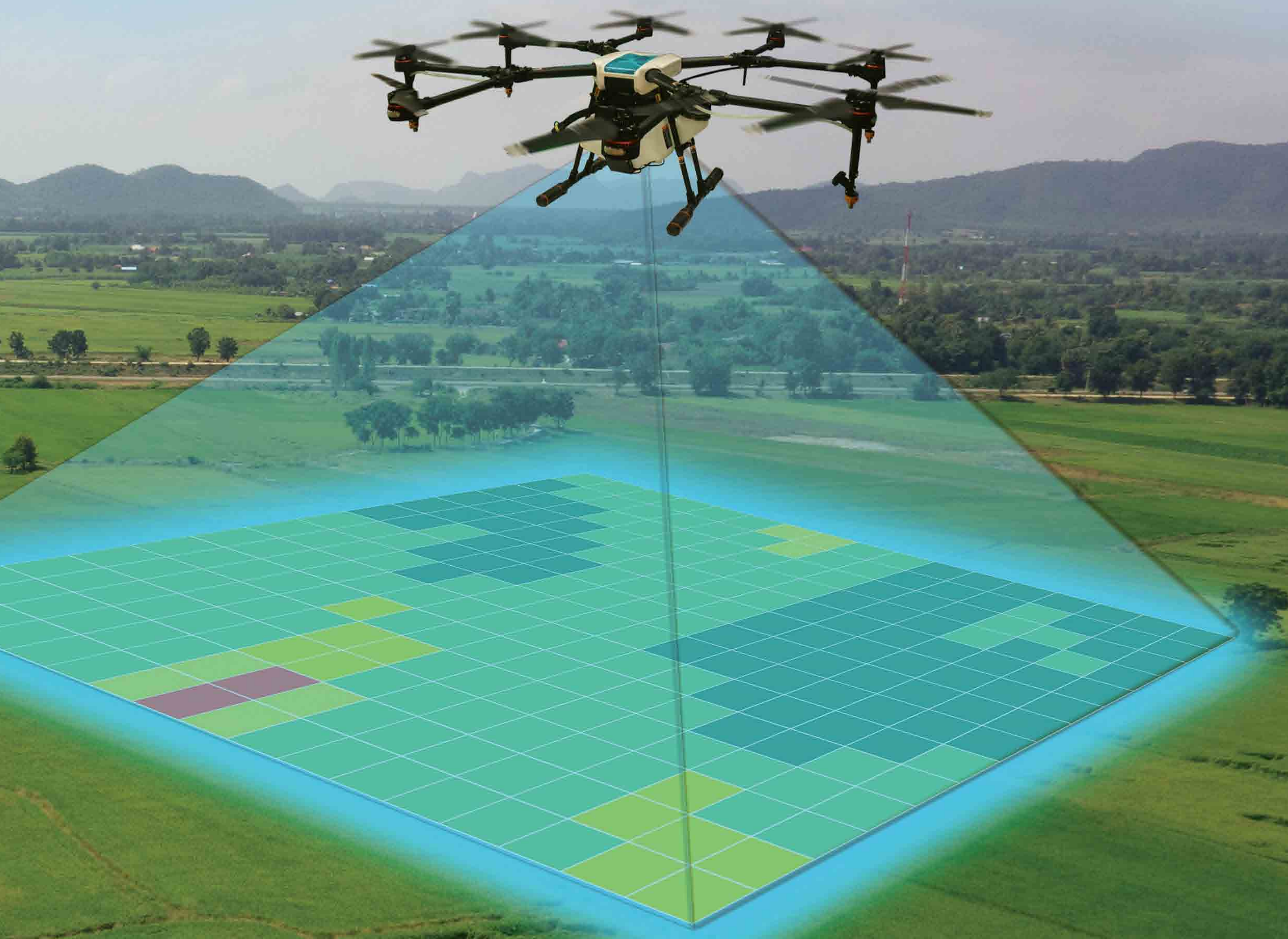
September 2019 | Volume 7

# VOLCANI VOICE

Agricultural Research Organization Volcani Center

## *Precision Agriculture*
*for sustainable agricultural production*



"This issue of Volcani Voice includes short papers on research projects conducted by Researchers of the A.R.O. They present different aspects of PA, mainly focused on the two bottom triangles of the PA pyramid. The vast diversity of the topics in this issue reflects the wide scope in which PA can potentially increase farming efficiency and support sustainable agriculture."

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www.agri.gov.il

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# Message from the Head of ARO

## Prof. Eli Feinerman

**Soils and water, the natural resources which underpin agricultural production, are under continuous stress. Every day, approximately 33000 hectares of land are lost from production because of urbanization, degradation and desertification processes. Land degradation, coupled with rapid human population growth, results in a significant reduction in the level of land per capita available for production. Fresh water is also scarce and insecure resource. Currently, water scarcity negatively affects more than 40% of the world population and, according to U.N. predictions, in 2050 more than half of the world population could suffer water shortages. The implications of the diminishing stocks of productive land and water are severe. People and ecosystems are left exposed and increasingly vulnerable. The impacts of climate change are global in scope and exceptional in scale.**

In fact, there will be about 10 billion people to feed in 2050, demanding production of more, healthier and cheaper food. To do that, over the next 30 years we will need to increase global agricultural production by 70 percent and as much as 100 percent in the developing world. We have to do that despite drought, despite climate change. Maintaining food production to feed a growing population during a period of climate change while preserving the environment is one of the major challenges of our time, and without drastic action today, adapting to its future impacts will be much more difficult and costly tomorrow.

Advanced research and applied science can yield technology that would play a key role to accomplish the task. While consumer-driven technology, such as mobile phones, is widely pursued by science, R&D and industry, agricultural technological breakthroughs are less attractive for the immediate fortune seeker, although their global importance is by far more critical.

Precision farming, which encompasses data sciences, sensors, information and communication technologies, as well as robotics and cyber, is one of the leading technological disciplines that carries the potential to enable a more sustainable agriculture. Its multidisciplinary nature creates a demanding research ecosystem. Volcani has the unique combination of researchers in the core technological disciplines, in the Institute of Agricultural Engineering, embraced by all agricultural disciplines of its five other Institutes. This unique combination has yielded a number of scientific and technological advancements that take the reader to the future and provide a glimpse of tomorrow's high-tech agriculture.

> "Maintaining food production to feed a growing population during a period of climate change while preserving the environment is one of the major challenges of our time, and without drastic action today, adapting to its future impacts will be much more difficult and costly tomorrow."

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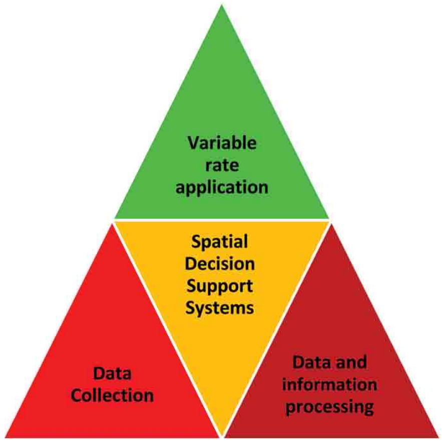
# Message from the Editor

## Volcani Voice on Precision Agriculture

Precision Agriculture (PA) has been mentioned in the agricultural management area since the early 1990s. The first international conference on PA took place in Warwick (U.K.), in 1997. Since then, for more than 20 years, PA has been in a constant state of evolution and its definition is constantly being updated. Until now (2019), there is no single definition of PA. The International Society for Precision Agriculture (ISPA, www.ispag.org) has recently launched an initiative to find a broadly acceptable definition of PA, using tools of crowd sourcing. It is generally accepted that precision agriculture addresses the variability of agricultural entities, such as within-field variability or trees or soils or animals, or whatever the relevant management unit is. In all cases, precision agriculture involves extensive use of advanced technologies to address and manage the needs of the individual management unit.

It is also generally accepted that, for implementing PA, a number of technological challenges are involved. Following is a graphical representation of a pyramid consisting of four triangles, two of which are basal, representing technological solutions that are indispensable for PA.




Data acquisition and sensors are a basis upon which the rest of the process rests (bottom left triangle). Technologies for data acquisition are usually "borrowed" from the medical or the defense fields, for which significant budgets are allocated for their development. Nevertheless, an in-depth understanding of their physical principles and appropriate adjustments are essential to make them usable for PA.

Another basis is the technology linking the acquired data (sensory or otherwise collected) to the agricultural domain (bottom right triangle). For example, color of images to soil characteristics, or spectral signatures to nutrient levels, or temperature to water status or cows chewing to food uptake, and so forth. This is a unique level where broad multi-disciplinary work is essential: an in-depth knowledge of the agricultural domain and its interaction with the acquired information is required.

The next level is associated with spatial decision support systems (the middle triangle) and last, but not least, the technologies that enable variable application of resources (top triangle).

This issue of Volcani Voice includes short papers on research projects conducted by Researchers of the A.R.O. They present different aspects of PA, mainly focused on the two bottom triangles of the PA pyramid. Each paper presents a unique data acquisition process, from discrete sensors, through proximal sensing, to remote sensing; various data processing algorithms are applied, and appropriate decision-support frameworks are utilized. The vast diversity of the topics in this issue reflects the wide scope in which PA can potentially increase farming efficiency and support sustainable agriculture.

**Dr. Victor Alchanatis**

Victor Alchanatis is a senior research scientist at the Institute of Agricultural Engineering at ARO. His research interests include sensing technologies and their application to agricultural and environmental systems: optical sensing in the visible, near-infrared and thermal infrared spectrum, hyper-spectral and multi-spectral image processing, computer vision and classification systems. These sensing technologies are applied to precision farming in field crops, orchards and protected cultivation, as well as for non-destructive testing of fruits and vegetables in post-harvest systems. He has authored and co-authored more than 70 papers in international peer-reviewed journals and more than 100 in other journals and conference proceedings. He is on the editorial board of leading journals on precision agriculture and agricultural engineering.

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# Unmanned aerial vehicle (UAV) for precision agriculture

By Dr. Yafit Cohen

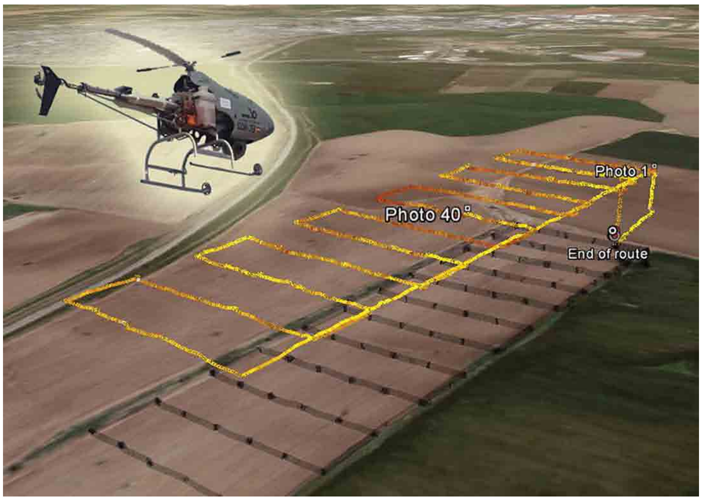
**ABSTRACT**

**Addressing in-field variability is a major challenge in modern agriculture, as it is considered to be a key component in attempting to enhance the yield/resources-inputs ratio. In general, assimilating Precision Agriculture (PA) principles to address in-field variability involves four components: (1) data collection, (2) data analysis, (3) development of designated spatial decision support systems (SDSS) or the creation of prescription maps, and (4) based on the products of the three preceding components, variable rate resource application. Currently, data collection technologies and variable rate application (VRA) technologies are the most advanced and are widely used. Unmanned Aerial Systems (UAS) are being promoted as a promising platform for data collection for precision agriculture. This paper discusses their unique characteristics, and compares them with satellite platforms.**

## INTRODUCTION

Addressing in-field variability is a major challenge in modern agriculture, as it is considered to be a key component in attempts to enhance the yield/resources-inputs ratio. In general, assimilating Precision Agriculture (PA) principles to address in-field variability involves four components: (1) data collection, mostly by the use of sensing technologies, (2) data analysis, to create in-field variability maps, (3) development of designated spatial decision support systems (SDSS) or the creation of prescription maps, and (4) variable rate resource application based on the products of the three preceding components. Currently, data collection technologies and variable rate application (VRA) technologies are the most advanced and are widely used (Zhang and Kovacs, 2012).

Operational success of VRA requires accurate maps of crop growth, crop nutrient deficiencies, weeds, insect infestations, and other crop and soil conditions. Valuable data/maps are agricultural-task dependent, as different map qualities are required for different




tasks. Other than data analysis, there are various factors that affect the value of the data to the farmer, including time resolution, spatial resolution, and specificity. Specificity relates to the question: do the data contain specific attributes related to specific deficiencies, such as of nitrogen and water, or specific attributes related to the presence of specific weeds, pests, or diseases?

## SATELLITE AND UAV PLATFORMS

Satellite images collected during the growing season have been used over the last 30 years to monitor crop growth, crop stress, and to predict crop yield. Israeli farmers use satellite images mainly to explore the variability in their fields and orchards, to locate anomalies, and to direct field monitoring. The use of manned airborne platforms is limited in Israel as in other countries by high operational complexity, costs, and lengthy delivery of products. Unmanned Aerial Systems (UAS), are being promoted as an alternative platform for data collection. The ultra-high spatial resolution (centimeters), relatively low operational costs, and the near real-time image acquisition attracts numerous companies and farmers to consider these platforms ideal tools for mapping and monitoring in PA. Most UAVs to that end are equipped with very small cameras providing images in the visible range. The availability of UAVs equipped with small multi-spectral (MS) cameras in the visible and near infrared range (VIS-NIR) is rapidly increasing. Significant attention has been paid to the collection, calibration, geo-registration and mosaicking of data collected from small UAVs. In a way, because of their ultra-high spatial resolution and

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their near real-time production, the UAV images bring the field to the farmer and may be used as a tool to simulate a field survey. Farmers have realized these advantages and either buy their own system and acquire images whenever they need, or order imaging campaigns from a commercial company. Over the last 3 years, Israeli companies have advised local farmers as well as farmers around the world with field imaging services employing UAVs. An example of a UAV image above a vineyard is presented in Figure 1. Both canopy width (density) variability and soil variability are well evident in the image. There are rows or parts of rows with very narrow canopy, as in the northern part of the vineyard, indicating a kind of stress. Patches of lighter soil are evident along the vineyard, apparently as a result of surface water runoff and erosion. The high resolution of the UAV image enables a good separation

Figure 1. A UAV image above a grapevine showing variability in both crop and soil. The image is a combination of 3 bands: Near-infrared, red and green. The imaging campaign was ordered by the Carmel Winery (Zikhron Ya'aqov, Israel; http://www.carmelwines.co.il/en/) and conducted by Agricam (http://www.agricam-ag.com/).

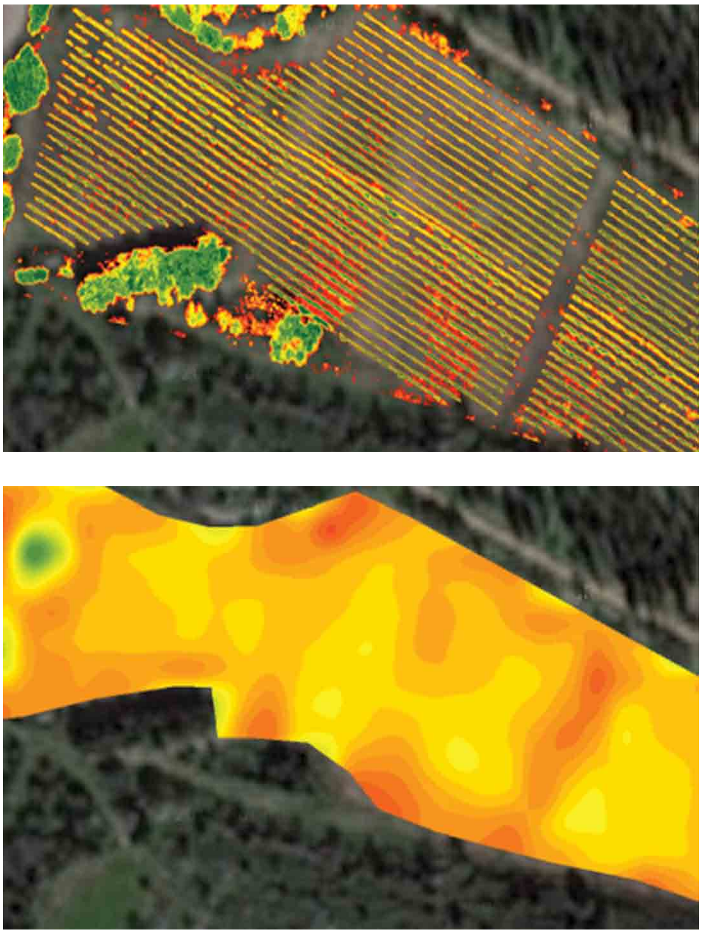

Figure 2. NDVI map of the vineyard derived from a UAV multispectral image (above) and from a Sentinel2 multispectral image (below), both showing variability in crop density. Green: high crop density, Yellow: medium crop density and Red: low crop density.
Both NDVI maps were produced by Agricam Ltd. for Carmel Winery.

of the narrow-canopy rows from the soil. When transformed to Normalized Difference Vegetation Index (NDVI) units (Figure 2), the variability in crop density is more prominent and reveals the existence of weeds in-between vineyard rows. Comparison between the UAV and free-of charge Sentinel2 satellite images (10m spatial resolution; Figure 2), both converted to NDVI, reveals remarkable differences.

It should be emphasized, though, that the remarkable differences between the two images is derived from the narrow-row shape of the vineyard and the coarse resolution of the Sentinel2 images. Milder differences might occur between the UAV image and the 2-10m-spatial-resolution-satellite image with field crops or even with table grapes at full crop cover. An example can be seen at: http://agridrone.co/evidence-satellite-ndvi/.

