# Mobile Plant Health Visualizer Based on SI-NDVI Imaging and Augmented Reality Visualization for Space Greenhouses


Conrad Zeidler*

EDEN Research Group, Institute of Space Systems, German Aerospace Center (DLR), Bremen, Germany, conrad.zeidler@dlr.de

Lennart Kuhr*

Institute of Machine Tools and Production Technology, Technical University of Braunschweig, Germany, l.kuhr@tu-braunschweig.de

Jordan B. Callaham

Department of Horticultural Sciences, University of Florida, United States, jordanc@ufl.edu

Johannes Schöning

Human-Computer Interaction (HCI) at the University of St. Gallen, Switzerland, johannes.schoening@unisg.ch

*Indicates co-first authors



Augmented reality (AR) technologies have gained importance in human-computer interaction (HCI) for workflow optimization, including in the space sector, where AR has been investigated to facilitate astronauts' workflows during space missions. One potential application for AR is in future greenhouses on the Moon and Mars to support in performing various plant cultivation tasks. Monitoring plant health is critical to achieving optimal crop yields, and Single-Image Normalized Difference Vegetation Index (SI-NDVI) imaging has been identified as a promising method for detecting plant stress before visual appearance. However, current methods for using SI-NDVI imaging require either multiple static-mounted imagers or expensive robotic systems, increasing the cost and complexity of such systems. In this paper, we present the development of a mobile plant health visualizer (MPHV) with a novel approach using AR to overlay a false color hologram based on SI-NDVI measurement in the real world. We report on the implementation and initial performance of the MPHV in detecting and visualizing plant stress responses in real-time and in situ using salinity stress tests on tomato plants. Our results demonstrate that the MPHV is a practical, and relatively simple system generating plant health information on-site, both in space and on Earth, with potential applications in greenhouses. This paper aims to demonstrate the significance of HCI in developing and optimizing systems for space missions.



CCS CONCEPTS • J.2 [Physical Sciences and Engineering]: Aerospace • H.5.1 [Information Interfaces and Presentation]: Multimedia Information Systems — Artificial, augmented, and virtual realities • I.3.8 [Computer Graphics]: Applications

**Additional Keywords and Phrases:** Augmented Reality, Vegetation Index, Early stress detection, Plant health monitoring, Imaging, Greenhouse, Operations, EDEN ISS, External sensor integration, Controlled Environment Agriculture


## 1 INTRODUCTION AND MOTIVATION

Food is a vital element in crewed space missions, as it plays a critical role in ensuring the success of the expedition. Space greenhouses have been identified as an essential solution to meet the food production requirements for long-duration space missions. [1] However, the reliability and productivity of plant production within greenhouses depend highly on the correct functionality of the utilized technical subsystems. Technical subsystems can become inoperable, and their failure can have a negative impact on plant yield. Additionally, the spread of plant diseases significantly threatens food production in space. Therefore, deploying plant health monitoring (PHM) systems is crucial to detect plant health anomalies early and to prevent plant disease outbreaks [2].

In the context of plant production as part of future space exploration missions, additional constraints affect PHM systems' required utility and efficiency. One of the constraints is the limited availability of expert knowledge and workforce on-site during a mission. To address this challenge, automated image acquisition and remote PHM assessment have been introduced as part of the EDEN ISS project [3]. However, the PHM system utilized on EDEN ISS relied on a static camera system [4] that lacked mobility, leading to an inflexible assessment of the greenhouse plants. Additionally, the extraction of plant health information from the acquired images was conducted remotely, leading to limited autonomy of the operating crew.

Recent research has shown that using augmented reality (AR) technology can provide advantageous capabilities to support human operators in various contexts [5, 6] e.g. also within the space domain [7–14]. AR technology allows for real-time, context-aware, and handsfree interaction with digital content, enabling operators to visualize and interact with complex data sets in their natural environment [12].

