], the construction, evaluation, and adoption of real-time light optimization require further research.

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References

- Shry, C.; Reiley, E. *Introductory Horticulture*; Cengage Learning: Boston, MA, USA, 2016.
- Zhu, X.-G.; Long, S.P.; Ort, D.R. What is the maximum efficiency with which photosynthesis can convert solar energy into biomass? *Curr. Opin. Biotechnol.* **2008**, *19*, 153–159. [[CrossRef](#)] [[PubMed](#)]
- Pinho, P.; Jokinen, K.; Halonen, L. Horticultural lighting—Present and future challenges. *Lighting Res. Technol.* **2012**, *44*, 427–437. [[CrossRef](#)]
- Möglich, A.; Yang, X.; Ayers, R.A.; Moffat, K. Structure and function of plant photoreceptors. *Annu. Rev. Plant Biol.* **2010**, *61*, 21–47. [[CrossRef](#)] [[PubMed](#)]
- Morrow, R.C. Led lighting in horticulture. *HortScience* **2008**, *43*, 1947–1950. [[CrossRef](#)]
- Piromalis, D.; Arvanitis, K.; Papageorgas, P.; Ferentinos, K. Smart precision lighting for urban and landscape closed controlled horticultural environments. In *Urban Horticulture*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 107–140.
- Pattison, P.; Tsao, J.; Brainard, G.; Bugbee, B. Leds for photons, physiology and food. *Nature* **2018**, *563*, 493–500. [[CrossRef](#)]
- Dillon, H.E.; Ross, C.; Dzombak, R. Environmental and energy improvements of led lamps over time: A comparative life cycle assessment. *LEUKOS* **2020**, *16*, 229–237. [[CrossRef](#)]
- Kagel, H.; Jacobs, H.; Bier, F.F.; Glöckler, J.; Frohme, M. A Novel Microtiter Plate Format High Power Open Source Led Array. In *Photonics*; Multidisciplinary Digital Publishing Institute: Basel, Switzerland, 2019; p. 17.
- Kamilaris, A.; Kartakoullis, A.; Prenafeta-Boldú, F.X. A review on the practice of big data analysis in agriculture. *Comput. Electron. Agric.* **2017**, *143*, 23–37. [[CrossRef](#)]
- Muangprathub, J.; Boonnam, N.; Kajornkasirat, S.; Lekbangpong, N.; Wanichsombat, A.; Nillaor, P. Iot and agriculture data analysis for smart farm. *Comput. Electron. Agric.* **2019**, *156*, 467–474. [[CrossRef](#)]
- Ries, H.; Leike, I.; Muschaweck, J.A. Optimized additive mixing of colored light-emitting diode sources. *Opt. Eng.* **2004**, *43*, 1531–1537.
- Neumann, A.; Wierer, J.; Davis, W.; Ohno, Y.; Brueck, S.; Tsao, J. Four-color laser white illuminant demonstrating high color-rendering quality. *Opt. Express* **2011**, *19*, A982–A990. [[CrossRef](#)]
- Hillman, W.S.; Galston, A.W. Inductive control of indoleacetic acid oxidase activity by red and near infrared light. *Plant Physiol.* **1957**, *32*, 129. [[CrossRef](#)] [[PubMed](#)]
- Caldwell, M. Plant response to solar ultraviolet radiation. In *Physiological Plant Ecology I*; Springer: Berlin/Heidelberg, Germany, 1981; pp. 169–197.
- Blackmore, S.; Godwin, R.J.; Fountas, S. The analysis of spatial and temporal trends in yield map data over six years. *Biosyst. Eng.* **2003**, *84*, 455–466. [[CrossRef](#)]
- Richardson, A.D.; Duigan, S.P.; Berlyn, G.P. An evaluation of noninvasive methods to estimate foliar chlorophyll content. *New Phytol.* **2002**, *153*, 185–194. [[CrossRef](#)]
- Emmi, L.; Paredes-Madrid, L.; Ribeiro, A.; Pajares, G.; Gonzalez-de-Santos, P. Fleets of robots for precision agriculture: A simulation environment. *Ind. Robot Int. J.* **2013**, *40*, 41–58. [[CrossRef](#)]
- Yong, H.; Hui, F.; Lei, F. Information processing system for precision agriculture based on GPS and GIS. *Trans. Chin. Soc. Agric. Eng.* **2002**, *1*, 145.
- Zude-Sasse, M.; Fountas, S.; Gemtos, T.A.; Abu-Khalaf, N. Applications of Precision Agriculture in Horticultural Crops. *Eur. J. Hort. Sci.* **2016**, *81*, 78–90. [[CrossRef](#)]
- Wang, N.; Zhang, N.; Wang, M. Wireless sensors in agriculture and food industry—Recent development and future perspective. *Comput. Electron. Agric.* **2006**, *50*, 1–14. [[CrossRef](#)]
- Li, Q.; Wang, M.; Gu, W. Computer vision based system for apple surface defect detection. *Comput. Electron. Agric.* **2002**, *36*, 215–223. [[CrossRef](#)]
- Rocha, A.; Hauagge, D.C.; Wainer, J.; Goldenstein, S. Automatic fruit and vegetable classification from images. *Comput. Electron. Agric.* **2010**, *70*, 96–104. [[CrossRef](#)]