As mentioned above, satellite images in the VIS-NIR range are usually used for general in-field variability mapping for rational field monitoring, to detect problems and as an aid for VR application. Also, most of the UAV images for agricultural purposes provide merely a general picture of crop and soil variability. Yet, having spatial resolution of centimeters and even of millimeters, the UAV images potentially can provide data with high specificity for some agricultural tasks. For example, weed species and their accurate locations can be detected in UAV images by the unaided eye. Also, with an expert eye, damage resulting from water deficiencies or specific insects or diseases can be detected and diagnosed. Much effort is invested at present to develop algorithms that can interpret UAV images into semantically meaningful information and translate them into specific prescription maps for various agricultural tasks. Research and development teams in academia

→ and private industry have indicated that there is much potential in machine-learning techniques to develop reliable algorithms (e.g. Hung et al., 2014). For that to succeed, enriched databases of images linked with on-the-ground data need to be generated.

## UAV AND PRECISION AGRICULTURE AT THE A.R.O.

On-going research at the Institute of Agricultural Engineering of the A.R.O. is focusing on enhancing the ability to map water-status variability in crop fields by aerial thermal imaging for irrigation management (Cohen et al. 2016). Manned aerial platforms have been used for the thermal imaging trials. During the spring of 2016, a trial was performed to conduct thermal imaging by UAV using our thermal imaging system, one that weighs little more than 1.5 kg. Our thermal imaging is composed of a 700g SC655 thermal camera (FLIR® Systems, Inc.), a controller, and a power supply unit. The camera has an accuracy of ±2⁰ Celsius, as is required for accurate estimation of crop water status. Figure 3 presents a thermal mosaic of experimental sub-plots of potato under different irrigation treatments with four replicates. The thermal mosaic had high temperature and geographic accuracies. Irrigation treatments were 100% and 70% of commercial amounts and 2 irrigation treatments that had 70% of commercial amounts at the beginning of the season and then, when water stress was detected by thermal images, irrigation was modified to 110% (orange) and 100% (green) of commercial amounts. The mild differences between irrigation treatments were well depicted by the UAV thermal-mosaic. For comparison, in a regular image acquired by a UAV, much fewer differences were observed (Figure 4).

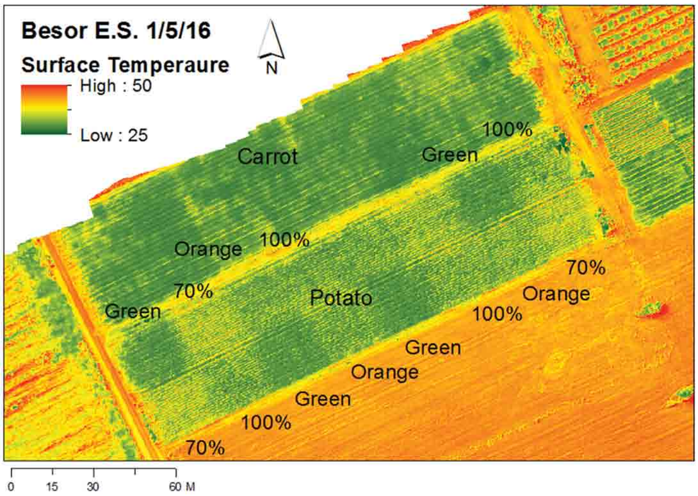


Figure 3. A UAV thermal mosaic of an experimental potato plot at the Besor Experiment Station, under various irrigation treatments. The image was acquired by Aeromap, Ltd. (http://www.aeromap1.com/ ). A similar thermal imaging campaign was conducted by P.A.M., Ltd. (http://pam-can.com/ )

Figure 3. A UAV in the visible range of an experimental potato plot at the Besor Experiment Station, under different irrigation treatments. The image was acquired by P.A.M., Ltd. (http://pam-can.com/ )

It is important to mention that the imaging trial, covering 8 hectares, lasted 1-2 hours and included 3 sets of 20-minute flights, with power-supply batteries switched between flights. This experience emphasizes the limitations of the UAV-imaging capabilities. Thermal imaging services by UAVs are suggested to farmers by commercial companies. Yet, most of the available thermal cameras designated for UAVs do not have the adequate resolution needed for irrigation decision making.

There are various kinds of UAVs. They can be distinguished by their size, their payload size, the range they can travel and their endurance time in the air (see for example: https://www.e-education.psu.edu/geog892/node/5). Most UAVs that are used for imaging of agricultural fields are small, have a relatively light payload (up to 1 kg) and a short endurance time (up to 1 hour). On one hand, this is why most of the UAV-imaging services suggested to farmers concentrate on images in the visible range. On the other hand, this limitation inspired the development of small cameras in the near-infrared and the far-infrared (thermal) ranges that would fit small and inexpensive UAVs. In some cases, the physical size of the cameras compromises their performance and caution should be taken when using them. Recently, the A.R.O. purchased "Sniper", an unmanned helicopter with a fuel engine that can carry up to 2.5 kg and with 1.5 hours flight time (http://www.alphaunmannedsystems.com/ ). This system will be used to enhance our capabilities in various research areas, including precision agriculture and phenotyping. ❑

## ACKNOWLEDGMENT

I thank my colleague Victor Alchanatis of the A.R.O. and also Dror Dotan of Carmel Winery for his consent to publish the UAV image above the vineyard.

***FURTHER READING***
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*Cohen, Y., Alchanatis, V., Saranga, Y. et al. (2016). Mapping water status based on aerial thermal imagery: comparison of methodologies for upscaling from a single leaf to commercial fields Precision Agric, online. doi:10.1007/s11119-016-9484-3*

## Dr. Yafit Cohen

Yafit Cohen is a senior research scientist at the Institute of Agricultural Engineering of the A.R.O. She possesses a B.A. and Ph.D. in geography from Bar-Ilan University, with specialization in Geographical Information Systems and Remote Sensing. She served as a post-doctoral fellow at the Technion, Haifa, Israel during 2002 and specialized in remote sensing for land-use recognition and mapping. Since 2003, she is a research scientist at the Institute of Agricultural Engineering of the A.R.O. She is also an adjunct faculty member at the Faculty of Agriculture, Hebrew University of Jerusalem, Rehovot, Israel, where she teaches Geographic Information System (GIS). Her main scientific interests are remote-sensing for precision-agriculture practices, especially for irrigation and fertilization; and spatio-temporal analysis of insect distribution in agricultural environments, such as the medfly and the red-palm-weevil.

Over the past 15 years, she has served as a member of a number of scientific committees, has served as a guest editor of a special issue of the journal Biosystems Engineering, and serves today as a member of the editorial board of the journal Remote Sensing.

Expertise: Precision agriculture, thermal and hyper-spectral imaging, GIS, spatial decision support systems for integrated pest management, automatic monitoring of insects.

# Mapping canopy chemical traits and composition using imaging spectroscopy for sustainable agriculture

By Dr. Tarin Paz-Kagan

**ABSTRACT**

**Mapping and monitoring chemical traits and composition of plant canopies are essential tasks for sustainable management of agricultural systems, as they can detect nutrient status, stress, and disease infestation, as well as predict yield. Herein is a partial summary of the applications of imaging spectroscopy for canopy chemical traits and composition within the context of agriculture. The use of state-of-the-art remote sensing technologies, such as imaging spectroscopy, has a large capability in quantifying and mapping canopy chemical traits and species composition. Imaging spectroscopy is based on hyperspectral sensors measuring hundreds of narrow spectral bands that enable detailed detection of plant traits, such as chlorophyll, nitrogen, protein, cellulose, and lignin contents. The chemical information can be used for developing species composition maps, as each plant species has a unique molecular and biochemical composition that enables its identification and mapping based on its spectral reflectance signal. Imaging spectroscopy technology, which detects within-field variability can help develop site-specific, decision-support systems for precision agriculture, replacing the uniform management common in traditional agriculture, resulting in increased profitability and more sustainable agricultural management.**

## INTRODUCTION

Knowledge of chemical traits and composition of plant canopies is essential for sustainable agricultural management [1], [2]. Precision agriculture uses information technologies, particularly remote sensing integrated with multiple sources of data, to formulate decisions aimed at increased profitability and reduced environmental impact [3]. One aspect of precision agriculture is using various remote sensing techniques for monitoring canopy chemical traits, thereby detecting nutrient status, stress and diseases, and predicting yield. Precision agriculture takes into account field variation for developing site-specific management to improve efficiency and productivity. Traditional methods for canopy chemical and composition analysis requires intensive fieldwork and biochemical laboratory analysis [4], both of which are costly and time-consuming. Furthermore, these methods may be inapplicable in areas of poor accessibility or for large areas [5].

Remote sensing includes both state-of-the-art active and passive sensors. These remote sensors can provide detailed information on canopy chemistry and composition. State-of-the-art active sensors include laser-light remote-sensing such as Light Detection and Ranging (LiDAR) using pulsed laser light to measure the range from the sensors to objects on the surface. These light pulses generate three-dimensional data-sets of an object and its surface characteristics (such as Digital Elevation Models (DEM), Digital Surface Models (DSM), and Digital Terrain Models (DTM)) [7]. Passive sensors can be considered hyperspectral or multispectral, and have various spectral ranges: visible, near-infrared, and short-wave infrared (VIS, NIR, and SWIR). The multispectral images, which include mainly red-green-blue (RGB) and NIR bands, have proven to be useful in many agricultural applications. However, the multispectral images lack the spectral range and precision to profile materials that only hyperspectral sensors can, using over a hundred narrow spectral bands [6].

This summary, focuses on passive hyperspectral sensors and their application for mapping canopy chemical traits and composition in precision agriculture. The main difference between hyper- and multispectral sensors (the latter having 3-10 spectral bands) is the number of bands and their bandwidth [8]. Imaging spectroscopy sensors acquire images across many narrow contiguous spectral bands, mainly throughout the 400-2500 nm spectral region, providing spectral information on the observed surfaces [9], [10]. These can capture a range of absorption features or wavelengths related to leaf or canopy chemistry [11]. Important canopy chemical traits include chlorophyll (a and b), carotenes that capture light and photosynthetic activity, canopy water content, nitrogen required for carbon fixation, and nutrients such as phosphorus (P), calcium (Ca), magnesium (Mg) and potassium (K) that regulate growth. Nonstructural carbohydrates (NSC) generated in leaves, composed of sugars and starch, may subsequently be transformed into cellulose and lignin to support plant cell structure, can also be identified using imaging spectroscopy [12]–[14].

Hyperspectral sensors were initially developed for satellites, later to be mounted on aircrafts. There is a tradeoff in the platform selection, as aircraft platforms are costly and limited in availability, and have complicated logistics, but have a high spatial resolution enable of trees canopies identification, while hyperspectral satellites usually have coarse spatial resolution [15]. Recently, Unmanned Aerial Vehicles (UAVs) have emerged as a popular and cost-effective technology composed of aerial platforms capable of carrying small-sized, lightweight sensors [16]. Meanwhile, technology developments of hyperspectral sensors have resulted in smaller and lighter sensors that can now be integrated into UAVs for either scientific or commercial purposes [15]. Imaging spectroscopy sensors that have been used to detect canopy chemical traits and composition include the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), Compact Airborne Spectrographic Imager (CASI), Hyperion, Carnegie Airborne Observatory (CAO), Airborne Imaging Spectroradiometer for Applications (AISA), and HyMap [17]. Recently, several hyperspectral that were used to detect canopy chemical traits and composition sensors have become commercially available for UAV systems [18]. However, the drawback of using the imaging spectroscopy approach, even

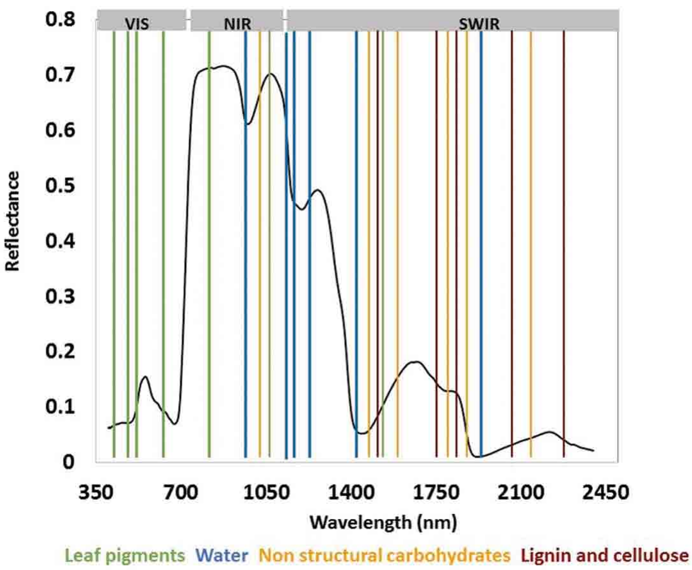


Figure 1. Example of plant spectral signatures along with the location of diagnostic wavelengths of canopy traits including leaf pigment (green), water (blue), nonstructural carbohydrate (yellow), and lignin and cellulose (red).

using state-of-the-art sensors, stems from cost-benefit considerations, usually due to high cost, poor accessibility, and high qualifications and skills required in processing and handling the large and complex datasets that are generated [1].

## MAPPING PLANT CHEMICAL TRAITS

Over the past 20 years, a large and growing body of literature has discussed the use of imaging spectroscopy to quantify pigments and non-pigment chemicals in plant canopies [e.g., 19]. Imaging spectroscopy has been used for mapping photosynthetic pigments that usually include chlorophylls a and b, and several carotenoid pigments [20]. Mapping pigments usually includes wavelengths in the spectral range of 300-900 nm, covering the necessary pigment signals at the red, NIR, and red-edge regions [21]. Quantifying pigment content from remotely sensed data advances the understanding of photosynthetic processes, such as light regulation, photooxidation, and chlorophyll fluorescence, providing insight into the condition of the plants [11]. Mapping non-pigments mostly includes wavelengths in the NIR and SWIR regions, from 700-2500 nm, for the detection of water, nitrogen, cellulose, and lignin [19]. Figure 1 shows an example of significant chemical pigment and non pigment signals in a plant spectral signature. Imaging spectroscopy offers opportunities for example to detect of plant diseases, before any visual symptoms appear, and later on mapping of the severity of infection by pathogens or insects [22], [23]. The reflectance signal is affected by changes in leaf structure due to alteration in the chemical composition of plant tissues that are highly pathogen-specific as well as fungi-specific that produce unique fungal structures on the leaf surfaces. For example, Zarco-Tejada et al. [24] used imaging spectroscopy for *Xyllella fastidiosa* detection, which is one of the most dangerous plant bacteria worldwide. The study demonstrated that changes in chemical traits retrieved from airborne imaging spectroscopy could reveal *X. fastidiosa* infection in olive trees even before symptoms are visible, by using physiological traits related to rapid changes in photosynthetic pigments, with more than 80% accuracy. Thus, remote detection of canopy chemical traits could become a critical component of the prevention and management of diseases in the agricultural systems.

## MAPPING CANOPY COMPOSITION

Imaging spectroscopy can detect differences in the reflectance signal resulting from unique plant chemical trait, and capture small differences in reflectance patterns among plant species [17] [25][26]. Species composition maps allow identification of invasive species, species composition, and development of agricultural segmentation at the landscape scale. Numerous case ↘

→ studies of successful plant-species detection using imaging spectroscopy have been documented for exotic and invasive plant species [27], [28]. Paz-Kagan et al. [29] used imaging spectroscopy to study two highly invasive plant species (IPS), *Acacia salicina* Lindl. and *Acacia saligna* (Labill.) H.L.Wendl.f in Israel. These two species, which spread over large areas of the coastal plain of Israel, create dense clusters of trees with yellow flowers that bloom in the late winter to early spring (Figure 2). Integration of hyperspectral data with multispectral data enables detection of invasive plant species at the landscape scale (100 $km^2$), and helps in understanding the mechanisms underlying successful invasions. This integration was achieved using species distribution maps developed by Paz-Kagan et al. [30], based on high spatial and spectral resolution airborne imaging spectroscopy data to calibrate multispectral satellite data. Detecting the flowers of invasive plant species, using a specific phenological (life cycle) timing of species, improved detection, and reduced the high spectral resolution requirements for plant species identification. Here, imaging spectroscopy was used to identify the invasive plant species based on a leaf signal, whilst multispectral satellite data further reinforced the identification of the species utilizing a flowering signal. Monitoring the flowering signal is also an essential task from an agricultural point of view, for timing pollination, crop ecophysiology monitoring, and yield prediction [31].