This paper presents a mobile plant health visualizer (MPHV) based on Single-Image Normalized Difference Vegetation Index (SI-NDVI) imaging and a novel AR plant health visualization approach. The SI-NDVI imaging is performed with a modified GoPro Hero 4 Black camera (GP4), while the image processing is done on a server. The AR plant stress response visualizations are streamed in real-time to a Microsoft HoloLens 2 (HL2) head mounted display (HMD). To test the performance and functionality of the MPHV, a salinity stress test on tomato plants (*Solanum lysopersicum* cv. 'Nugget') was conducted and evaluated to identify the system limitations and derive an outlook on future research and development.

## 2 RELATED WORK

As mentioned previously, PHM is crucial for future crop production systems to ensure optimal plant growth in space. In the context of human-computer interaction (HCI), various technologies such as AR or machine learning have already entered the research field of PHM.

As shown in Neto and Cardoso [15], AR used on smartphones can be used in early warning systems for fungal infection detection in terrestrial greenhouses. Another application is insect identification and pest control, displaying the type of insect, pest symptoms, or treatment in AR on mobile devices [16].

Artificial Intelligence has also been increasingly used to detect plant diseases in recent years. One example is an application developed by Mohanty *et al.* [17] that can be used on smartphones and uses a deep convolutional neural network to identify 14 crop species and 26 plant diseases. Another application devolved by Mathew and Mahesh [18], which uses the YOLOv5 deep learning method, can be used to detect early-stage bacterial spot diseases based on symptoms on bell pepper leaves in terrestrial farms. Additional applications of deep learning techniques for disease diagnosis and management in agriculture can be found in the literature review by Ahmad *et al.* [19].

These applications are designed to provide information to users in the field and support their operational work in real-time. However, using traditional RGB cameras many applications can only detect plant diseases, after the appearance of visual symptoms.

### 2.1 NDVI Imaging

In the 1970s, researchers started space-based remote sensing by launching multispectral imaging instruments aboard satellites to analyze and mitigate droughts. The corresponding data were analyzed using the characteristic spectral response of vegetated surfaces compared to unvegetated. Photosynthetic chlorophyll in healthy vegetation increases its absorption ratio in the visible band of the electromagnetic spectrum and its reflectance ratio in the near infrared (NIR) band. [20] This relation can be expressed by the Normalized Difference Vegetation Index (NDVI) which relates the reflectance ratios within the electromagnetic NIR and red band [21].

NDVI has become a standard for vegetation monitoring and is now also being used for plant health inspection on a smaller scale, particularly in Controlled Environment Agriculture (CEA) [22]. However, the related acquisition, processing and analysis of hyperspectral imagery remain a challenging research field as it involves large data volumes, high data dimensionality and costly hyperspectral instruments [23].

### 2.2 SI-NDVI Imaging

SI-NDVI allows the use of simplified image acquisition and processing by less costly imagers based on modified commercial off-the-shelf RGB cameras. SI-NDVI imaging relates the reflectance ratios within the electromagnetic NIR and blue band allowing plant stress to be detected before the appearance of visual symptoms. During the image processing, one SI-NDVI value is calculated for each raw image pixel to generate quantitative readings of SI-NDVI histograms and qualitative interpretable false color images (FCIs). In Beisel *et al.* [22], the University of Florida Spectral Imager (UFSI) is presented which is a heavily modified GP4 using the Back-Bone Ribcage AIR modification kit, providing multiple mechanical mounting points. In addition, the infrared blocking filter of the GP4 was removed, and an NDVI-7 dual bandpass filter allowing light transmission in the ranges 400 to 575 nm and 675 to 775 nm and a M12 5.4-mm MP-10 with infrared correction lens was added. [22]

Testing of two UFSIs under analog space conditions inside the EDEN ISS greenhouse in 2018 [4] revealed limitations of the stationary UFSI installation. Due to their fixed mounting, the UFSIs could not be used flexibly from multiple perspectives and simultaneously for all greenhouse plants. To circumvent these limitations, multiple UFSIs or a robotic camera system could be integrated. However, this would increase costs and complexity. Another limitation of the initial deployment resulted from the remote and manual generation of the histograms and FCIs within the science office off-site from the greenhouse. As a result, there was a subsequent delay in providing processed results to the on-site operator, limiting the operational autonomy, even more relevant for future space missions with their telemetry limitations [2].