24. Cope, J.S.; Corney, D.; Clark, J.Y.; Remagnino, P.; Wilkin, P. Plant species identification using digital morphometrics: A review. *Expert Syst. Appl.* **2012**, *39*, 7562–7573. [[CrossRef](#)]
25. Neto, J.C.; Meyer, G.E.; Jones, D.D.; Samal, A.K. Plant species identification using elliptic fourier leaf shape analysis. *Comput. Electron. Agric.* **2006**, *50*, 121–134. [[CrossRef](#)]
26. Li, K.; Sha, Z.; Xue, W.; Chen, X.; Mao, H.; Tan, G. A fast modeling and optimization scheme for greenhouse environmental system using proper orthogonal decomposition and multi-objective genetic algorithm. *Comput. Electron. Agric.* **2020**, *168*, 105096. [[CrossRef](#)]
27. Shamshirband, S.; Khoshnevisan, B.; Yousefi, M.; Bolandnazar, E.; Anuar, N.B.; Wahab, A.W.A.; Khan, S.U.R. A multi-objective evolutionary algorithm for energy management of agricultural systems—A case study in iran. *Renew. Sustain. Energy Rev.* **2015**, *44*, 457–465. [[CrossRef](#)]
28. Krüger, C.; Castellani, F.; Geldermann, J.; Schöbel, A. Peat and pots: An application of robust multiobjective optimization to a mixing problem in agriculture. *Comput. Electron. Agric.* **2018**, *154*, 265–275. [[CrossRef](#)]
29. Hemming, S.; de Zwart, F.; Elings, A.; Righini, I.; Petropoulou, A. Remote control of greenhouse vegetable production with artificial intelligence—Greenhouse climate, irrigation, and crop production. *Sensors* **2019**, *19*, 1807. [[CrossRef](#)]
30. Ferentinos, K.P.; Albright, L. Optimal design of plant lighting system by genetic algorithms. *Eng. Appl. Artif. Intell.* **2005**, *18*, 473–484. [[CrossRef](#)]
31. Ziamtsov, I.; Navlakha, S. Machine learning approaches to improve three basic plant phenotyping tasks using three-dimensional point clouds. *Plant Physiol.* **2019**, *181*, 1425–1440. [[CrossRef](#)]
32. Breen, M.; Upton, J.; Murphy, M.D. Development of a discrete infrastructure optimization model for economic assessment on dairy farms (diomond). *Comput. Electron. Agric.* **2019**, *156*, 508–522. [[CrossRef](#)]
33. Durmus, D.; Davis, W. Appearance of achromatic colors under optimized light source spectrum. *IEEE Photonics J.* **2018**, *10*, 1–11. [[CrossRef](#)]
34. Abdalla, D.; Duis, A.; Durmus, D.; Davis, W. Customisation of Light Source Spectrum to Minimise Light Absorbed by Artwork. In Proceedings of the CIE 2016 Lighting Quality & Energy Efficiency, Melbourne, Australia, 3–5 March 2016; pp. 22–31.
35. Durmus, D. Impact of Surface Reflectance on Spectral Optimization for Melanopic Illuminance and Energy Efficiency. In Proceedings of the Optical Devices and Materials for Solar Energy and Solid-state Lighting 2019, Burlingame, CA, USA, 29 July–2 August 2019; p. PT2C. 5.
36. Botero-Valencia, J.-S.; Valencia-Aguirre, J.; Durmus, D.; Davis, W. Multi-channel low-cost light spectrum measurement using a multilayer perceptron. *Energy Build.* **2019**, *199*, 579–587. [[CrossRef](#)]
37. Tominaga, S.; Tanaka, N. Estimating reflection parameters from a single color image. *IEEE Comput. Graph. Appl.* **2000**, *20*, 58–66. [[CrossRef](#)]
38. Cuttle, C. Damage to museum objects due to light exposure. *Int. J. Lighting Res. Technol.* **1996**, *28*, 1–9. [[CrossRef](#)]
39. Durmus, D.; Abdalla, D.; Duis, A.; Davis, W. Spectral optimization to minimize light absorbed by artwork. *Leukos* **2020**, *16*, 45–54. [[CrossRef](#)]
40. Durmus, D.; Davis, W. Blur perception and visual clarity in light projection systems. *Opt. Express* **2019**, *27*, A216–A223. [[CrossRef](#)] [[PubMed](#)]
41. Vázquez, D.; Fernández-Balbuena, A.; Canabal, H.; Muro, C.; Durmus, D.; Davis, W.; Benítez, A.; Mayorga, S. Energy optimization of a light projection system for buildings that virtually restores artworks. *Digit. Appl. Archaeol. Cult. Herit.* **2020**, *16*, e00128. [[CrossRef](#)]
42. Durmus, D. Optimising Light Source Spectrum to Reduce the Energy Absorbed by Objects. Ph.D. Thesis, The University of Sydney, Sydney, Australia, 21 October 2017.
43. Gómez-Lorente, D.; Rabaza, O.; Estrella, A.E.; Peña-García, A. A new methodology for calculating roadway lighting design based on a multi-objective evolutionary algorithm. *Expert Syst. Appl.* **2013**, *40*, 2156–2164. [[CrossRef](#)]
44. Canham, A.E. Artificial lighting for plant growth. *Trans. Illum. Eng. Soc.* **1954**, *19*, 235–261. [[CrossRef](#)]
45. Weir, J. Artificial lighting for commercial horticulture. *Lighting Res. Technol.* **1975**, *7*, 209–225. [[CrossRef](#)]
46. Barta, D.; Tibbitts, T.; Bula, R.; Morrow, R. Evaluation of light emitting diode characteristics for a space-based plant irradiation source. *Adv. Space Res.* **1992**, *12*, 141–149. [[CrossRef](#)]
47. Brown, C.S.; Schuerger, A.C.; Sager, J.C. Growth and photomorphogenesis of pepper plants under red light-emitting diodes with supplemental blue or far-red lighting. *J. Am. Soc. Hortic. Sci.* **1995**, *120*, 808–813. [[CrossRef](#)]