## FUTURE APPLICATIONS

Imaging spectroscopy provides dynamic information, increasingly relevant to the development and expansion of precision agriculture [32][33]. However, there are limitations and challenges of imaging spectroscopy in canopy chemical traits and composition mapping. The availability of imaging spectroscopy data is still limited and expensive and has a low temporal resolution. Hyperspectral data accumulate, but their analysis requires expertise in data processing, computing capabilities, algorithms, and software development. The new developments of small hyperspectral sensors with UAS platforms that are now entering the market for agricultural applications would quicken and enhance the wider developments of precision agriculture [15]. In addition, the upcoming hyperspectral satellite missions, such as the Environmental Mapping and Analysis Program (EnMAP)[34], the Italian hyperspectral mission PRISMA[35], and an Italian-Israeli hyperspectral orbital mission SHALOM [36], will enable temporal and spatial monitoring of agricultural systems in Israel [37]. New sensors with high temporal and spectral resolutions, soon to be marketed, will become an integral part of monitoring, tracking, and predicting the status of agricultural areas. It is expected that the current trend in development of user-friendly sensors of increasing quality will continue, to eventually allow the application of imaging spectros-

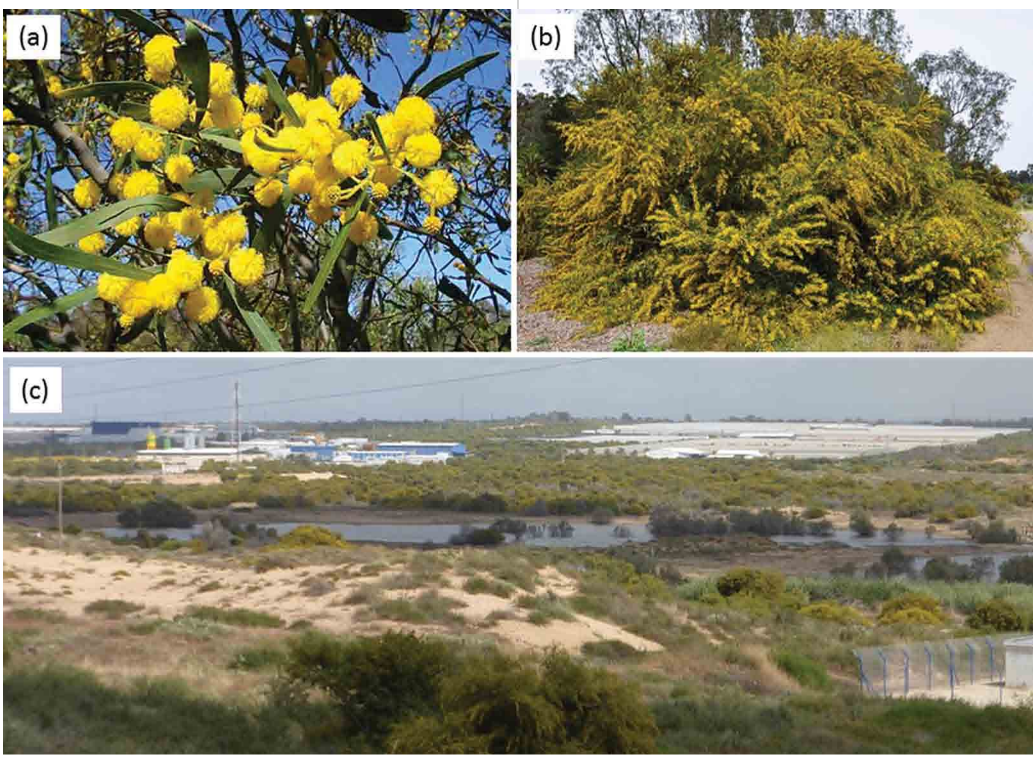


Figure 2. Acacia saligna flowering branch (a); Acacia saligna during the flowering stage - flowering canopy (b); expansion of the A. saligna invasive species in the study area (c)[29].

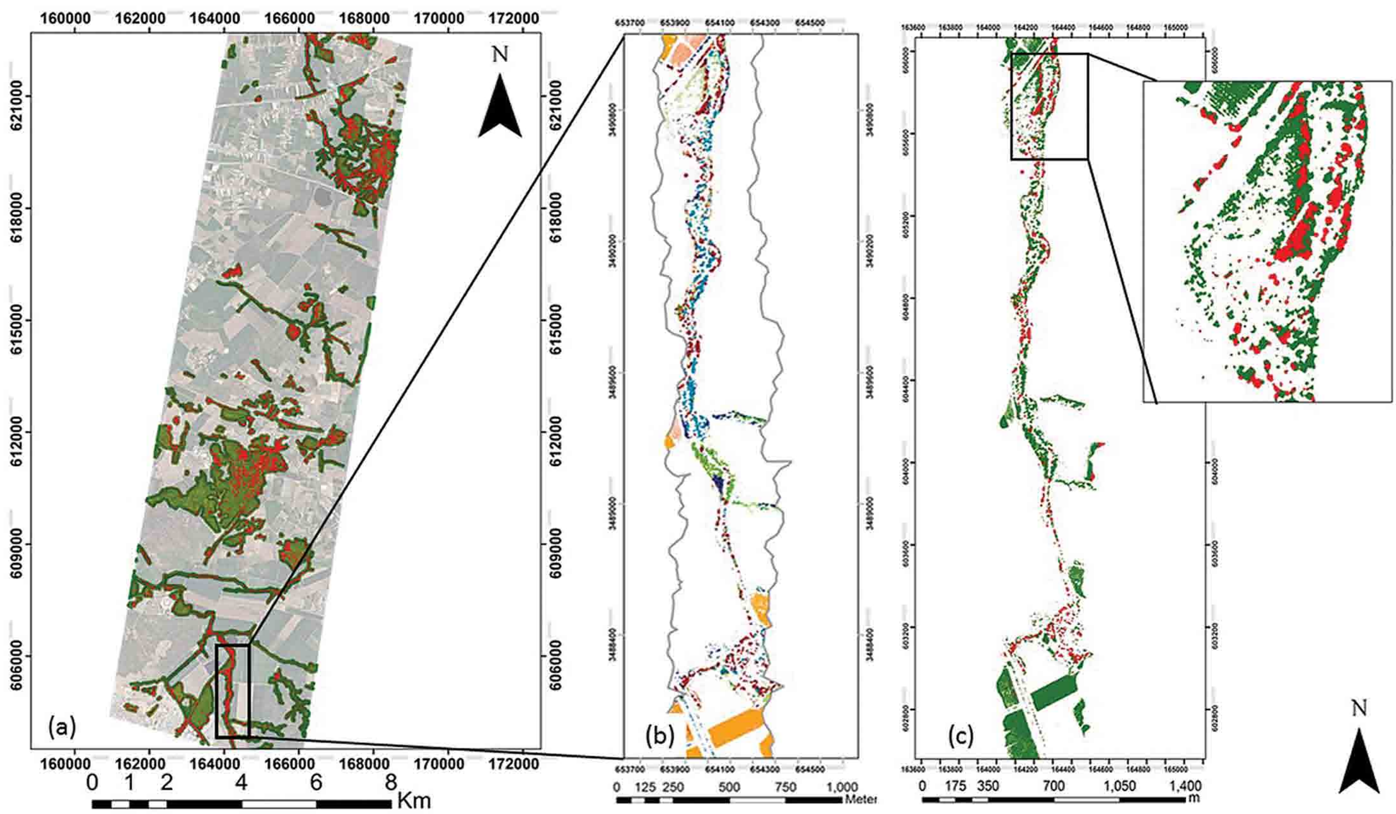


Figure 3. The Acacia invasion plant species distribution (IPS) map based on WorldView-2 imagery (a), zoomed for the Dorot species distribution map and IPS maps (b, c). The green color represents the potential invasion area, and the red color represents the location of Acacia trees [29]. The colors in (b) are related to the different plant species their full names are specified detailed in [30].

copy for operation by non-expert users. Although not yet within reach, the ultimate goal should be a fully automated pipeline for imaging spectroscopy data, including data preparation and execution (calibration of sensors, ground control measurements, and the execution itself), data processing and interpretation for developing spatial decision-support systems for sustainable agricultural management.

## CONCLUSIONS

Three decades of imaging spectroscopy have demonstrated the potential benefit of its application to remote sensing techniques, for an improved understanding of plant canopy chemical traits and composition. High spectral and spatial resolution can allow estimation of plant biochemical and phylogenic conditions in the canopy, monitor plant stress, identify diseases and mortality, and monitor invasive species and species composition, which are essential considerations for optimal agricultural system management. Imaging spectroscopy and other applications will reinforce the importance of remote sensing in future agricultural management. Remote sensing applications can facilitate decision-making associated with agricultural production, as well as assist government policy decision-making related to climatic and environmental challenges, and for national agricultural management. ❑

## ACKNOWLEDGMENT

I thank my colleagues Prof. Arnon Karniel, Micha Silver, Natalya Panov, from Ben-Gurion University, for the excellent collaboration in mapping *Acacia salicina* and *Acacia saligna* in Israel.

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# Estimating Crop Water Consumption Using a Time Series of Satellite Imagery

By Dr. Offer Rozenstein and Dr. Josef Tanny

**EMPOWERING DATA-DRIVEN FARMING**

**We are using the latest innovations in satellite remote sensing to estimate crop water use and provide timely and consistent feedback to farmers. This information is crucial for efficient irrigation management and can inform practices that increase agricultural productivity and sustainability from small to large scales.**

**BACKGROUND**

Monitoring changes in the status of soils and crops in agricultural fields throughout the growing season is key to increasing production efficiency. As the crop develops from seedling to a fully mature plant, its transpiration changes accordingly, and so do its water requirements. Early in the growing season, the majority of the evapotranspiration, which represents the combined water loss due to evaporation from the soil surface and transpiration from the crop, is attributable to soil evaporation. Yet, as the crop develops, the relative contribution of transpiration to evapotranspiration increases as the vegetation cover increases, and eventually declines with maturity and senescence. Therefore, information about daily crop evapotranspiration can facilitate better irrigation planning and, ultimately, increase water use efficiency.

The crop coefficient, which represents the crop water demand, is a useful and widely applied approach to irrigation management. The United Nations' Food and Agriculture Organization (FAO) has provided details on the development and use of the crop coefficient, for different crops in different parts of the world. However, these crop coefficients have been shown to vary among sites and seasons. Additionally, in cases of atypical crop development and water-use patterns caused by weather anomalies, adopting the FAO-recommended crop coefficient values often results in imprecise crop water use estimations. As a result, local adaptations to the FAO-recommended crop coefficient are implemented to form local coefficient tables, but even these sometimes fail to capture deviations from standard conditions due to variations in fertilization, planting density, and stress factors. In addition, the spatial variation in crop water use due to spatial heterogeneity in soil characteristics, such as water holding capacity and nutrient availability, is not reflected in standard coefficient tables. Accordingly, in the absence of reliable, real-time information about crop water use, there is a need for better crop coefficient estimates.

One approach to address this need is satellite remote sensing imagery. This technology is attractive for modelling crop water use because it provides a synoptic coverage at fixed time intervals, and can therefore monitor changes over time. Moreover, spectral indicators derived from remote sensing imagery are highly correlated with crop characteristics including biomass, Leaf Area Index (LAI), plant height, and yield. Similarly, these spectral indicators can serve as near-real-time surrogates for crop water use since they depict a similar temporal pattern. The reason is that both plant transpiration and light absorption increase roughly at the same rate throughout the growing season. In order to model the crop water consumption with satellite observations, we are performing evapotranspiration measurements in the field on the same days as the satellite overpass occurs.

The basic limitation of satellite remote sensing application for irrigation management is the compromise between the revisit interval of the sensor and spatial resolution. Sensors with a short revisit interval, such as the moderate-resolution imaging spectroradiometer (MODIS) that provides daily coverage, are characterized by a coarse spatial resolution (>250 m), whilst sensors with medium spatial resolution, such as the Landsat series, are characterized by longer revisit intervals (16 days). Cloudy conditions further reduce the temporal resolution for all optical sensors, thus posing another limitation on operational applications. Irrigation management decisions for field crops should ideally be based on a dense interval series of imagery that are fine-grained enough to distinguish between field plots. Commercial high spatial resolution satellite sensors are usually not employed for crop monitoring because their imagery is not public domain and comes at a significant cost, rendering them too expensive for most operational agricultural applications. Therefore, in spite of remote sensing models for crop water consumption, the limited availability of imagery with suitable temporal and spatial resolutions at no or low cost hindered the development of worldwide remote sensing applications for near-real-time irrigation decisions.

The successful recent deployment of the two Sentinel-2 satellites creates a unique opportunity for operational crop water consumption estimates. Sentinel-2 multispectral spaceborne imagery with a 5-day revisit interval (obtained by the combination of Sentinel-2A and Sentinel-2B data) can potentially create a dense observation interval series at 10-20 m spatial resolution, which would allow the application of this technique even for small fields. Sentinel-2 imagery offers an acceptable compromise between the revisit interval and spatial resolution, with increased spectral abilities for vegetation monitoring compared to previous public domain spaceborne imagery. Hence, the overreaching aim of this research was to develop methodology to estimate cotton water consumption based on Sentinel-2 imagery. The key objectives of this study were to (1) estimate daily crop water consumption experimentally in the field, and (2) develop empirical models that link crop water consumption with remotely sensed spectral indicators from Sentinel-2.

**METHODS**

The measurements took place during the summer of 2016 in a cotton field near Gedera, in the Shefela (Lowland) Region in Israel. Direct measurements of actual crop evapotranspiration were done by an eddy covariance system that measures at high frequency the water vapour concentration together with the wind speed and direction (Fig. 1). A total of seven relatively cloud-free Sentinel-2A images acquired during the cotton-growing season were analysed in this study, including five images that coincide with our agro-meteorological field measurements. We calculated 22 vegetation indicators based on different combinations of the unique Sentinel-2 spectral bands. We then checked to see which of these spectral indicators is most related to the crop ↘

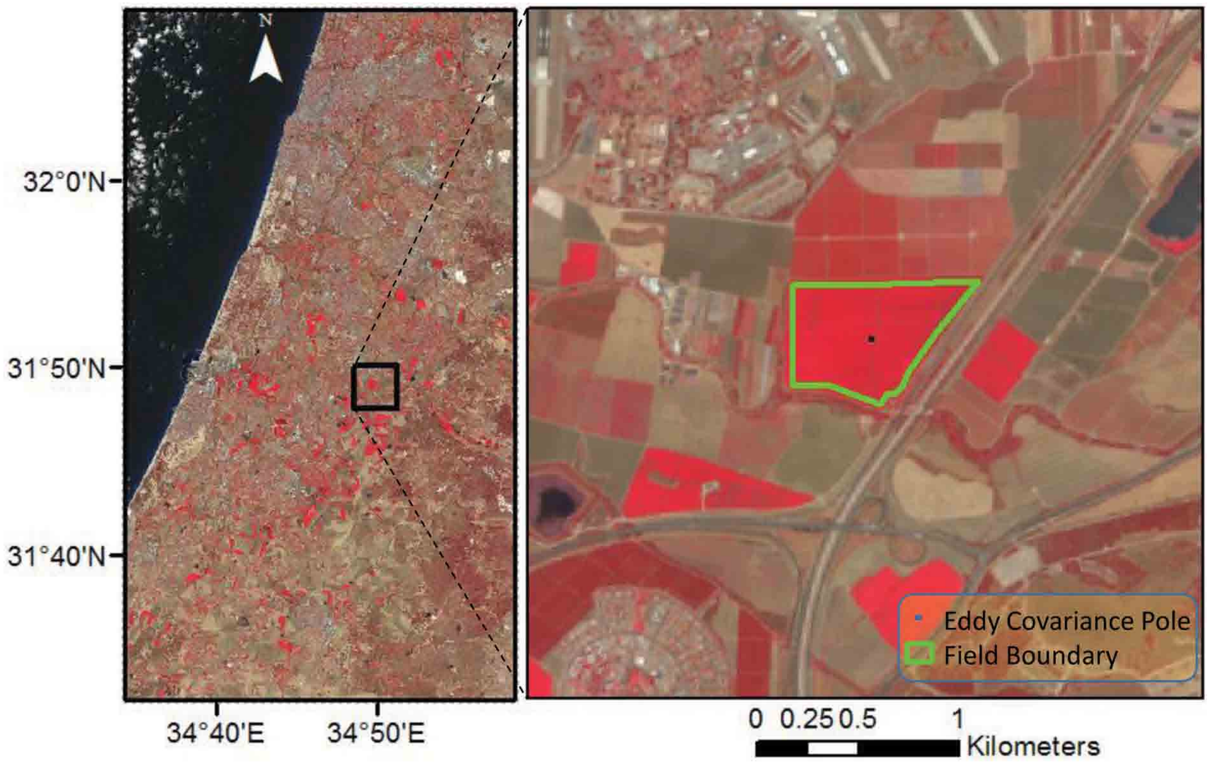


Figure 1. Left: Sentinel-2A false color regional image (RGB = bands 8,4,3) acquired on 25 July 2016. The black square represents the footprint of the image on the right, showing a magnification of the area around the study site.

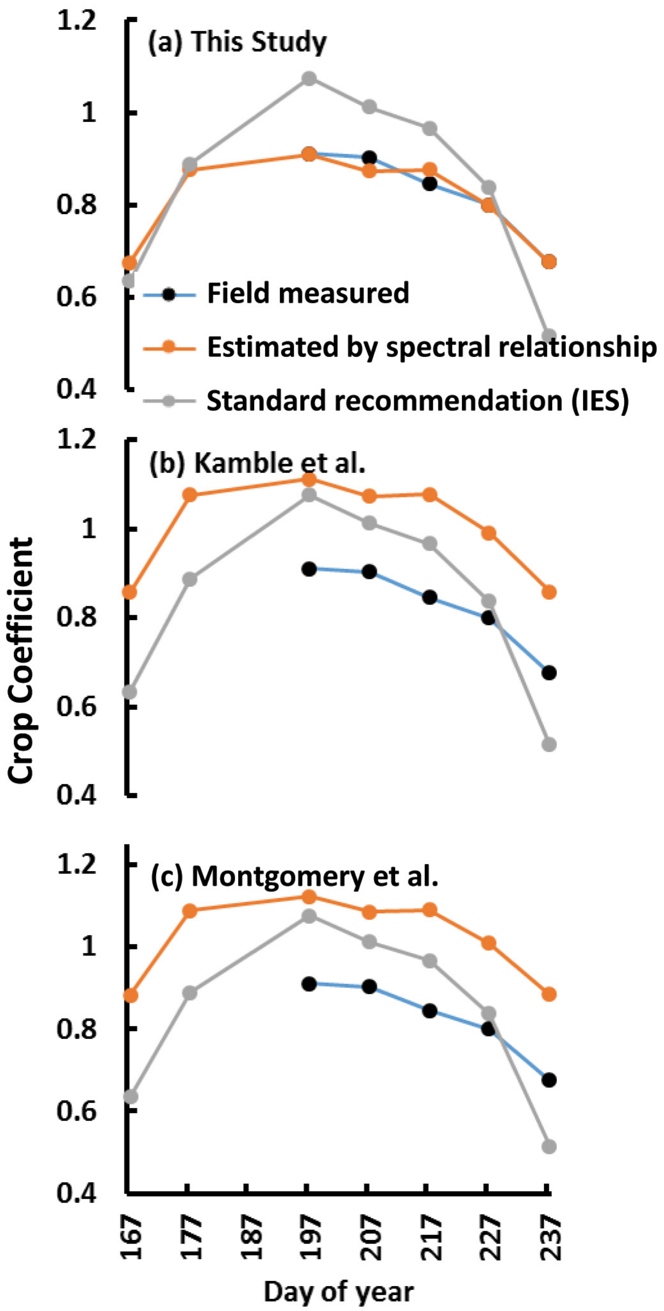


Figure 2. Field-measured water consumption for cotton in this study, and the standard recommendation by the Agricultural Extension Service of Israel (IES) for cotton growers in the Shefela, compared to estimates according to three models: (a) The model developed in this study; (b) Kamble et al. (2013); (c) Montgomery et al. (2015).