## 3 CONCEPT

To overcome the limitations of the EDEN ISS PHM approach, a new concept for plant stress visualization using an AR headset and a SI-NDVI imager was developed (see Figure 1). The plant health visualization process is divided into three steps: (1) raw plant image acquisition, (2) image processing and (3) false color hologram visualization on the AR headset.

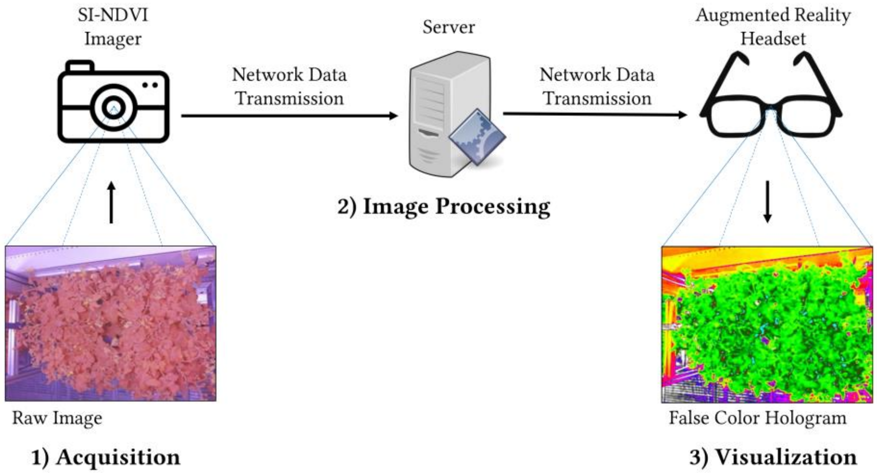


Figure 1: Mobile plant health visualization concept that generates false color images based on SI-NDVI calculations and visualizes them as false color holograms on an augmented reality headset.

A camera connected to the AR headset, previously modified by removing the infrared filter in front of the RGB lens and adding a dual wavelengths filter (SI-NDVI filters), captures the raw plant images (step 1). These images are forwarded to a server and SI-NDVI calculations are performed for each pixel within. Based on the SI-NDVI calculations the image is converted to an FCI (step 2) and streamed to the AR headset to overlay the user's field of view in the real world with the FCI (step 3). The false colors qualitatively visualize plant stress compared to similar plants or to other plant parts.

The resulting MPHV (see Figure 2) allows real-time detection and in situ visualization of plant stress. In this context, in situ visualization refers to visualization within the greenhouse on-site in the vicinity of the plants. This increases the user's autonomy by allowing them to easily and quickly locate plant stress, investigate its cause, and having the handsfree to initiate countermeasures with remote support from Earth. In addition, all plants as well as individual plant parts can be flexibly examined from various perspectives without the need to install additional stationary cameras reducing invests, space requirements, weight and complexity of the system as well as maintenance time and potential system failures. This makes the system more flexible and easier to integrate into different setups.

## 4 IMPLEMENTATION

Within the following, the implementation of the MPHV is presented from a software and hardware perspective following on the work of Kuhr [24].

### 4.1 Hardware

The FCI is visualized as a false color hologram using the HL2 AR headset. Real-time images are captured (step 1) using an UFSI developed by the University of Florida [4, 22] (see Chapter 2.1), as the HL2's built-in infrared and RGB cameras are unsuitable for this application. Furthermore, the UFSI has already been validated for plant stress monitoring under laboratory [22] and analog space conditions [3, 4]. Image processing (step 2) is outsourced to an external server (i7 processor with a CPU clock speed of 4.6 GHz) for optimal computing power and extended battery life of the MPHV. The raw UFSI images are streamed wireless to the server for processing, and the false color hologram is streamed wireless back to the HL2 for visualization (step 3). This wireless network requires an additional bridge router as the UFSI provides an access point only. The UFSI camera is mounted onto the HL2 centrally and in direction of sight to avoid misalignment between the real-time image and the overlaid false color hologram using a 3D printed mechanism [25] that connects the GoPro's Back-Bone Ribcage AIR modification kit to the HL2's chunnels (see Figure 2). The MPHV can be operated for approximately 2 hours before the UFSI battery is discharged.