48. Goins, G.D.; Yorio, N.C.; Sanwo, M.; Brown, C. Photomorphogenesis, photosynthesis, and seed yield of wheat plants grown under red light-emitting diodes (leds) with and without supplemental blue lighting. *J. Exp. Bot.* **1997**, *48*, 1407–1413. [[CrossRef](#)] [[PubMed](#)]
49. Stutte, G.W. Light-emitting diodes for manipulating the phytochrome apparatus. *HortScience* **2009**, *44*, 231–234. [[CrossRef](#)]
50. Schuerger, A.C.; Brown, C.S. Spectral quality affects disease development of three pathogens on hydroponically grown plants. *HortScience* **1997**, *32*, 96–100. [[CrossRef](#)] [[PubMed](#)]
51. Poulet, L.; Massa, G.; Morrow, R.; Bourget, C.; Wheeler, R.; Mitchell, C. Significant reduction in energy for plant-growth lighting in space using targeted led lighting and spectral manipulation. *Life Sci. Space Res.* **2014**, *2*, 43–53. [[CrossRef](#)]
52. Oh, J.H.; Kang, H.; Park, H.K.; Do, Y.R. Optimization of the theoretical photosynthesis performance and vision-friendly quality of multi-package purplish white led lighting. *Rsc Adv.* **2015**, *5*, 21745–21754. [[CrossRef](#)]
53. Massa, G.D.; Kim, H.-H.; Wheeler, R.M.; Mitchell, C.A. Plant productivity in response to led lighting. *HortScience* **2008**, *43*, 1951–1956. [[CrossRef](#)]
54. Durmus, D.; Davis, W. Object color naturalness and attractiveness with spectrally optimized illumination. *Opt. Express* **2017**, *25*, 12839–12850. [[CrossRef](#)]
55. Schuerger, A.C.; Richards, J.T. Effects of artificial lighting on the detection of plant stress with spectral reflectance remote sensing in bioregenerative life support systems. *Int. J. Astrobiol.* **2006**, *5*, 151–169. [[CrossRef](#)]
56. Olvera-Gonzalez, E.; Alaniz-Lumbreras, D.; Torres-Argüelles, V.; González-Ramírez, E.; Villa-Hernández, J.; Araiza-Esquivel, M.; Ivanov-Tsonchev, R.; Olvera-Olvera, C.; Castaño, V. A led-based smart illumination system for studying plant growth. *Lighting Res. Technol.* **2014**, *46*, 128–139. [[CrossRef](#)]
57. Pinho, P.; Hytönen, T.; Rantanen, M.; Elomaa, P.; Halonen, L. Dynamic control of supplemental lighting intensity in a greenhouse environment. *Lighting Res. Technol.* **2013**, *45*, 295–304. [[CrossRef](#)]
58. Jha, K.; Doshi, A.; Patel, P.; Shah, M. A comprehensive review on automation in agriculture using artificial intelligence. *Artif. Intell. Agric.* **2019**, *2*, 1–12. [[CrossRef](#)]
59. Grzesiak, M.T.; Hura, K.; Jurczyk, B.; Hura, T.; Rut, G.; Szczyrek, P.; Grzesiak, S. Physiological markers of stress susceptibility in maize and triticale under different soil compactions and/or soil water contents. *J. Plant Interact.* **2017**, *12*, 355–372. [[CrossRef](#)]
60. Ferrández-Pastor, F.J.; Alcañiz-Lucas, S.; García-Chamizo, J.M.; Platero-Horcajadas, M. Smart Environments Design on Industrial Automated Greenhouses. *Proceedings* **2019**, *31*, 36.
61. Shadrin, D.; Menshchikov, A.; Somov, A.; Bornemann, G.; Hauslage, J.; Fedorov, M. Enabling precision agriculture through embedded sensing with artificial intelligence. *IEEE Trans. Instrum. Meas.* **2019**, *69*, 4103–4113. [[CrossRef](#)]



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