→ coefficient based on our field measurements of crop water consumption. In order to compare our findings with previous studies we estimated the crop coefficient according to relationships found in previous studies between the crop coefficient and a spectral indicator, and to the standard crop coefficient recommendations by the Agricultural Extension Service of Israel.

## RESULTS

We found that most of the spectral indicators can be used to estimate the crop coefficient, but that the three best ones rely on the red-edge spectral bands, which are unique to Sentinel-2. For the particular field in our study, the relationships that were found in other studies between spectral indicators and the crop coefficient grossly overestimated the crop water consumption that we measured in the field. The Agricultural Extension Service recommendation was also higher than the crop coefficient derived from the measured crop water consumption (Fig. 2).

## CONCLUSION

Sentinel-2 data are superior to older generations of public domain satellite data in terms of spatial, temporal and spectral resolutions. This allows, for the first time, to estimate crop water consumption, an important parameter for irrigation management, at a high frequency that can support irrigation decisions, at a fine spatial resolution of 10 m that well captures within-field variability, and at higher accuracy than before, owing to the unique spectral bands of the sensor that cover the red-edge region. ❑

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His major fields of research are agricultural meteorology and environmental physics. In recent years Dr. Tanny has specialized in measuring and modeling crop evapotranspiration, and evaporation from water bodies, using advanced micro-meteorological methods and a variety of models. Dr. Tanny's research is also focused on microclimate and crop water use in protected cultivation systems like screenhouses and greenhouses.

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# Robotics, autonomous systems and smart automation in agriculture

By Prof. Avital Bechar

**ABSTRACT**

**Fundamental and applied research in robotics for agriculture, human-robot collaborative systems and sensor technologies has been conducted in the Agricultural Robotics Laboratory. The goal is to develop new concepts and approaches for the operation and development of agricultural robots. These are to be applied in an ongoing research, such as selective tree pruning by human–robot systems, autonomous spraying in greenhouse specialty crops, early disease detection, and real-time, accurate yield assessment and plant status evaluation.**

Agricultural productivity has increased significantly over the years as a result of intensification, mechanization and automation (Zhang, 2013). In the 20th century, technological progress in developed countries reduced the manpower traditionally available for farming activities by a factor of 80 (Ceres et al., 1998). Automation has considerably increased the productivity of agricultural machinery by increasing efficiency, reliability, precision, and reducing the need for human intervention. However, agriculture still lacks trained workers. The challenging situations generated by the absence of workers are amplified by the trend toward increased farm size, decreased numbers of farmers and increased environmental impact of food production, requiring even more efficient agricultural practices (Nagasaka et al., 2004). The productivity of conventional farming, in which crop cultivation and management are manually conducted by farmers, can be significantly improved by using intelligent machines (Xia et al., 2015).

Robots are perceptive machines that can be programmed to perform specific tasks, make decisions, and act in real time. They are required in various fields that normally call for reductions in manpower and workload, and are best-suited for applications requiring repeatable accuracy and high yield under stable conditions (Holland and Nof, 2007). However, they lack the capability to respond to ill-defined, unknown, changing, and unpredictable events. The design of autonomous robotic systems frequently faces two important challenges. The first deals with the non-linear, real-time response requirements underlying sensor–motor control formulations. The second deals with how to model and use the human approach to address each different situation (Ng and Trivedi, 1998).

Unfortunately, unlike industrial applications which deal with relatively simple, repetitive, well-defined and predetermined tasks in stable and replicable environments, agricultural applications for automation and robotics require advanced technologies to deal with complex and highly variable environments and produce. Furthermore, agricultural production deals with live produce (fruit, vegetables, grains and flowers) which is highly sensitive to environmental and physical conditions (Eizicovits and Berman, 2014), such as temperature, humidity, gas, pressure, abrasion and acceleration. Such produce requires gentle, accurate and often complicated handling operations to maintain sufficient quality to travel the distance and time separating their production site from consumers. This situation makes the replacement of human ability by machines or automation extremely challenging and still today most fruit, vegetable and flower growing and production tasks, including trellising, harvesting, sorting and packaging, etc. are still performed manually. Manual labor is a major cost component in field operations, reaching up to 40% of the total cost (Bechar and Eben-Chaime, 2014) and the high manual-labor requirement impedes cost reductions and increases the demand for robotics and automation.

Most agricultural operations occur in unstructured environments characterised by rapid changes in time and space, similar to military, underwater and space environments (Bechar and Edan, 2003). The terrain, vegetation landscape, visibility, illumination, and other atmospheric conditions are ill-defined, vary continuously, have inherent uncertainty, and generate unpredictable and dynamic situations (Bechar, 2010). Figure 1 illustrates the influence of sun direction and illumination on the visibility of pepper rows in greenhouses. Complexity increases when dealing with natural objects, such as fruits and leaves, because of high variability in shape, texture, colour, size, orientation and position which, in many cases, cannot be determined a priori.


Figure 1. Pictures of an aisle between two pepper rows in a greenhouse taken from a robotic platform at five different times of day (Dar et al., 2011).

Research on autonomous systems and robotics in agriculture started in the early 1960s, focusing mainly on the development of automatic steering systems (Wilson, 2000). In the 1990s, the overwhelming majority of mechanical operations in field-crop farming involved heavy, powerful and high-capacity machines, characterised by high-energy demands and handling and operating costs. However, in the new millennium, research at various universities and research institutions around the world has undergone a complete paradigm shift. The automation of agricultural robots is essential for improving work efficiency and should include the potential for enhancing the quality of fresh produce, lowering production costs and reducing the drudgery of manual labour (Choi et al., 2015).

**LIMITATION, INCENTIVES AND CONDITIONS FOR ROBOTIC SYSTEMS IN AGRICULTURE**

Cultivation and production processes are complex, diverse, labour-intensive and usually unique to each crop and the wide variety of agricultural productions and their diversity worldwide make it difficult to generalise applications for automation and control (Schueller, 2006).

The technical feasibility of agricultural robots for a variety of agricultural tasks has been widely validated. Nevertheless, despite the tremendous amount of research, commercial applications of robots in complex agricultural environments are not yet available (Urrea and Munoz, 2015). The main causes for these failures were excessive cost of the developed system, its inability to execute the required agricultural task, low durability of the system, and its inability to successfully reproduce the same task in slightly different contexts or to satisfy mechanical, economic and/or industrial aspects. In addition, most approaches were adapted from an industrial point of view. The usage of robotics in agriculture has to comply with the following rules (Bechar and Vigneault, 2016):

i. The capricious requirements for manipulating specific produce must be considered first.

ii. The agricultural task and its components must be feasible using the existing technology and the required complexity.

iii. The cost of the agricultural robotics alternative must be lower than the expected revenue. It need not be the most profitable alternative.

The main limiting factors lie in production inefficiencies and lack of economic justification. Development of an agricultural robot must include the creation of sophisticated, intelligent algorithms for sensing, planning and controlling to cope with the difficult, unstructured and dynamic agricultural environment (Edan and Bechar, 1998).

Agricultural robots require the development of advanced technologies to deal with complex and highly variable environments and produce (Nof, 2009). In addition, the seasonality of agriculture makes it difficult to achieve the high level of utilisation found in industrial manufacturing. However, even if the technical and economic feasibility of most of the field robotics applications is not reached in the near future using the existing knowledge and technologies, partial autonomy will add value to the machine long before autonomous production robots are fully available. For many tasks, the Pareto principle applies. It claims ↘

→ that roughly 80% of a task is easy to adapt to robotics and/or automation, but the remaining 20% is difficult. Therefore, by automating the easy parts of a task, one can reduce the required manual work by about 80%. Intervention of human operators in the operations loop generally improves the performance of the global system by increasing guidance accuracy, enhancing target identification, shortening processing time, reducing system complexity, and handling unknown and unpredictable events that fully autonomous systems cannot deal with (Bechar et al., 2009). Introducing a human operator (HO) into the operations cycle to interact with, instead of just supervising the system, is a relatively new trend in agricultural robotics research, which can help improve performance and reduce system complexity. By taking advantage of human perception skills and the accuracy and consistency of the autonomous system, the system is simplified, resulting in improved performance and reduced cost.

Furthermore, the development of partially autonomous robots is an excellent transitional path to developing and experimenting with software and hardware elements that will eventually be integrated into fully autonomous systems.

Although limited in number, some robotics applications are now commercially available. These applications were implemented step-by-step, resulting in good performance of some dedicated tasks. Examples include milking robots (Kolbach et al., 2013) and autonomous combines or tractors (Schueller, 2006). The implementation process for the development of these first autonomous robots has indicated that the drawbacks and inefficiencies require solutions that use the advantages of the human to enable the robot to react and cope with dynamic and complex conditions, thus, incorporate collaborative human–robot systems, at least for a while (van Henten et al., 2013).

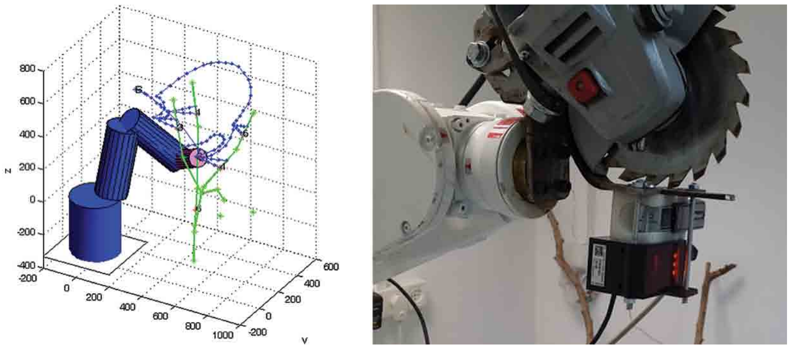

Figure 2. Left: calculation of optimal trajectory, right: Visual servoing end-effector system (Bechar et al., 2014)

## AGRICULTURAL ROBOTS AND AUTONOMOUS SYSTEMS RESEARCH AT THE A.R.O.

In the Agricultural Robotics Laboratory (ARL) of the Institute of Agricultural Engineering, we conduct fundamental and applied research in robotics for agriculture, human-robot collaborative

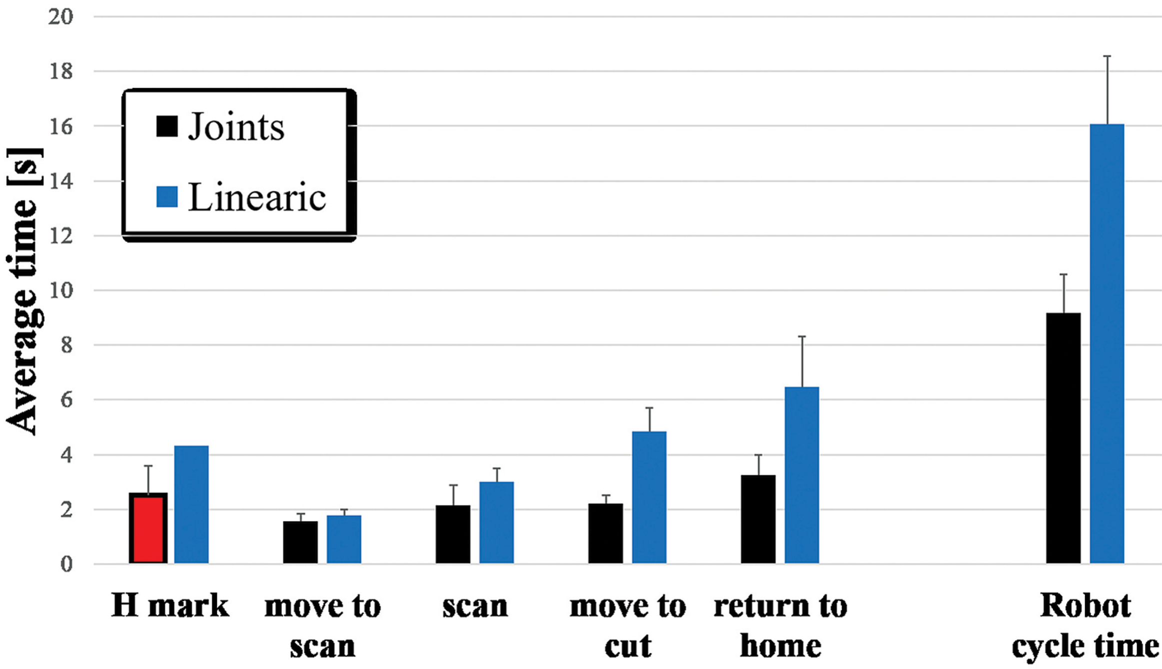


Figure 3. Amount of time for different movement stages in the linear movement and robot joint space.

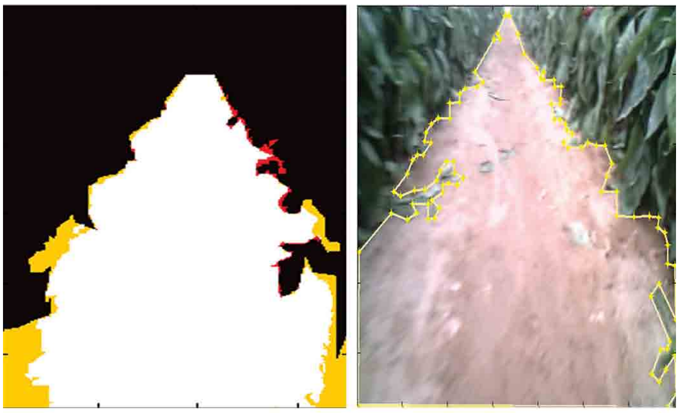

Figure 4. An autonomous sprayer.

systems, sensor technologies and in developing new concepts and approaches for the operation and development of agricultural robots.

In ongoing research, selective tree pruning by human–robot systems (HRS) is being developed (Bechar et al., 2014), and a visual servoing methodology and human-robot system for selective tree pruning has been tested. The system consists of a manipulator, a color camera, a single-beam laser distance sensor, a human–robot interface (HRI), and a cutting tool based on a circular saw specifically developed for this task. The cutting tool, the camera and the laser sensor are mounted on the end effector of the manipulator, aligned parallel to each other (Figure 2 right). The system works in two phases. Firstly, the camera transfers a 2D image of the tree to a HO, who marks the branches to be removed on a screen. Secondly, the system works in autonomous mode. The manipulator manoeuvres the laser sensor to measure the branch distance and calculates an optimal trajectory in 6-dimensional configuration space to the cutting point (Figure 2, left) and using image processing techniques to evaluate the branch orientation. Then, it follows the trajectory to perform the cut.

An experiment with 21 subjects operating the human-robot system was conducted in the laboratory to evaluate the system performance and optimal concept of operation. The results indicate that the average cycle time was 9.2 s per branch (Figure 3) for motion planning in the robot joint space and returning to the home position after performing the cut. The cutting point accuracy was between 8-22 mm from the point marked by the human operator and the branch orientation accuracy was 9.4 degrees on average and median of 5.75 degrees.

In other research, an autonomous system was developed and mounted on a commercial sprayer (Figure 4) for a selective spraying task in greenhouses. An adaptive vision algorithm was developed to detect and follow the aisle between two pepper rows. The algorithm used a classification and regression tree (CART), a decision tree to classify images from a RGB camera and create an adaptive unique feature (detection algorithms) for the current conditions in the greenhouse. The algorithm was tested on different plots and under different conditions, and achieved a detection performance of 92%.

Robotic systems for disease detection in greenhouses are expected to improve disease control, increase yield, and reduce pesticide application. The system under development is based on red, green, blue (RGB) hyperspectral and multispectral cameras and a laser beam sensor mounted on a 6-degrees- of-freedom robotic manipulator, which facilitates reaching multiple detection poses. Several detection and classification algorithms have been developed based on color and morphology, using classical image analysis methods, principal component analysis, linear discriminant analysis, coefficient of variation, and machine-learning algorithms such as deep learning. The system identified powdery mildew and tomato spotted wilt virus (TSWV) in pepper plants, with detection rates of 95% and 90%, respectively (Schor et al., 2016), at an average cycle time of 26.7 s per plant (Figure 5).

Yield assessment is a major need in various crops. We are developing a multi-frequency sonar-based technology to evaluate the yield and plant status (in manner of the number of leaves). Sonar technology has three outstanding advantages: (1) it enables accurate distance measurement; (2) it penetrates into the foliage and thus provides information from the inner parts of the plant; (3) wide-band sonar enables the extraction of acoustic information about different textures. Sonar technology thus allows sensing the entire plant or tree, including its inner and outer parts, without the need to evaluate or extrapolate hidden fruit or to conduct just a sample scan. This technology could also provide a yield map at the plant level.

