Estimating Processing Tomato Water Consumption, Leaf Area Index, and Height Using Sentinel-2 and VENµS Imagery

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Abstract: Crop monitoring throughout the growing season is key for optimized agricultural production. Satellite remote sensing is a useful tool for estimating crop variables, yet continuous high spatial resolution earth observations are often interrupted by clouds. This paper demonstrates overcoming this limitation by combining observations from two public-domain spaceborne optical sensors. Ground measurements were conducted in the Hula Valley, Israel, over four growing seasons to monitor the development of processing tomato. These measurements included continuous water consumption measurements using an eddy-covariance tower from which the crop coefficient ($K_c$) was calculated and measurements of Leaf Area Index (LAI) and crop height. Satellite imagery acquired by Sentinel-2 and VENµS was used to derive vegetation indices and model $K_c$, LAI, and crop height. The conjoint use of Sentinel-2 and VENµS imagery facilitated accurate estimation of $K_c$ ($R^2 = 0.82$, RMSE = 0.09), LAI ($R^2 = 0.79$, RMSE = 1.2), and crop height ($R^2 = 0.81$, RMSE = 7 cm). Additionally, our empirical models for LAI estimation were found to perform better than the SNAP biophysical processor ($R^2 = 0.53$, RMSE = 2.3). Accordingly, Sentinel-2 and VENµS imagery was demonstrated to be a viable tool for agricultural monitoring.

Keywords: Sentinel-2; VENµS; Eddy covariance; crop coefficient; LAI; vegetation indices

1. Introduction

Agriculture accounts for 70% of global freshwater usage [1,2], and therefore, increasing the agricultural water-use efficiency will improve agricultural sustainability. Where water is a limited resource, optimal water management is vital for food security. Crop coefficient ($K_c$)-based estimation of crop water consumption is one of the most commonly used irrigation management methods [3,4]. $K_c$ is defined as the ratio between the actual evapotranspiration from a crop field and the environmental evaporative demand [3]. One of $K_c$ estimation’s most reliable sources is vegetation indices (VIs) derived from optical remote sensing [5–14]. Until recently, this method’s application was hampered by the insufficient amount of public domain imagery at a high revisit time with fine spatial resolution. Since 2017 the Sentinel-2 constellation consists of two satellites and serves as a reliable satellite imagery source with high spatial (10, 20, or 60 meters; depending on the band) and temporal resolution (5 days). Despite that, in cloudy regions, even such a high temporal resolution might not be sufficient [15]. For example, despite the Sentinel-2 five-
day revisit time, no cloud-free images were acquired for one and a half months in February and March 2018 over one of our experimental sites in Israel. Optical imagery from one satellite system could supplement the imagery from another system to address this problem. Previous studies have analyzed the performance of such conjunction of imagery from different platforms, for example, Landsat-7 and Landsat-8 [16], MODIS and Landsat-8 [17], as well as Landsat-8 and Sentinel-2 [18–21], and finally, Landsat-7, Landsat-8, and Sentinel-2 combined [22]. Similarly, the present study exploits the possibility of conjoint use of imagery acquired by the Sentinel-2 and the new Vegetation and Environment monitoring on a New MicroSatellite (VENµS) satellite, which has similar spectral bands in the visual, near infrared spectral region, and a 5–10 m spatial resolution (depending on the Collection) as Sentinel-2 in addition to a very high temporal resolution of two days [23].

Tomatoes are grown in many regions around the world. Previously, several studies were devoted to estimating tomato Kc based on lysimeters [24,25] or eddy covariance measurements [26,27] without the correlation to the satellite remote sensing data. Another approach previously used a mechanistic crop model to derive the crop evapotranspiration and correlate it with optical remote sensing data. In this way, previous work [28] used the EPIC model [29], which, in turn, used variables derived from Sentinel-2 imagery.

Additionally, satellite imagery was previously used to estimate other vegetation variables such as LAI and height [11,30–34]. Much like with Kc, VIs are good surrogates for other crop variables since there are similarities in the temporal change dynamics of VIs with LAI and height [35,36]. LAI is a good proxy of the vegetation state [37–39] and a good yield predictor [40]. Similarly, vegetation height estimation is useful for crop management [41]. Therefore accurate estimations of LAI and height from satellite imagery are desired.

Recently, the use of machine learning algorithms has become widespread in remote sensing. In the present study, the LAI biophysical processor [42] implemented in the ESA SNAP (Sentinel Application Platform) 7.0 software (http://step.esa.int/main/download/snap-download/, accessed on 21 February 2021) was tested. The LAI biophysical processor is a “black-box” module developed for Sentinel-2 imagery that cannot currently be used with other imagery.

Therefore, this study’s overarching aim was to derive empirical models to estimate vegetation variables based on a combined time series of spaceborne optical imagery from VENµS and Sentinel-2 and field measurements. Specifically, the goal was to develop reliable Kc, LAI, and height estimation models for processing tomato based on Sentinel-2 and VENµS imagery.