Figure 2: Mobile plant health visualizer consisting of an University of Florida Spectral Imager (modified GoPro Hero 4 Black) mounted onto a Microsoft HoloLens 2. [24]

### 4.2 Software Development

The developed solution consists of a C# script and a C++ library integrated into a Unity scene, along with the GoPro server and Remote Holographic Player client on the HL2. The software architecture involves the UFSI streaming raw RGB image frames at 30 FPS, with every fifth frame retrieved for real-time visualization of the FCI without lag. Based on the FCI generation introduced by the University of Florida (see Chapter 2.2), a C++ functionality is developed to allow real-time FCI generation. This functionality includes raw image pre-processing, calculating a SI-NDVI value for each pixel, and assigning a new color to each pixel according to its SI-NDVI value. The FCI is then copied to the memory that is shared with Unity's runtime allowing the C# script applying the color data of the current FCI to a 2D texture container, which is then streamed to the HL2 for visualization using the Remote Holographic Player application. The three-dimensional position (and hence size) of the displayed two-dimensional hologram is also controlled by the C# script and can be modified within Unity. The Jolly Green Cyan Look Up Table (LUT) [22] is used for intuitive visualization of SI-NDVI values. Healthy vegetation is colored green, with green color saturation increasing with increasing SI-NDVI values. Lower SI-NDVI values are colored yellow, followed by red and purple to represent unhealthy vegetation in decreasing order of SI-NDVI values.

## 5 EVALUATION - SALINITY STRESS TEST

A salinity stress test was conducted to investigate the MPHV's capability to detect and visualize plant stress responses.

### 5.1 Setup

Two Orange Cherry tomato (*Solanum lysopersicum* cv. 'Nugget') plants were used for the salinity stress test after approximately 75 days of growths. They were sown at the same date, grew until the salinity stress test under the same conditions in a grow box (200 x 60 x 40 cm) with white walls (see Figure 3) and were vegetatively healthy. The tomato plants were illuminated during the first 3 weeks for 16 h/day and after that for 12 h/day by a 6-band multispectral spLED GmbH BloomPower black180 (390 nm - 1.68%; 460 nm - 8.40%; 612 nm - 8.40%; 660 nm - 78.15%; 730 nm - 1.68%; 6400 K - 1.68%) with a photosynthetic photon flux density (PPFD) of 600 µmol $m^{-2}$ $s^{-1}$ at a distance of 35 cm. The distance between LED grow light and the tomato plant canopies was approximately 50 cm.


Figure 3: Setup of the salinity stress test with two tomato plants under LED grow light in the grow box before salt treatment (left); The orange arrows show the leaves of the stressed tomato plant and the light blue arrows show the leaves of the control tomato plant examined for the salt treatment (right).

### 5.2 Procedure

For the salinity stress test, the MPHV was set to operational mode and spatial calibration of the system was performed. The two tomato plants were examined in the grow box under the LED grow light. The MPHV was worn throughout the salinity stress test by a 1.90 m person. The entire salinity stress test was recorded by the HL2.

In a first step, using the MPHV, three leaves of each tomato plant were examined at three different heights (top, middle, bottom) from two perspectives, i.e. the side view and the top view, and at a distance of approximately 50 cm to obtain a baseline for later comparison. This reduced the potential angle influence on the calculated false color hologram colors on the MPHV. Leaves were selected on sample basis for the entire plant. Since the MPHV is a mobile application for plant stress detection, no fixed mounting of the MPHV was intended.

In a second step, one of the two tomato plants, hereinafter referred to as the stressed tomato plant, was treated once with 400 ml of a 3% sodium chloride solution (see Figure 3). The other tomato plant was the control tomato plant and received no salt treatment. Two hours after the salt treatment, the same leaves of the two tomato plants were examined using the MPHV from the same distance, perspectives and angles to allow comparison with the images from the first step.

### 5.3 Results

Two hours after the salt treatment, no difference was visible to the human eye between the stressed tomato plant before and after the treatment. The same applied to the control tomato plant. However, in the area of all examined leaves of the stressed tomato plant, significant color changes from green to yellow/red/purple, from yellow to red/purple or from red to purple between the superimposed false color hologram before and after the salt treatment could be detected with the help of the MPHV. This could be observed both in the top-view and, although not as clearly, in the side-view perspective (see Figure 4). The shift to colors associated with lower SI-NDVI values could be an indication plant stress due to the salt treatment.