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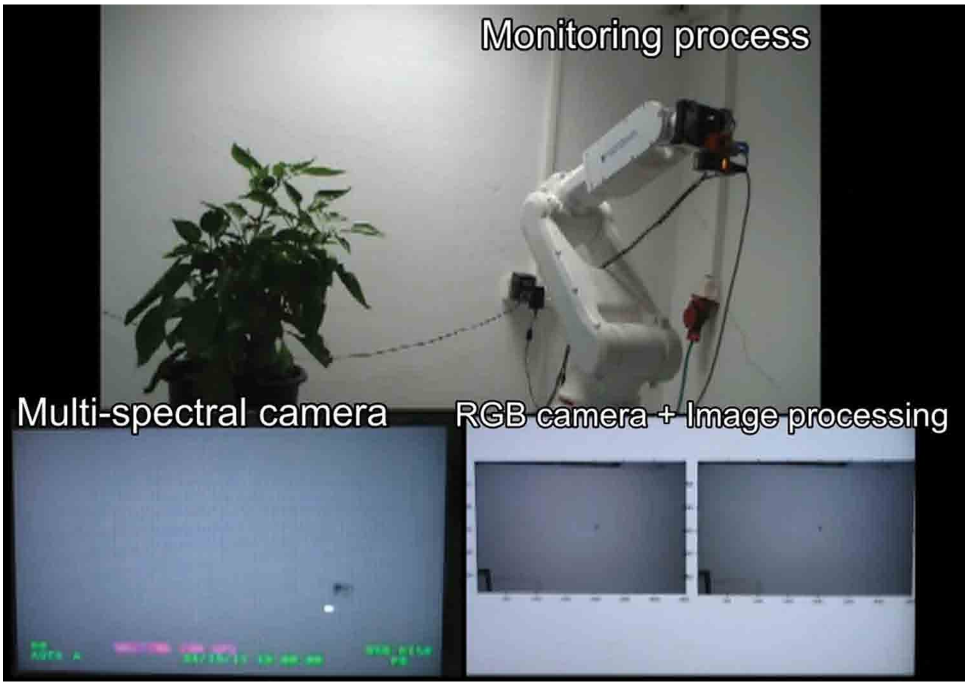


Figure 5. Laboratory experiment of a disease-monitoring robot.

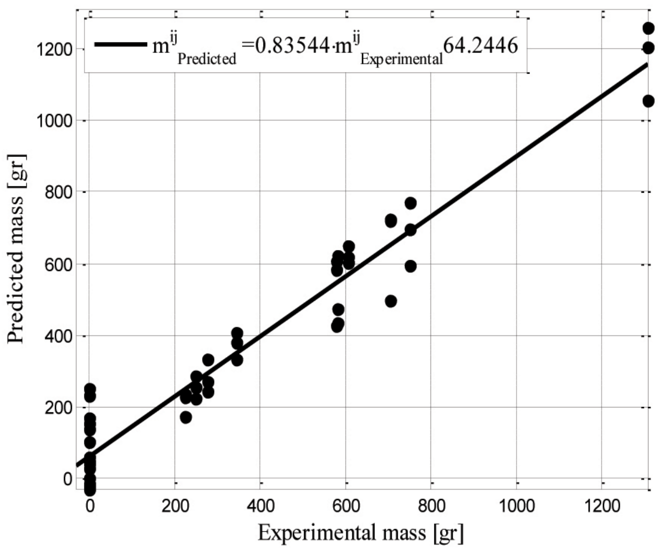


Figure 6. Neural network prediction of fruit mass.

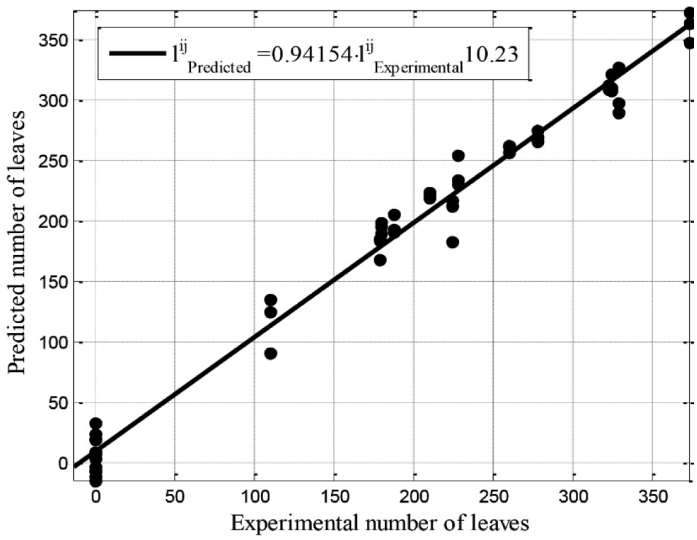


Figure 7. Neural network prediction of number of leaves.

→ In preliminary experiments conducted in a greenhouse environment, we were able to distinguish among various objects, such as a plant and a wall/screen and, in addition, detect the end of a crop row and to evaluate the amount of leaves and fruits on the plants. An algorithm was developed to evaluate the coverage of leaves on pepper plants and fruit yield, based on the acoustic signature of the echoes. The performance was very high, reaching accuracies of 100 gr and 30 leaves per plant in the assessment of fruit and leaves (in comparison to the real values) with correlation values R2 of 0.86 and 0.95 (Figures 6 and 7). ❑

***ACKNOWLEDGMENTS***

*I thank my colleagues Itamar Dar, Guy Lidor, Roee Finkelstein, Rafi Regev, Aharon Hoffman, Zeev Schmilovitch, Victor Bloch, Ron Berenstein, Aviv Dombrovsky and Yigal Elad of the A.R.O., Yossi Yovel from Tel Aviv University and Yael Edan and Sigal Berman from Ben-Gurion University for the excellent collaboration.*

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# Tensor-Based Segmentation of a 3-D Plant Model, the Next Step Toward Robust Weed Detection and Accurate Organ Level Growth Analysis

By Dr. Ran N. Lati, Bashar Elnashef and Sagi Filin

**Analyses of the geometrical shape of plants is of great value for many precision agriculture purposes. Among them is the estimation of growth parameters which provide the basis for biological modeling and site-specific weed management. With today's rapid increase in computational power, 3-D modeling has become an attractive means for providing detailed 3-D plant models. Nonetheless, the existing modeling approaches are limited in the number of species and growth stages that can be handled, and do not address advanced parameter analysis at the organ level, such as leaf size and stem length. Organ-level analysis of 3-D data is a complex process that requires preliminary segmentation of the 3-D point cloud into leaf- and stem-related points. Despite their importance, only a few segmentation models have been reported, and many studies still perform this task manually. This paper presents a novel data-driven segmentation model as a basis for organ-level plant analysis. Application of this model to a variety of species at different growth stages has given accurate segmentation results regardless of plant morphology and growth stage. An accurate, nondestructive, and autonomous organ-level phenotyping ability, such as the one described here, may be useful for precise weed management and other precision agriculture purposes.**

Weeds are recognized as the main biotic factor that limits crop production worldwide. Most conventional weed management is based on broadcast herbicide application. Increased environmental concerns have led to great pressure on agricultural producers to reduce herbicide use. This requires the adoption of novel yet practical agricultural solutions to manage weeds efficiently while reducing herbicide use. Site-specific weed management (SSWM) aims to reduce herbicide usage by monitoring weed location within the field and targeting the application to infested areas exclusively. Approaches such as weed/crop shape, texture, area, or reflectance-based differentiations have been evaluated for weed detection and mapping. Yet, lack of robust detection technology is recognized as the limiting factor to commercial development of SSWM. In this regard, image-based 3-D reconstruction models may offer thorough information about plant geometry along with accurate whole-plant morphological parameters such as height and biomass estimations. 3-D models were successfully used for weed detection, but were less effective for weeds growing in the crop row (intra-row) with overlapping canopies. Such scenarios call for a more detailed analysis that includes organ-level parameters, such as leaf shape and size. However, if an organ-level analysis is the objective, a preliminary step, in which the 3-D points are segmented into leaf- and stem-related points, must be performed. Organ-level segmentation models are few, most likely because of the shape complexity of plant morphologies and the resulting point clouds that depict them. The major objective of our study was to develop a segmentation model to classify plant organs out of an image-based point cloud as a basis for organ-level morphologi-

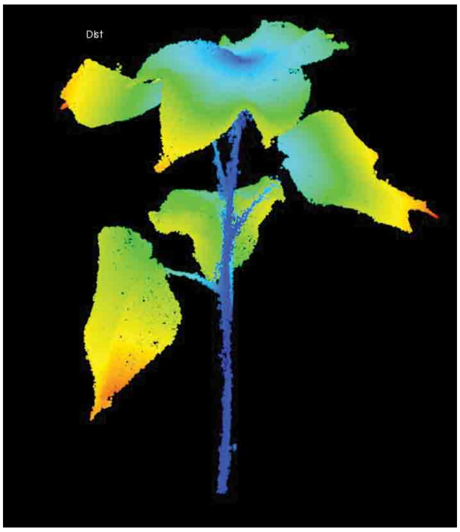


Figure 1. Tensor map that demonstrates feature-saliency. Points with high surfaces are displayed in light hues (orange-to-green), while points with low surfaces (stem-related) are displayed in dark blue hues.

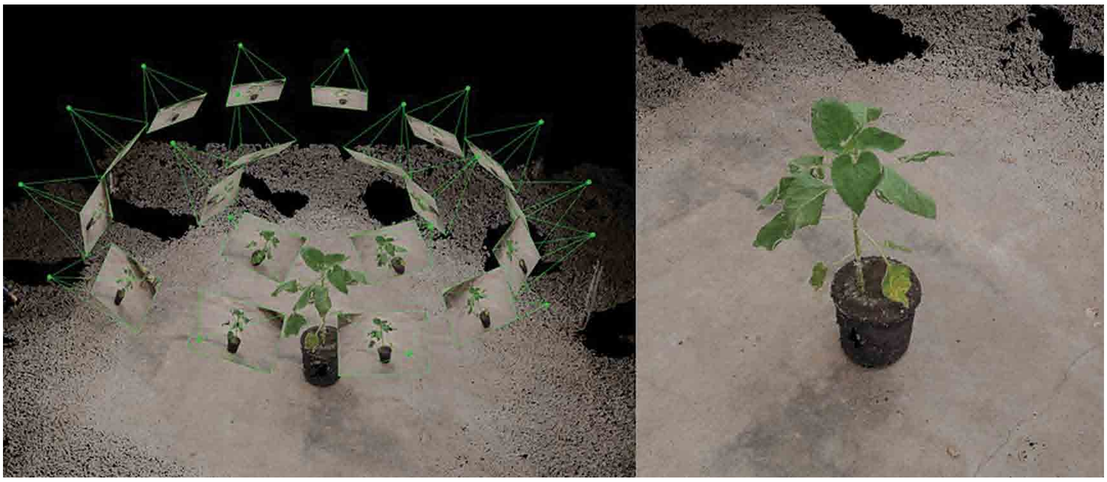

Figure 2. Camera positions (green sphere), orientations (green lines) and imaged areas (2-D image planes) during the plant imaging process (left), and the resulting 3-D model of the entire scene before the pre-processing stage (right).

cal analysis. Emphasis was placed on the generality of the model in terms of handling varying plant geometries and growth stages without particular adaptation or preliminary assumptions.

**METHODS**

In this study, we proposed the use of a data-driven tensor-based analysis for plant 3-D model segmentation. The tensors we derived provided us with a means to geometrically classify 3-D point clouds into saliency components in the form of lines and surfaces (Figure 1). The tensor analysis was made locally around each point instead of enforcing global geometrical models (such as cylindrical and other surface forms) to classify and segment the data into stem- and leaf-related points. Thus, we achieved a computationally efficient model. To further improve our results, the classification was then reweighed as a function of the point distance from the classified stem as well as by measures of asymmetry in point distribution around each point, an indication of the closeness of a point to its boundary. To evaluate the performances of the segmentation model, corn (*Zea mays*), cotton (*Gossypium hirsutum*), and wheat (*Triticum vulgare*) plants were grown under greenhouse conditions and imaged at various growth stages. These species were chosen for their range of geometries, dimensions, canopy architecture, leaf shape, and growth characteristics they represent. They are also considered major crops in many parts of the world. The plants were imaged over a five-week period, beginning post emergence. The plants were 3-D reconstructed using a standard structure from motion (SfM) multi-view stereo application/software. About 20–30 images were taken around the plants from two heights and inclinations with ~60% overlap between images (Figure 2). Because the reconstructed point clouds cover the entire scene, prior to the derivation and evaluation of the morphologic parameters, a pre-processing stage was ↘

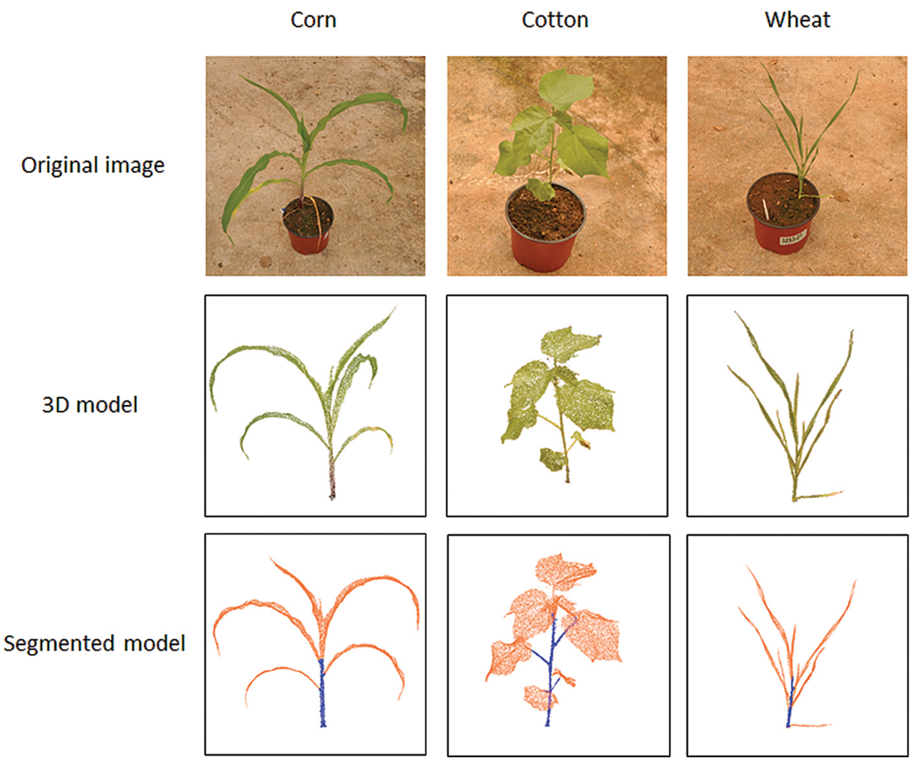


Figure 3. Results of the tensor-based segmentation model applied on 3-D models of different crop species. Original images (top), reconstructed 3-D model (middle) and segmentation results (bottom) of corn (left) cotton (middle) and wheat (right) plants. The orange pixels represent the leaf-related points while the blue pixels represent the stem-related points.

applied, which consisted of scaling and cropping the plant-related points. Segmentation results were evaluated both qualitatively and quantitatively. The qualitative evaluation was based on visual interpretation of the segmentation results for different species, and at different phenological stages. The quantitative evaluation was performed by comparison of the outcome to a manual point cloud segmentation which was performed independently of the application of our algorithm. Comparison analysis was held using a confusion matrix, which measures the true and false-positive classification of leaf- and stem-related points, as well as accuracy of the complete process (kappa value). This analysis was performed on six of the models – for all three species and at two growth stages, 20 days after seeding (DAS) and at 40 DAS.

## RESULTS and DISCUSSION

The application of the segmentation algorithm to all three species is shown in Figure 3. In all cases, the model correctly classified the stem- and leaf-related points. The surface of each individual leaf was extracted, allowing analysis on the single organ level as well as for the overall canopy. Notable are the differences in canopy and leaf shape, such as the rounded cotton leaves compared to the narrow and long ones of wheat; single thick stem of corn (~1.5 cm) compared to the multiple narrow tillers of wheat (~0.4 cm). The handlings of the different growth stages, which are typically associated with different aspects of segmentation difficulties, are shown in Figures 4 and 5. Figure 4 shows the segmentation results for ~1.5 cm young seedlings imaged 8 DAS. At this early growth stage, the wheat plant stem diameter is very small (~1 mm) and the leaf width is approximately 2 mm; geometrical differences between these organs are negligible at this early growth stage. The corn plant is also problematic for segmentation as the leaf bases (next to the stem) appear cylindrical and may be mis-classified as stem. Yet, for both seedling types and ensuing geometrical challenges, the model yielded accurate segmentation results and was sensitive enough to identify differences between leaf and stem geometrical features. Figure 5 shows the segmentation results of fully developed plants imaged 50 DAS. It demonstrates the ability of the model to handle complex and developed foliar geometries and structures, as well as a large number of developed and overlapping leaves, and yet to provide reliable points classification. Table 1 shows an example of the analysis accuracy using the confusion matrix. The misclassification errors of both leaf- and stem-related points and the accuracy of the overall process, as reflected via the kappa values, were small (<2.5%), irrespective of the

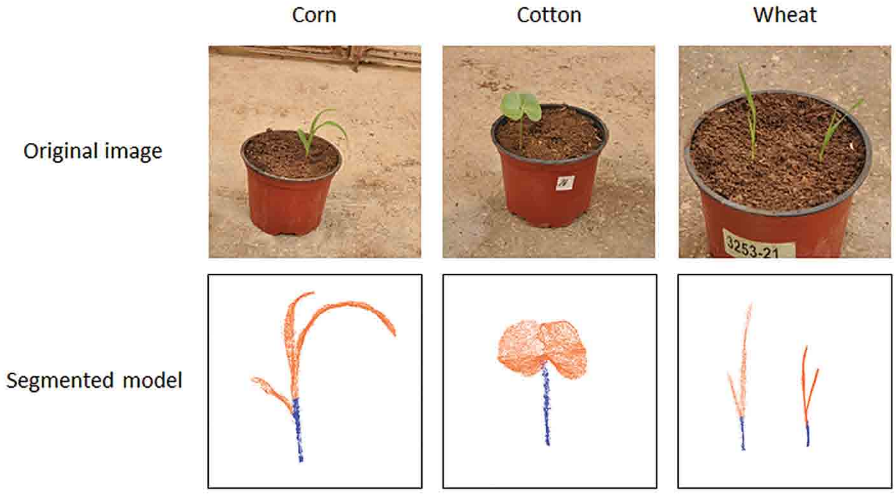


Figure 4. Results of the tensor-based segmentation model applied on young seedlings. Original images (top) and segmentation results (bottom) of corn (left) cotton (middle) and wheat (right) plants. The orange pixels in the bottom images represent the leaf-related points while the blue pixels represent the stem-related points.

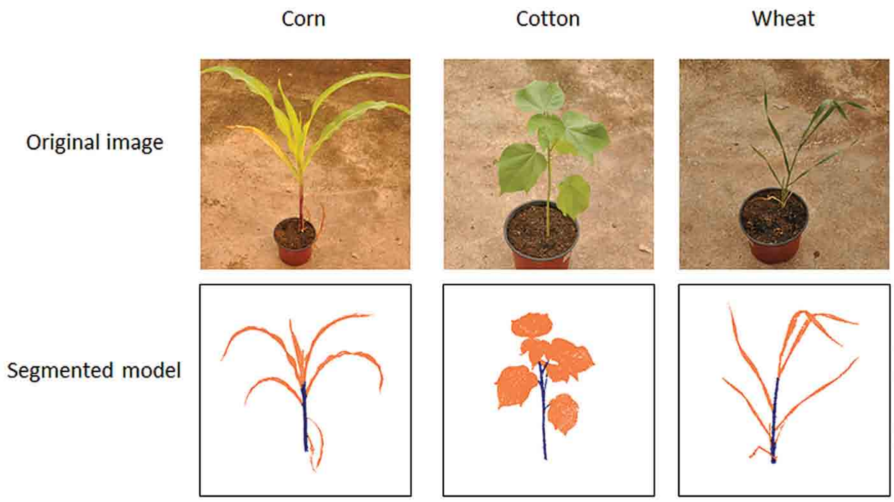


Figure 5. Results of the tensor-based segmentation model applied on fully developed plants. Original images (top) and segmentation results (bottom) of corn (left) cotton (middle) and wheat (right) plants. The orange pixels represent the leaf-related points while the blue pixels represent the stem-related points.

plant species and growth stage. These results demonstrate the ability of the model to handle varying growth stages and canopy architectures for all scenarios regardless of the segmented organ. Furthermore, Figure 6 shows classification of the leaf-related point into individual leaves. These abilities allow monitoring and evaluations of advanced morphological parameters such individual leaf shape, size and angle. The model presented here can improve currently used plant growth analysis methodologies and provide single organ-level characterization, which can be useful for robust intra-row weed detection and identification as well as for plant phenotyping purposes. ❑

**Dr. Ran N. Lati**

I hold a B.Sc and M.Sc in crop protection from the Hebrew University of Jerusalem. My Ph.D is from the Department of Mapping and Geo-Information Engineering in the Technion focused on using 3-D image-based models for weed detection and characterization. The overall objective of my research is to develop Precise Weed Management (PWM) and\or Integrated Weed Management (IWM) programs and to promote alternative weeding tactics. By doing so I hope to minimize the use of herbicides and reduce herbicide-dependence of current weed control systems.

Table 1. Example of the segmentation accuracy analysis held by the confusion matrix. This analysis was held for a corn plant that was imaged 20 days after seeding. In the bottom right corner is the kappa value representing the accuracy of the overall process.

| | Leaf points | Stem points | Total points | Error (%) |
|---|---|---|---|---|
| Leaf points | 46681 | 44 | 46725 | 0.094168 |
| Stem points | 53 | 3222 | 3275 | 1.618321 |
| Total points | 46734 | 3266 | 50000 | |
| Error (%) | 0.113408 | 1.347214 | | 0.072 |

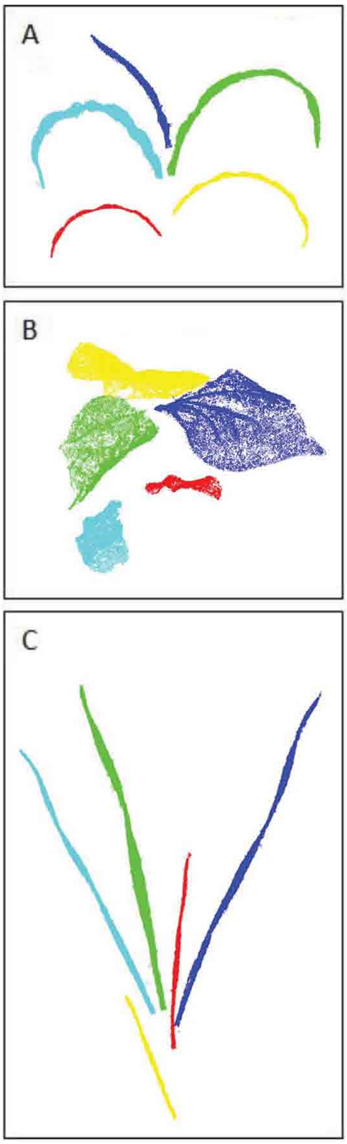


Figure 6. Extraction and separation of individual leaves of corn (A), cotton (B) and wheat (C) plants resulting from the tensor-based segmentation model.

# Ground-based plant and climate monitoring of crops for tracking water use and water status

By Dr. Shabtai Cohen

**OVERVIEW**

**Ground-based plant and climate monitoring today includes a range of techniques and associated instrumentation used to monitor plants in the field with sensors mounted on or inside the plant, as well as nearby. These methods today can compete with or supplement remote sensing, which is typically done from airborne or satellite platforms. As the range of electronic technologies advances, the options and technological solutions for monitoring plants improve and decrease in price. We have developed and adapted a group of sensors to monitor water use and water status of crops, as well as climactic parameters, and developed methods to compute atmospheric "dryness" for setting amounts of irrigation over the range of conditions in Israel. In many cases, the use of these technologies has led to large reductions in the amount of water used for irrigation, resulting in a significant savings of capital for farmers and water for the Israeli economy. Herewith are reviewed some of the technologies and sensors that are being developed and used for sensing plant water status and water use, and climate demand for water, at the Volcani Center. Experiments using sensors for irrigation research in deciduous orchards and screen-covered banana plantings are described.**

**INTRODUCTION**

A number of years ago I had the unfortunate opportunity to visit a relative who was in the hospital and unconscious after an accident. As a layman, it was not clear to me what his condition was but the displays from the sensing technologies being used to monitor what was going on in his body looked good and were helping the doctors get important information needed for treatment. These sensing systems, which included pulse, blood pressure, blood oxygen and a range of other parameters that many of us are somewhat familiar with, told a story about how well his body was functioning. The sensors were all sending information to one computer that was logging and analyzing the data. Today we expect to have these systems in our hospitals and they are allowing doctors to have unprecedented amounts of highly detailed information for basing their decisions. Actually, in some cases, 'decision support systems' have been developed based on our understanding of bodily functions, which automatically recommend a medical course of action or make decisions automatically. Similarly, agricultural scientists have developed a range of sensors and monitoring techniques to sense climate around the crop and plant processes, analyze the data to give useful information to researchers and farmers, and in some cases recommend or control farm decisions. We can say that these technologies are helping the plant communicate with us.

At the Volcani Center, Dr. Josef Tanny and I, along with colleagues, students and engineers, have developed, adapted and implemented a number of sensor systems to monitor climate, atmosphere and plant water use and morphology. We have used these technologies in a wide range of projects, which, besides agricultural water use, include human thermal comfort in urban settings, plant-disease epidemics, and managing reservoirs and forests. However, most of our work focuses on how plants feel, how much water they use and need, and how much to irrigate. This information is vital for fine tuning irrigation and improving agricultural water use efficiency, a major objective of agricultural research in Israel. These technologies include the ability to:

1. Measure sap flow in plants. Sap is the water that moves up through the stem and evaporates into the atmosphere. Knowing how much sap is lost is a key factor in deciding how much to irrigate.

2. Monitor the vertical flux of water vapor above crops and forests to know how much water the whole agricultural system or ecosystem is using and is returning to the atmosphere above. Knowing how large systems interact with the atmosphere is important for management and for improving our ability to predict weather as well as climate change.

**3.** Measure atmospheric dryness from climate sensors at special weather stations, many of which have been integrated into the Israeli agro-meteorological grid. Water coming through the plant evaporates into the atmosphere due to this atmospheric dryness, and we irrigate accordingly.

**4.** Stems of healthy plants grow during at least part of the year, and they also contract and expand slightly during the course of a day as the plant sucks water from the soil or relaxes at night. The magnitude of the minute contractions and expansions as well as the growth rate can indicate whether the plant has enough water or is suffering from drought. Fruits and leaves grow during the season and their daily growth rate can also be indicative of plant health.

The past 10 years have seen an explosion in the development and use of miniature advanced micro-processors and micro-controllers. These are small electronic boards that require very little electricity to operate, but are essentially computers designed to monitor and store information from a range of sensors as well as communicate with the outside world by transmitting the data to storage devices, cellphones and the internet. The price of these electronic boards has plummeted as they have gone into mass production, making advanced sensor platforms economical for use in the field, orchard or managed forest.
Electrical storage (in batteries) and increasing efficiency of solar charging systems to keep our systems operating continuously under field conditions are enabling us to deploy more of our sensor systems over longer periods of time (months and years).

Together the sensors, micro-processor/controllers and electrical support systems have led to an unprecedented ability to monitor plants in field situations. A few of the technologies and test cases are:

<u>Sap flow sensors</u>

Plants take up carbon dioxide from the atmosphere during photosynthesis to produce food for all life on our planet. But when they do that water is lost to the atmosphere as evaporation. Sap is the water that flows from the soil through the plant and into the leaves to provide the water needed during photosynthesis. Sap used by the plants must be resupplied to the soil as irrigation. Two types of sap flow sensors were developed at the Volcani Center in the 1980s and 1990s by a group of researchers led by Dr. Yehezkel Cohen. Both types of sensors are implementations of heat pulse technology. This technology uses a tiny heater that is placed in a medium where fluid is flowing. A pulse of electricity, usually for less than one second, is given to the heater, which can increase in temperature to 80 degrees centigrade. Although the heater cools quickly, the heat moves along with the liquid and is tracked by tiny thermometers. Analysis of the temperature signals gives the flow rate. One of the Volcani-developed systems is designed for trees and the second for herbaceous species including corn, cotton and pepper plants. A third technique, developed by a French scientist, which uses a continuously heated heater, called the "thermal dissipation" technique, is much cheaper to build and has been adapted in the past decade by our group for use on various tree species including citrus, deciduous orchards, banana plants and date palms. Adaptation of the sensor systems involved development of appropriate packaging for long-term survival in the field, the electronic backbone needed to operate the probes, connect them to micro-processors, and provide online communication from the field installations to a laboratory computer via cellphones or the internet. Some of the communication is already wireless and in the future it will all be wireless. We have also found that sap flow is variable inside the plants and between plants, so we have to monitor a number of plants to get accurate results. The need for many sensors in an experiment has led us to adapt technologies that we can build ourselves in the lab for very little money using relatively cheap, readily available parts.

<u>Eddy covariance, Surface Renewal, Flux Variance</u>

Water that evaporates from the leaves moves into the atmosphere around the plant and from there into the atmosphere above. Flow in the atmosphere is not smooth, but rather turbulent, as can be seen is a smoke trail that winds around instead of going straight. Air moves as parcels, which we can think of as gusts of wind. Sometimes parcels move upward and sometimes downward but, overall, evaporated water vapor from the plant moves upward. Measuring this movement involves tracking the upward and downward moving air parcels. A straightforward method for doing this, called the eddy covariance method, measures vertical wind speed and air humidity with very fast sensors, typically 10 times per second, and basic analysis of the data, which can be quite complex, is done automatically. Dr. Josef Tanny has been a pioneer in application of this method in Israeli agriculture, including use of the technique in crops grown under screens such as peppers and bananas. As with the sap flow measurements, knowledge of water evaporation from an agricultural field is vital for irrigation scheduling, but the eddy covariance equipment is too expensive for farmers. Other less demanding methods are being developed that take advantage of our understanding of water vapor movement in the lower atmosphere but require less expensive equipment, like minute electronic thermometers and radiation sensors.

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→ Atmospheric dryness or "Reference crop evapotranspiration"

Almost all Israeli farmers use electronic irrigation controllers and they adjust their irrigation according to atmospheric dryness, which is translated to irrigation amounts and computed from climate data that includes temperature, humidity, wind speed and solar radiation. The Israel Meteorological Service and the Ministry of Agriculture's Soil Conservation Department have set up a network of stations that monitor climate, compute atmospheric dryness and make that data available to everyone through their website (www.agrometeo.co.il) run by Marc Perel. A joint committee of the Ministry of Agriculture's extension service (Shaham), a Volcani representative, and the Israel Meteorological Service established standards for the calculation of atmospheric dryness in Israel, in accordance with international standards. The calculation is based on a basic understanding of water use of a well irrigated, cut grass field, which is significantly different from that of crops and forests in Israel. Ongoing research is focusing on improvements of the calculations for various situations, and adjusting the atmospheric dryness to get a reasonable number to put in our irrigation controllers. In the future, irrigation controllers with internet access will automatically adjust irrigation amounts daily according to the appropriate formula calculations that we are developing.

Stem growth and stem contractions:

Dendrometers – sensing stem contractions

As the soil around a plant's roots dries, the plant also dries slightly, which causes the plant to apply more suction at the roots and further dry out the soil. The suction, which is a result of the reduction in plant hydration, can be measured as plant water potential, a physical term. Plant water potential is currently considered the best indicator of how dry the plant "feels", but it is difficult to measure. Most of the changes in water potential in the stem cause shrinking (or expansion if water potential increases) of the soft tissues below the bark. The stem contractions are easily measured with a number of electronic transducers which translate the movement of the sensor into an electronic signal. Contractions of 10 microns (a hundredth of a mm) are relatively easy and cheap to measure, making the use of dendrometers (stem diameter sensors) popular, and some commercial companies are using them for informing irrigation scheduling. However, there are other things that influence the diameter of the stem and therefore the measurements can be ambiguous. Two of these are the stem growth and the movement of sugars in the stem during the day. Stem growth does not occur always, and can be seasonal. Sugar movement is also problematic. A current Ph.D. student, Ori Achiman, is developing a mathematical description of these relationships that should improve our use of dendrometers for determining how dry a crop feels for use in irrigation scheduling.

Case studies:

Sensor assisted Irrigation of Deciduous Orchards

Working with dendrometers and several other crop and soil sensors in an apple orchard in the Golan Heights, we disconnected several trees from irrigation in the summer and found that dendrometers were more sensitive to water stress than sap flow in the stem, which apparently adapted to drier soil for the first few days (Naor and Cohen, 2003). Later work focused on a protocol for irrigation with online sensors, using two types of soil-moisture sensors and dendrometers for stem contraction. The research, done in a nectarine orchard in the Golan Heights, showed that all three could be used and that stem contraction was extremely sensitive, but that during a phase of fruit growth when we could safely reduce irrigation, two of the three sensing techniques (including the dendrometers) exceeded their useful range (Nevo et al., 2015, Nevo, 2015).

Banana irrigation under screens:

Banana is a tropical grass, and grows well in the hot Jordan Valley, where it used to be irrigated extensively with water drawn from Lake Kinneret. In the 1960s, before the transition to drip irriga-

Figure 1. Sensors for measuring sap flow in pepper plants. The sensors were custom-built in Volcani's workshop.

Figure 2. Banana plants with sap flow sensors built in our lab (left). Calibration of the banana sensors in a greenhouse using a series of banana plants on electronic scales (right).

tion, bananas received about 5000 mm per year, or on average 14 liters per m2 per day. The transition to drip irrigation, along with a series of field experiments conducted over 15 years at the Zemah Experiment Station led by Yair Israeli, reduced the irrigation rates by about half in the late 1980s to 2700 mm. During a trip abroad, the researchers saw bananas grown in greenhouses, which improved fruit quality and plant performance. This led to a series of experiments that resulted in a transition to covering bananas with screens. At first, irrigation under the screens was the same as outside. But a project led by Josef Tanny in 2004-2007, which included measurements of climate parameters inside screenhouses and outside, along with measurements of crop water use with sap flow systems and agronomic monitoring by the staff at Zemah, showed that irrigation could be cut by another 25% and irrigation rates were set to less than 2000 mm.

Measuring banana water use with sap flow probes is especially challenging because the banana stem is different from that of trees and the sap flows deep inside. We built special probes for bananas, which are 15 cm long and are inserted carefully into the soft internal tissue that transports water at the base of the stem (see Figure 2).

Bananas are sensitive to salinity and Kinneret water is marginally saline. Experiments with better water quality, led by Dr. Avner Silber, showed that further cuts were possible, but the price of better water is prohibitive. Avner also noted that the relationship between irrigation below the nets and that outside should not be constant, because the build-up of dust on the nets in the summer should further reduce water requirements.

A current project of ours is monitoring climate inside and outside of the screenhouses and irrigating accordingly. Current technology allows the climate sensor data logging equipment to calculate the reference crop water use under the screen online and have that data ready for the irrigation manager through the internet every morning automatically. This "dynamic" irrigation has allowed a further reduction of 15% in irrigation rates, depending on which screen is used.

Over the past two years, the unscreened plantation received ↘

Figure 3. Sap flow sensors used in pine (left) and orchard trees (top right). The sensor assembly, built in our laboratory, is shown in the lower right.

Figure 4. Climate sensors deployed above a banana plantation for computing atmospheric "dryness" and irrigation requirements. These include standard high-quality solar radiation (left), air temperature and humidity (middle) and wind-speed sensors.