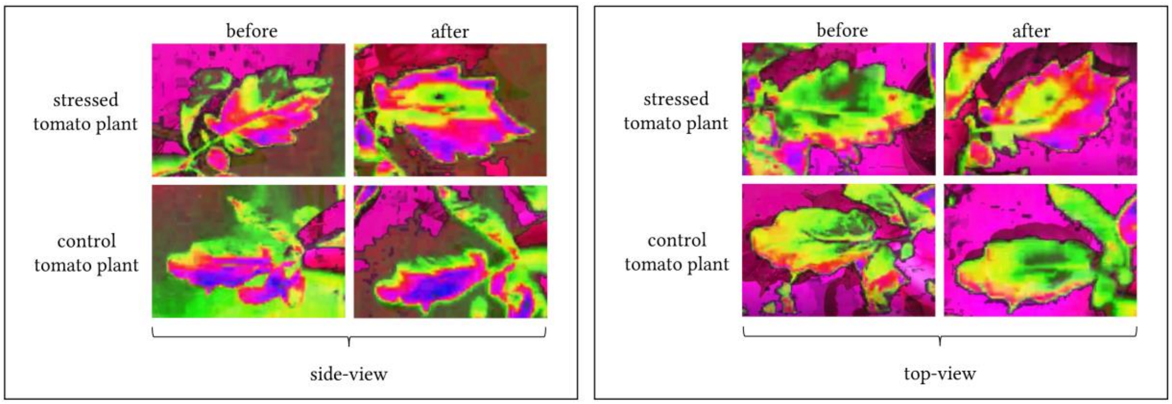


Figure 4: Exemplary video stream screenshots of the mobile plant health visualizer user perspective (using the Jolly Green Cyan Look Up Table) during the salinity stress test. Side-view of middle level leaves before and after the salt treatment for a stressed and control tomato plant (left). Top-view of middle level leaves before and after the salt treatment for a stressed and control tomato plant (right).

No changes in false color hologram colorization and associated measured SI-NDVI values were detected during the salinity stress test for any of the control tomato plant leaves examined with the MPHV from both perspectives. Thus, no false positive plant stress detection was experienced.

These results show that it was possible to correctly detect plant stress with the MPHV even before any change in the stressed tomato plant was visible to the human eye. Ten hours after the salt treatment, the stressed tomato plant lost stability and collapsed. During the entire salinity stress test, the stems of both tomato plants were visualized unchanged in dark green color on the false color hologram.

## 6 DISCUSSION

### 6.1 Server Approach

The deployment of the software code to the server instead of the HL2 leads to multiple advantageous and disadvantageous. The deployment method was chosen to prevent processing performance issues caused by the lower computing power of the HL2 effecting the fluent displaying of the false color hologram.

Measurements showed that the implemented solution enabled image processing at a frame rate of 7 FPS. The wireless connection of the UFSI, server, and HL2 during the use of the MPHV was not a limiting performance factor regarding fluent visualization with network traffic measurements of approximately 12%. With the UFSI streaming raw images at 30 FPS, the image processing could be identified to be the significant limitation to the fluent visualization of the false color hologram. However, the tests showed that the image processing frame rate of 7 FPS was still sufficient for the respective application.

Although the tests presented in this paper identified the UFSI's battery life to be the limiting factor of the operation time, outsourcing the processing from the HL2 could prove beneficial to the available battery life and allow for longer operation time. Using less of the HL2 processing power also allows to start additional applications in parallel onboard the HL2.

However, one major disadvantage of this solution is that some inputs to control the visualization of the FCI such as launching the visualization, spatial calibration or changing settings cannot be made without using Unity on the server.