Figure 5. A minute "surface renewal" sensor (foreground in focus) for monitoring air parcels moving in the lower atmosphere. The sensor is mounted near the bottom of a meteorological mast with eddy covariance and energy balance equipment (background, out of focus).

→ 2200 mm, under the 10% screen using the recommended irrigation 1775 mm, and with dynamic sensor-based irrigation only 1465 mm, or less than a third of that in the 1960s. We are confident that the experiments will lead to adoption by the growers soon after completion of the project.

<u>Water use of forest trees</u>

Israel's water budget is tight and we use water frugally. We assume that rainwater percolating into the soil will refill our aquifers, from which we draw drinking water. A relevant question in managing natural systems, like our forests, is how much water they use and whether they use more than 'barren' land with no trees. If we are already asking that, perhaps we would like to know whether pine trees use more water than oak trees, and whether the aquifer would benefit from thinning our forests. These are questions that trouble forestry researchers in the department of natural resources (at the A.R.O.), in particular Dr. Yagil Osem and Dr. Gabi Schiller as well as Prof. Dan Yakir's group at the Weizmann Institute, who have long-term experiments monitoring the Jewish National Fund's Yattir Forest, east of Be'er Sheva' at the northern edge of the Negev Desert, and the Qedoshim Forest, near Bet Shemesh in the Judean Hills. With both groups, we have introduced networks to evaluate water use of forest trees using sap flow sensors. And yes, a pine tree forest uses almost all the rain water, leaving very little to percolate into the aquifer, while 'barren' land uses less. But it gives us a number of benefits (called ecosystem services) as compared to barren land, so we are forced to think carefully about planting forests and their associated cost/benefits.

## CONCLUSIONS

Current technological advances in electronics and wireless and internet communications are making sensing technologies attractive due to their relatively low cost and effectiveness, and long-term monitoring in the field is becoming more common. Our team has been successful in developing, adapting and implementing a group of technologies for monitoring climate and crop water use and evaluating climate "dryness" for plants. These sensing technologies are important for irrigation scheduling. They have helped us develop irrigation strategies for orchard crops as well as crops grown under screens, including peppers and bananas. In the case of bananas under screens, a series of projects has led to large reductions in irrigation and concomitant savings in water. ❑

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# The challenges of precision agriculture in grazing systems: the spatial dimension and GPS

By Dr. Eugene David Ungar

**OVERVIEW**

**The gap between what is "possible-in-principle" and "achievable-in-practice" is large when it comes to the application of precision agriculture to extensive grazing systems. Part of the challenge is that these systems are spread over large and remote areas, and are also spatially heterogeneous, both in primary production and in pattern of utilization by grazing animals. Certain tools associated with precision agriculture that operate in a spatially explicit way – remote sensing, GIS (geographic information system) and GPS (global positioning system) – are being harnessed to study grazing systems. Satellite-based remote sensing holds much promise in terms of which plant characteristics can be inferred. The most important ones are cover classification, and the quantity and quality of plant biomass. Animal-borne GPS-enabled devices can tell us where an animal goes and when, but one has to contend with the fact that herds comprise many individuals. In the case study presented here, a GPS-based herd tracking system was developed to map the cumulative presence of a number of goat herds employed to forage along fire-breaks in the Jerusalem Hills. The combination of utilization maps generated by such wide-scale herd monitoring and remote-sensing of the vegetation should facilitate a quantum leap in the depth at which grazing systems can be studied and managed.**

Grazing systems of one kind or another occupy at least a quarter of the land surface of our planet and are of huge economic and ecological importance. However, many of them are extensive, low-input/low-output systems that operate in harsh physical and economic environments into which technology penetrates slowly; thus, the gap between "possible-in-principle" and "achievable-in-practice" is large. Discussion of precision agriculture has been restricted to crops, with no mention of rangelands. However, one might well ask whether precision agriculture could be relevant to grazing systems. One complication in attempting to answer this question would be that, by definition, a grazing system comprises two very different actors.

The first is the vegetation, which in some broad sense resembles a crop, therefore we might expect the tools of precision agriculture to be readily applicable to rangelands. However, rangeland paddocks are relatively large and their value per unit area is low, so that data acquisition and analysis become expensive. Furthermore, the heterogeneity of natural vegetation is far greater than that encountered in crops, and it occurs at a variety of spatial scales, from centimeters to hundreds of meters. In fact, one could justifiably ask: "In this context, what kind of decision support can we expect of precision agriculture, given that these areas are neither cultivated, planted, irrigated, fertilized, sprayed, nor mechanically harvested?" But they are ***grazed***, and the timing and intensity of grazing can have a strong impact on the future productivity of the vegetation. Most importantly, timing and intensity of grazing are also under some degree of management control, so that the ability to map characteristics of the vegetation such as potential productivity, standing biomass, and nutritional quality would constitute a quantum leap in our ability to study and manage grazing systems. Satellite-based remote sensing is an obvious means of progress towards this improvement, although it should be noted that ground-sampling of sufficient scope to enable high-quality calibration of the satellite data presents a major challenge. Nevertheless, as costs of satellite imagery fall and the technology improves in terms of spatial resolution, number of spectral bands, and imaging frequency, precision agriculture will become increasingly relevant for rangelands.

The second factor is the animal, and to balance the crop bias implied by the term precision ***agriculture***, we refer to precision ***livestock farming***. In the case of housed-ruminant production systems, the deployment of a sensor on every animal in a group (primarily for estrus detection) predates the term, but the repertoire of behavioral and physiological signals that can be sensed at the individual level has grown considerably. The nature of housed-animal production systems means that, for some purposes, many individuals can be monitored by a single device, such as a camera positioned strategically in a passageway leading to the milking parlor. However, even if such controlled and standardized measuring conditions could be created on rangelands, seemingly trivial "details" could kill the idea, for example, distances from the electricity grid or the cellular communication network.

Classic examples of the large gap between "possible-in-principle" and "practicable" abound in applications of the global positioning system (GPS). GPS chips have been attached to just about anything that moves, from bicycles to ballistic missiles; from marine mammals to flying insects; also, there must be about 2 billion GPS chips in smartphones around the world today and the unit cost is a few dollars. What could be simpler than slinging a GPS chip around the neck of every animal? Indeed, a major topic of interest in the study and management of grazing systems is the spatial dimension: how uniformly do the animals utilize the area available to them and how does the spatial pattern of animal presence relate to, and even influence, that of landscape heterogeneity?


Figure 1. The general-purpose i-gotU GPS logger (Mobile Action Technology, New Taipei City, Taiwan) at the heart of the GPS collars used to map animal location on rangeland. The device weighs 37 g, contains a 750-mAh battery and can store 262,000 locations. A simple-to-use software interface enables the device to be programmed to operate with GPS fix intervals of 1 s to 1 h; the optional power-saving mode can be used for fix intervals ≥7 s. Operation can be scheduled according to starting date and operating hours over a 24-h cycle, with a resolution of 1 h. A third-party external battery can be used in conjunction with the device's data/charging cable to greatly extend operating time.

Answers to these questions would also provide a quantum step forward in the study and management of grazing systems; clearly, the combination of spatially explicit data on primary production and spatially explicit data on its utilization by animals would raise potential benefits to yet another level.

However, incorporation of a chip into a commercial animal-borne GPS collar raises the few dollars cost of the GPS chip to many hundreds or even a few thousands for the finished product. The high cost of a collar is a major limiting constraint on exploitation of this powerful technology, but by working with flocks of sheep or goats, which are accompanied by a herder and are not free-ranging, some of the difficulties can be overcome. Firstly, the fact that the animals move across the landscape as a fairly coherent group means that their location can be well approximated by the position of any one animal, which enables just one collar per group to form a reasonable starting investment. Secondly, such flocks and herds usually spend the night in a corral, from which they emerge and to which they return each day. Thus, the animals do not have to be rounded up and corralled specifically to change the GPS collars; also changing collars on small ruminants is incomparably simpler and safer than doing it on cattle.

However, if the goal was to prepare the way for widespread, routine deployment of GPS collars, even one commercial collar per herd would be expensive. One way to bring down costs considerably would be to build the collars in-house, using basic electronic components such as the cheap GPS chip mentioned earlier; but this would not be practicable outside a research facility. We achieved a compromise solution by using an inexpensive, general-purpose GPS logger intended primarily for sports and leisure use (Figure 1). The i-gotU GPS logger (Mobile Action Technology, New Taipei City, Taiwan) fits into the palm of a hand and offers an impressive set of features; most importantly, it proved robust under field conditions and generated good quality data for our purposes. However, small size means small battery, and small battery means limited operating time between battery recharges, as with all electronic gadgets. This complicates collar construction because now we need an external battery; this necessitates connectors, and one thing leads to another, until we arrived at the rather amateurish-looking GPS collar shown in Figure 2. Nevertheless, the cost of our "cheap-and-nasty" collar is 10–20% of that of commercial ones; it is reliable, can be assembled in about 10 minutes, and can be dismantled quickly after deployment, to access the GPS logger and recharge the battery.

This basic design has been applied in several studies in Israel; they addressed small-ruminant herds in the northern Negev and the Mt. Carmel regions, and cattle herds at three other ↘

Figure 2. Goat herd grazing along a fire-break corridor in the Judean Hills. The brown-and-white goat in the center is wearing an in-house assembled GPS collar. The picture was taken along the seasonally active Refa'im riverbed in the 'Amminadav Forest. The dry riverbed of whitish pebbles and rocks runs horizontally across the middle of the photo, and goats graze the herbaceous and shrub vegetation along its banks. The edge of the main dirt road that runs parallel to the river bed is in the foreground.

→ sites. In the study described here, our objective was to map, over several annual cycles, the daily foraging routes of goat herds within a 100-km$^2$ region of the Judean Hills, south-west of Jerusalem. A large proportion of this region is covered by woodlands and planted pine forests managed by the Jewish National Fund; it contains some of the most scenic landscapes in the country and is dotted with sites of cultural importance. However, pines and picnic fires form a combustible mix; arson poses an additional threat, and serious wildfires are not uncommon. The basic idea could not be simpler: every kilogram of undergrowth vegetation consumed by the goats is that much less fuel for a wildfire. However, there are simply not enough goats available to adequately suppress the herbaceous and woody undergrowth vegetation across the entire region. Therefore, the herd "fire power" was focused along designated fire-break corridors, to keep them passable and safe for ground crews who need to operate along them when fighting a wildfire.

That, at least, is the theory. But testing whether this works in practice requires the ability to associate the state of the vegetation at each point with the amount of grazing that had occurred there; and this requirement cannot be addressed seriously without continuous GPS-based mapping of herd presence.

Our low-cost GPS collars for the herds were constructed and deployed, and were refreshed every few weeks throughout the year. For each collar that returned from the field, the data files that were downloaded needed organizing and merging into a cumulative database. Initial processing of this database is required, to create a clean data file, ready for analysis by geographic information system (GIS) software which is designed to process spatially referenced data. The objective is to isolate all GPS locations that represent a position that was logged while the herd traced out its daily foraging route across the landscape, between leaving the corral and returning to it; inclusion of locations logged when the herd was in the corral would create artificial peaks of calculated grazing pressure. The rigor with which this initial processing is performed depends on the context, and it can be crude-but-simple - delete coordinates in the corral area - or, as we chose, based on a computer code that analyzes each daily route to pin-point exit and re-entry times. These approaches yield slightly differing results for reasons related to inherent GPS error.

The resulting dataset - which we sampled at 1-min intervals - is then imported into GIS software to be become a geographic layer, which then can be combined with other geographic layers that describe biotic and abiotic features of the landscape. It is really this application of GIS software that enables us to extract value from the GPS data.

The first and obvious step in examining the collected GPS locations is to simply overlay the entire collection onto an orthophoto (geometrically corrected aerial photograph), as a cumulative cloud, with no regard for the inner structure of the data, as related to daily foraging routes, as shown in Figure 3. This visualizes in one glance where the herd did - and did not - go, and the varied density of GPS points across the landscape gives a clear impression of the relative intensity of animal presence.

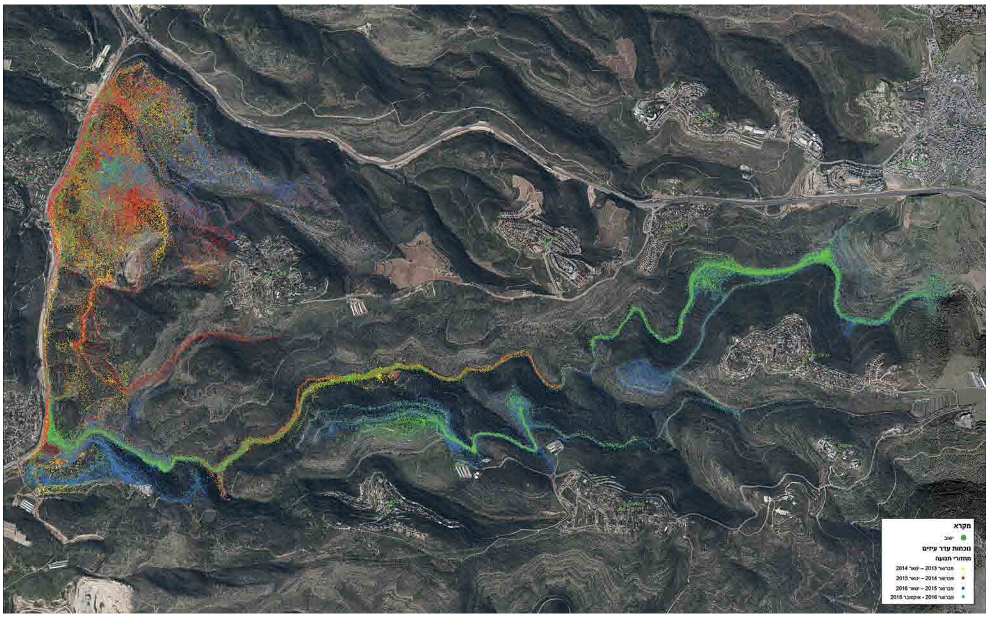

Figure 3. Visualization of the presence of one goat herd that grazed the Qedoshim Forest, in the Judean Hills, over four years. A serious wildfire occurred in this area in 1995, halting traffic on the main Tel Aviv–Jerusalem highway, Route 1 — which runs east-west in the top half of the image — and along Route 38 which runs south from it on the left of the image. Herd presence was determined by a GPS collar assembled in-house and installed on one animal in the herd. Each point represents one minute of presence of a herd of about 200 goats. Note how the spatial dispersion of the herd ranged from tight concentration along the fire-break corridor that follows the seasonally active Kesalon riverbed that runs east–west across the image and along a second fire-break corridor a short distance southward, to being relatively diffuse near the junction of routes 1 and 38. The approximately 520,000 GPS points are color-coded according to year.

The next step is to convert GPS locations to meaningful units as expressed in the language of range management: grazing-days per unit area. The concept of "grazing-days" encompasses both the number of animals and the duration of their presence. For example, 30 animals for 20 days and 15 animals for 40 days both comprise 600 grazing-days. We know that the area occupied by a herd at any point in time is approximately circular and we can estimate that area in various ways. Therefore, conceptually at least, we can draw such a circle around a GPS point and reason that the patch of rangeland under the circle accumulated animal presence (grazing-days) equal to the number of animals in the herd multiplied by the amount of time represented by one GPS point - in our case, 1 minute. If we divide that value by the area of the circle, we express this grazing pressure in standardized units of grazing-days per unit area. By means of suitable GIS tools this reasoning can be applied to the entire collection of GPS points and the result summed across all of them to generate a heat map of grazing-days per unit area. This is shown in Figure 4 at the regional level after one year of monitoring seven herds. Note that herd size is accounted for in this image, which would not be the case for a regional GPS point cloud.

The heat map of grazing pressure - expressed as grazing days per unit area — can be translated to units of herbage mass removed per unit area by assuming some normative value for the daily herbage intake of one animal. Some further assumptions underpin this approach but there is, as yet, no practicable animal sensor to measure the intake rate of grazing animals. Nevertheless, we conducted this exercise to gain a feeling for one of the two fundamental rate processes occurring in this system: herbage production and herbage consumption.

Is more widespread adoption of herd monitoring practicable? Based on our experience in the Judean Hills, we estimated that a land-management agency could scale this procedure up to the order of 100 herds for a total investment of $30,000 for the collars, 3 months labor, and a vehicle. The collars would probably be configured differently from the research mode, by using a power-saving mode in conjunction with a GPS fix interval of about 5 minutes. The power-saving mode would impose some loss of precision, and the relatively long fix interval (compared with our standard 10-s interval) would sacrifice some detail in tracing the meandering foraging route of the herd, but these would be acceptable compromises for a large-scale monitoring scheme, because they would greatly extend the period between col- ↘

→ lar changes. Algorithms have been developed to digest the many millions of data records such a scheme would generate and prepare them for GIS analysis. If land-management agencies see sufficient value in herd-location data to justify the cost of their acquisition, precision agriculture will have made a major entry into the vast and complex world of extensive grazing systems. ❑

### ACKNOWLEDGEMENTS

*We express our gratitude to the Jewish National Fund for financial support of the work reported here, and to its staff members Hanoch Tzoref, Moshe Zuckerman and David Evlagon for facilitating the field work. Special thanks go to: Reuven Horn who conducted much of the field work and data processing, Hagit Baram who developed the computer code for preprocessing the GPS data files, and Eitan Goldshtein and Maya Zahavi for generating the GIS figures.*

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Areas of interest: primary productivity of rangelands, grazing behaviour and management, applications of remote sensing, GIS and GPS, acoustic monitoring and modeling.