### 6.2 SI-NDVI Range Selection

In the current MPHV prototype, the non-vegetative objects visible on the false color hologram are colored based on low SI-NDVI values using the Jolly Green Cyan LUT. A SI-NDVI value below zero is considered to represent non-vegetative elements on a SI-NDVI image. To achieve an even better visual separation of the tomato plants from their surroundings on the false color hologram, the pixels with SI-NDVI values below a certain threshold such as zero could be displayed fully transparent to color only the plant material. For this purpose, the alpha value controlling the transparency of these pixels would be set to zero. In order to achieve a clear separation and at the same time correctly represent plant stress, a compromise must be made when setting the SI-NDVI threshold value, because if the threshold value is chosen too low, stressed plant parts could also be falsely displayed transparent instead of in the reddish spectrum. To determine the optimal SI-NDVI threshold value further research needs to be conducted.

### 6.3 Plant Stress Detection

During the salinity stress test, two limitation of the MPHV were identified regarding plant stress detection. The first limitation represents the dependence of the false color hologram colorization on the angle between the observed leaf and the MPHV (observation angle), with a constant angle between observed leaf and light source (LED grow light).

The second limitation is the dependence of the false color hologram colorization on the angle between the light source and the observed leaf, with a constant angle between observed leaf and MPHV. As already mentioned in Chapter 5.3, plant stress was not as clearly detectable in the side-view as in the top-view perspective. Thus, on the false color hologram in the side-view of the control plant, the upper leaf areas tended to be colored in colors corresponding to high SI-NDVI values and the lower leaf areas tended to be colored in colors corresponding to lower SI-NDVI values (see Figure 4). A reason for this could be based on the higher illumination exposure from the LED grow light of the upper leaf areas compared to the lower leaf areas.

Due to these limitations, plant stress detection is more practical in the top-view than in the side-view. Mishra *et al.* [23] also reported difficulties due to illumination effects in hyperspectral imaging at close range and stated that "there is still no standard method to deal with these illumination effects". Further tests with a static fixation of the MPHV and the object to be observed should be conducted to investigate the illumination effects on the stress monitoring capabilities of the MPHV.

Besides this, the tests conducted included only Orange Cherry tomato plants, as this plant species was already used in the initial validation of the SI-NDVI method [4]. Further tests need to show whether the MPHV could be used on other plant species and whether the Jolly Green Cyan LUT provides plausible plant health information within the visualized false color hologram or whether it needs to be adapted.

## 7 CONCLUSION AND OUTLOOK

In this paper, a mobile AR application was presented to detect and visualize in situ and real-time plant stress responses qualitatively even before the appearance of visual symptoms. The presented MPHV consists of an UFSI (a modified GP4) to conduct SI-NDVI imaging and a HL2 visualizing the SI-NDVI values in AR. The UFSI is mounted onto the HL2 using 3D printed mounting mechanism and connected to it via wireless network. A salinity stress test with two tomato plants demonstrated sufficient technical functionality and performance of the MPHV in detecting and visualizing plant stress.

Current SI-NDVI imaging methods require either multiple stationary imagers or expensive robotic systems. Due to the relatively simple MPHV, the complexity and costs of such systems could be reduced. The MPHV aims to support on-site operators with mobile and in situ plant health assessment capabilities, increasing their autonomy from remote support teams on Earth. Moreover, the MPHV enables close-up inspection of specific plant parts from different perspectives, and the plants can be inspected anywhere in the cultivation area.

In future work, the MPHV should be improved and the limitations of it mentioned above should be further investigated. These include the angular dependence of the AR hologram colorization on the angle of observation and the angle of illumination. Attaching a small LED grow light to the MPHV could ensure a constant illumination angle and thus represent a promising approach to eliminate the respective limitations. The ability of the MPHV to detect other causes of stress, such as light stress, also with focus on stress in other plant species will be investigated. Potential improvements to the MPHV could be achieved by adding gesture control and deploying the entire AR application on the HL2 or on future AR headsets with higher computing power to provide even more flexible operations.

In conclusion, the proposed MPHV provides promising insights into a novel, relatively simple and effective approach to PHM, both in space greenhouses and on Earth. By utilizing AR technology, the system provides a more flexible and interactive assessment of plant health, allowing for increased autonomy of on-site operators. Furthermore, the proposed MPHV could be applied to other CEA applications, making the system relevant and applicable beyond space exploration missions. The development and implementation of such systems demonstrate the significance of HCI in designing and optimizing technologies used in space missions.

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