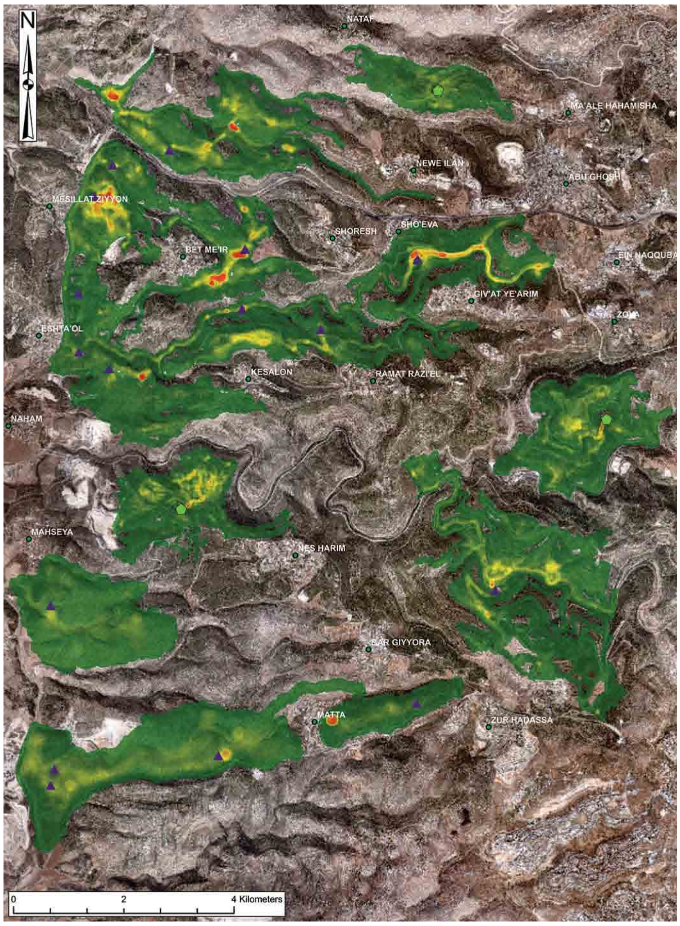


Figure 4. Heat-map of grazing pressure imposed by seven goat herds in the Judean Hills over 1 year, based on approximately 800,000 GPS points, each representing one minute of herd presence. Grazing pressure is expressed as grazing-days per unit area; it was computed from the GPS locations by factoring in: the area occupied by the herd at any given point in time, the number of animals in the herd, and the time interval between GPS fixes. Thus, the resulting values are comparable across the entire region despite differences in herd size. Values range from close to zero (dark green) to almost 500 grazing-days per 1000 $m^2$ (red). With this kind of information it becomes possible to approach the subject of grazing impacts in a quantitative way. Some of the regions of higher grazing pressure reflect the meandering contours of fuel-break corridors along seasonally active riverbeds, but there also are other patterns of spatial dispersion apparent in this image. Triangles show locations where night corrals are periodically established and populated.

VOLCANI VOICE
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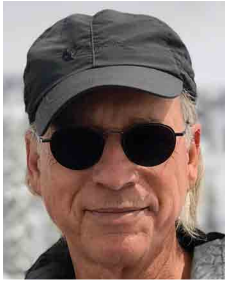
# Detection of the Red Palm Weevil

By Dr. Amots Hetzroni, Dr. Victoria Soroker, Dr. Yuval Cohen



**ABSTRACT**

**The red palm weevil is a major pest of ornamental palms in southern Europe and the Mediterranean and in date-growing countries of the Middle East. The larvae damage the vascular system of the trees, eventually causing their death. Detection of weevil activity is challenging because the pests are well-hidden, developing within the crown and stipe (stem) of the tree. We developed a sensor that identifies distinct sounds made by the larvae, facilitating the development of a human-and-machine learning system to detect infested palm trees. This system has a sensitivity of approximately 80% at an early stage of infestation, before symptoms become apparent. This prototype system could become the basis of a commercial tool for early detection of red palm-weevil infestation in date-palm plantations and ornamental palms.**

## INTRODUCTION

Pest management requires accurate monitoring of pest populations. The precise monitoring is particularly significant when invasive pests are involved. This information enables forecasting pest dispersal, which is essential to effectively maintain a manageable population. The red palm weevil (RPW), ***Rhynchophorus ferrugineus*** (Olivier, 1790) Coleoptera: Curculionidae), is an invasive palm pest in the Mediterranean region. The larvae develop within the palm tissue, mainly at the stem or crown, damaging the vascular system and eventually causing death of the tree (Cohen et al, 2017). Early detection of the RPW became a challenge in this region since the first weevils were detected almost thirty years ago. Today, the RPW is a major pest of ornamental palms in southern Europe and the Mediterranean and in date-growing countries of the Middle East.

Palms have only a single apical meristem generating all organs. It is situated at the top of each stem in the palm heart at the center of the crown. If the palm heart is seriously damaged, the tree dies. As monocot trees, palms cannot `cure` internal stem cavities caused by pests (Cohen, 2017). Therefore, detection of RPW infestation is particularly crucial at early infestation stage, before the apical meristem is damaged and while the trunk is still stable. At this stage, recovery of the palm tree is possible.

Early detection of RPW infestation is particularly challenging as the pests are well-hidden, developing within the palm crown and trunk tissues. This cryptic nature of the weevil activity challenges visual detection at initial infestation stages. Other detection methods have been proposed to cope with the problem, including chemo/olfactory sensing by dogs (Nakash, Osem & Kehat 2000; Suma et al. 2014), thermal imaging (Golomb et al. 2015), x-ray (Ma et al. 2012), and more (Soroker et al. 2017).

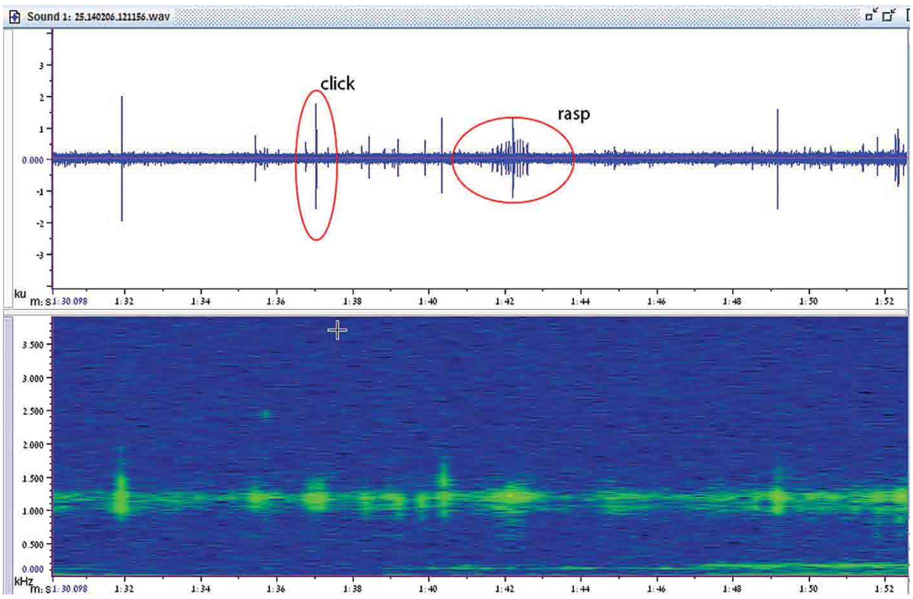



Figure 1. Typical acoustic signal from an infested stem depicting typical larva 'click' sounds. A specific 'rasp' sound was recorded at proximate 1:42 min; top – signal intensity; bottom – spectrogram (visualization of the spectrum of frequencies of the sound)

Acoustic detection of RPW larvae activities was suggested based on distinct sounds reported from the pest-infected palms (Mankin et al. 2007; Soroker et al. 2004). The larvae are large and active, often producing chewing and moving sounds that are audible to human ears. Thus, it is candidate for acoustical and vibrational detection and monitoring. The sounds are propagated through the fibrous material to the listener and can be captured by a suitable sensor. Typical red palm weevil (RPW) larva activity sounds like a train of clicks (Mankin et al., 2008; Herrick et al, 2012) (Figure 1). When a large number of large larvae reside inside palm tissue, the clicks can even be detected by the naked trained ear; however, detection is problematic at early infestation stages when the generated sound energy is too low to distinguish from the background. Even in the absence of external noise, palm interior is not serene. It is quite rich with sounds derived from insect activity such as feeding, movement, secreting, or spinning; or from the tree itself such as air bubbles, water uptake, or leaves blown even by light breeze.

**MATERIALS AND METHODS**

We designed an acoustic detector using a homemade tactile sensor based on a piezo-electric microphone with 50mm (dia.) membrane connected to a magnet via a hollow metal cone. Nails (100mm) with a flat circular head were hammered and fixed to the tree trunk (Figure 2). When conducting measurements, the sensor was attached magnetically to the nail. The amplified signal was recorded onto a portable computer (Figure 3).

Young date and Canary palms were infested with RPW in a quarantine facility and compared with control, non-infested palms. Natural infestation was performed on 65 trees in several experiments during 2013-14, by releasing adult male and female RPW to each tree, enclosed by a 50-mesh net. Recording sessions were conducted during morning hours, thereby avoiding the local prevalent winds. Recording clips were typically 3 min long. The observer logged information of events that might influence the quality of data, such as a car passing by, slammed doors, wind, etc. The observer also indicated his impression of the likelihood of infestation. The recorded files were used for automated evaluation and classification to determine if the signals came from infested or non-infested palms. Automatic acoustic detection was comprised of two phases, multivariate learning and classification. The detection was mainly based on a previous algorithm and code developed by our team (Pinhas et al. 2008). Palm infestation was confirmed by dissection of all palms, carefully inspecting each leaf and the internal palm heart and stem, collecting developing weevils and assessing damage.

Figure 2. Acoustic sensor attached to a date palm stipe (stem).

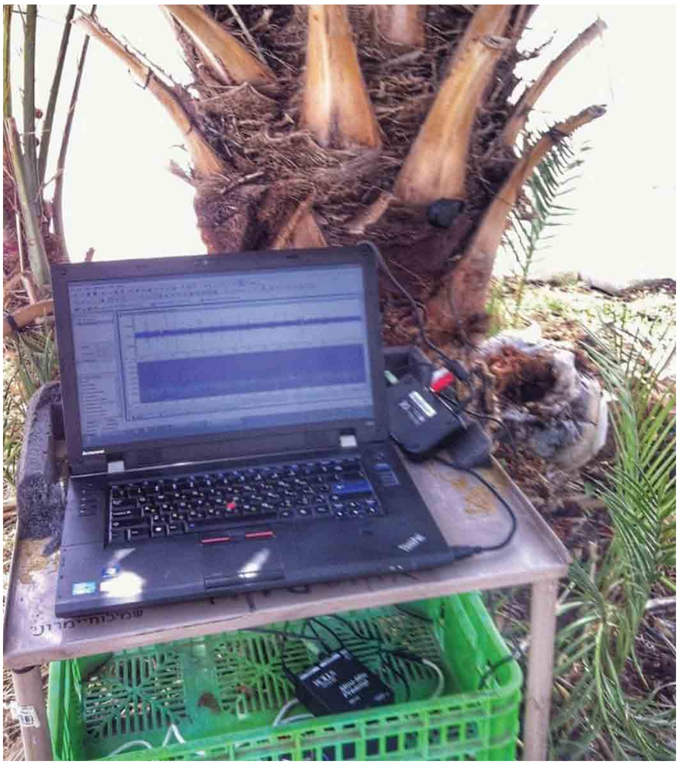


Figure 3. Acoustic data acquisition -- field setup.

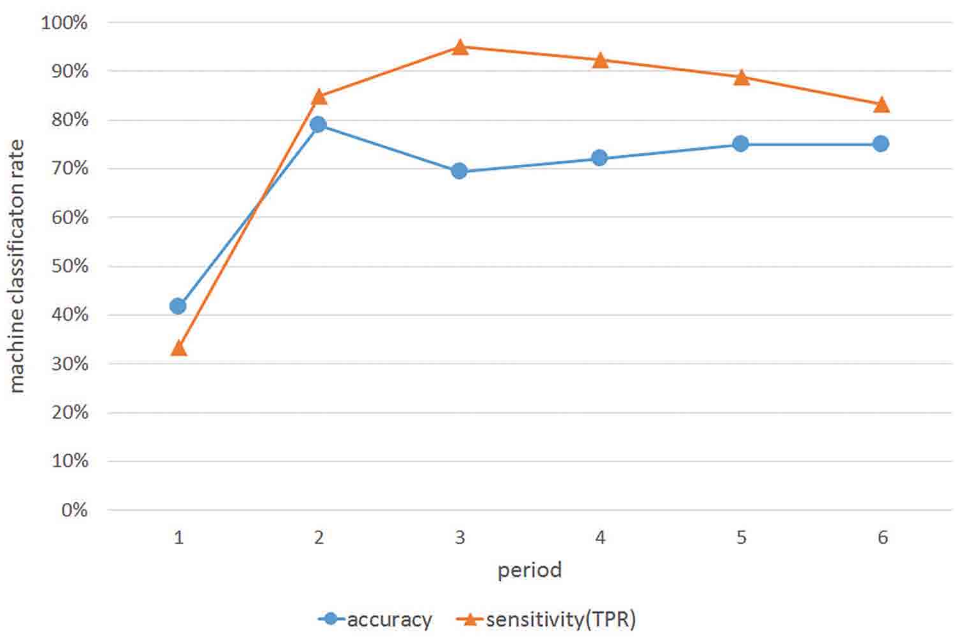



Figure 4. System accuracy and sensitivity through time (time depicted as `natural` periods associated with insect development and its establishment in the trunk)

## RESULTS AND DISCUSSION

Our findings indicated that system sensitivity (the proportion of infested palms that were correctly classified as such) was over 80% (shortly after infestation) peaking to 95% around the third week after infestation. Overall system accuracy (proportion of correctly classified trees – positive or negative) was between 70-80% (Hetzroni et al. 2016) (Figure 4).

In small potted palms, we were able to rank the tree infestation within less than three minutes. It seems, therefore, that a frequent single observation near the focus of the infestation should be sufficient. In large palms, we do not really know where that core of infestation is. Therefore, monitoring large palm trees might require listening in several locations along the trunk due to the attenuation of the signal energy as it traverses through the palm tissues.

Our studies demonstrate that manual and automated acoustic detections aided by filtering of external stimuli were sufficient to enable feasible and reliable RPW detection in young palm trees in an unshielded natural environment. ❑

### FURTHER READING

*Cohen, Y. 2017 Morphology and Physiology of the Palm Trees as Related to Rhynchophorus ferrugineus and Paysandisia archon infestation Management In: Soroker, V., and Colazza, S. (editors) Handbook of Rhynchophorus ferrugineus and Paysandisia archon - biology and management Wiley, Oxford, UK. Pp 39-53*

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*Herrick N.J., Mankin R.W. (2012) Acoustical Detection of Early Instar Rhynchophorus ferrugineus (Coleoptera: Curculionidae) in Canary Island Date Palm, Phoenix canariensis (Arecales: Arecaceae). Florida Entomologist 94(4):938-990.*

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*Nakash, J, Osem, J & Kehat, M 2000, A suggestion to use dogs for detecting the Red Palm Weevil (Rhynchophorus ferrugineus) infestation in date palms in Israel. Phytoparasitica, vol. 28, pp. 153-155.*

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Figure 5. The Red Palm Weevil (adult)

*and Paysandisia archon - biology and management. Wiley, Oxford, UK. Pp 69-104.*

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*Suma, P, La Pergola, A, Longo, S & Soroker, V 2014, The use of sniffing dogs for the detection of Rhynchophorus ferrugineus, Phytoparasitica, 42(2):269-274.*

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**Dr. Amots Hetzroni**

Dr. Amots Hetzroni is a Senior Scientist (Retired) in the Institute of Agricultural Engineering at the A.R.O. Volcani Center, Israel. His degrees are from the Faculty of Mechanical Engineering of Tel Aviv University, Israel; the Faculty of Agricultural Engineering of the Technion, Haifa, Israel; and the Department of Agricultural Engineering, Purdue University, U.S.A. He performed postdoctoral research in the Department of Horticulture at Purdue University, and sabbatical leaves in the Department of Agricultural and Biological Engineering at Purdue University; the Department of Biological and Agricultural Engineering at the University of Georgia; and the Biodiversity Research Group at the University of Queensland, Australia. Dr. Hetzroni's areas of interest include information technology in agriculture, developing internet domains, monitoring pest dispersion, precision agriculture, bioacoustics, distribution modeling, and population dynamics.

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**Dr. Yuval Cohen**

Dr. Yuval Cohen is a Senior Scientist in the Department of Fruit Tree Sciences at the A.R.O. Volcani Center, Israel. His degrees are from the Department of Botany at the Hebrew University of Jerusalem. He performed postdoctoral research at the University of California, Berkeley, U.S.A., and spent sabbatical leave at the University of California, Davis. Dr. Cohen's research is focused on subtropical fruits, especially date palms and mangos. He combines horticultural studies with physiological as well as molecular biology approaches. Yuval has studied different aspects of date-palm biology and physiology, including research on date palm fertilization and fruit set, fruit quality, effects of plant regulators on vegetative growth, and on reproduction and date propagation. He collaborated with other research groups to promote solutions for efficient irrigation, precision agriculture and plant protection of date palms. Yuval also coordinates the Israeli mango breeding project.

**Dr. Victoria Soroker**

Dr. Victoria Soroker is a Senior Scientist in the Department of Entomology at the A.R.O. Volcani Center, Israel. Her first two degrees are from the the Tel Aviv University in Ramat Aviv Israel and PhD from the Department of Entomology, Hebrew University of Jerusalem. She performed postdoctoral research at the State University of New York at Stony Brook, USA.

Dr. Soroker's research is focused on arthropod chemical ecology and integrated pest management. She combines behavioral, analytical and molecular studies both in the field and lab. Among other subjects, Soroker's lab focuses on integrated pest management of date palm pest and red palm weevil in particular. In the last ten years, Soroker is also heavily involved in the study of honeybee colony losses: breeding for pest resistant bees and studying the major pest of the honeybees - the Varroa mite. She collaborated with other research groups in Israel and worldwide to promote solutions for precision agriculture and honeybee health.

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