2. Materials and Methods
2.1. Test Sites and Field Measurements

The field data used in this study were collected during four experiments in commercial processing tomato fields in the Hula Valley, Israel (Figure 1, Table 1). Two experiments took place in Gadash farm in 2018 and 2019, and two more experiments were conducted in Kibutz Gadot in 2019 and 2020. LAI was measured by a SunScan Canopy Analysis System—SS1 manufactured by Delta-T Company (Cambridge, UK) during the two experiments conducted in 2019 and one experiment conducted in 2020. The SunScan is a widely used, accurate, nondestructive LAI measurement system that was successfully employed in many previous studies [31,43,44]. Plant height was measured using a measuring tape during all four experiments conducted in 2018–2020. Each LAI and vegetation height value used in the empirical modelling presented here is an average value of at least 30 field measurements. Both LAI and vegetation height were measured throughout the growing seasons; therefore, they represent the typical range of these variables.

The number of satellite images used for the development of the various models was not uniform because each model was based on the period for which field measurements were available, and therefore, a different number of corresponding satellite images. For example, LAI could not be measured using the SunScan system when the plants were very
small, while vegetation height was easily measured at any time. Accordingly, the LAI models were based on shorter time-spans and fewer images than height models.

Each processing tomato field consisted of ridges and furrows. The distance between the rows was 2 m. Even during the vegetation development peak, the plants did not cover the furrows completely; thus, some soil reflectance signal is mixed with vegetation over the entire growing season. This mix of soil and vegetation reflectance hinders the vegetation variables estimation using remote sensing [45]. The Sentinel-2 and VENμS spectral bands used to derive vegetation indices were averaged for an area corresponding with the eddy-covariance footprint. In-field paths and their surrounding area were masked out from analysis polygons to remove bare soil areas and avoid edge effects. These excluded areas consisted of roughly 20% of the overall polygon areas. Therefore, each analysis consisted of either two or four vegetated regions separated by the paths (Figure 1).

Figure 1. The locations of experimental plots: (A) Map of Northern Israel; (B) Map of the Hula Valley; (C) Gadash; (D) Gadot. The fragmented shape of the analysis polygons results from excluding unvegetated paths in the fields. Sources of the basemaps: Esri, Sentinel-2, VENμS.
Table 1. The summary of four field experiments conducted in two locations in Israel.

| Site  | Period * | # Crop Height Measurements | # LAI Measurements | Polygon Size (# Sentinel-2 Pixels) | ETa Data Source | Distance and Bearing To The Meteorological Station |
|-------|----------|----------------------------|--------------------|-----------------------------------|----------------|-----------------------------------------------|
| Gadash| 9-May-18 30-Jul-18 | 8                          | -                  | -                                 | -              | -                                            |
| Gadash| 3-May-19 24-Jul-19 | 7                          | 6                  | 425                               | Gadash         | 250 m SE                                      |
| Gadot | 25-Apr-19 14-Aug-19| 11                         | 11                 | 249                               | Gadot          | 1.5 km SW                                     |
| Gadot | 7-May-20 3-Aug-20  | 9                          | 6                  | 332                               | Kavul          | 7 km NNW                                      |

* Period indicating the start and end date of the eddy covariance measurement.

2.2. Agro-Meteorological Measurements

The reference evapotranspiration, $ET_a$, was calculated based on nearby meteorological stations according to the FAO56 Penman–Monteith method based on meteorological measurements of air temperature, relative humidity, wind speed, and solar irradiance [3]. The actual evapotranspiration ($ET_c$) was measured using eddy covariance systems [26]. Based on these two measurements, the crop coefficient, $K_c$, was calculated as: $K_c = ET_c/ET_a$. $K_c$ is an important variable used to determine the irrigation dose [9]. The resulting $K_c$ time series were smoothed using cubic or second-order splines.

2.3. Satellite Imagery

Sentinel-2 is an Earth observation mission and part of the European Space Agency (ESA) Copernicus program. It includes two satellites, each equipped with a Multi-Spectral Instrument (MSI), namely, Sentinel-2A (launched June 2015) and Sentinel-2B (launched March 2017). VENµS is a joint satellite mission of the Israeli and French space agencies (ISA and CNES) launched in August 2017. VENµS has a two-day revisit time over Israel and a multispectral camera with 12 narrow spectral bands in the range of 415–910 nm [46]. VENµS and Sentinel-2 produce 10 and 12-bit radiometric data, respectively. The radiometric correction procedure of VENµS imagery was updated in 2020. The imagery acquired before the update is known as Collection 1; the imagery acquired after the update is known as Collection 2. VENµS captures imagery with a spatial resolution of 10 m. Sentinel-2 RGB and NIR bands also have a spatial resolution of 10 m, and other bands are coarser: narrow NIR, SWIR, and red edge bands, 20 m; coastal aerosol, water vapour, and SWIR-cirrus bands used mostly for atmospheric correction, 60 m. Atmospherically corrected reflectance products from both sensors were used in this analysis. Level-2 VENµS products, initially distributed at 10 m spatial resolution, were later distributed at a resolution of 5 m when an updated processing procedure was initiated in 2020. This product was used for the analysis of the 2020 experiment in Gadot. Sentinel-2 level-2A data were obtained from the ESA Copernicus Open Access Hub website (https://scihub.copernicus.eu/dhus/#/home, accessed on 21 February 2021). VENµS level-2 products were obtained from the Israel VENµS website maintained by Ben-Gurion University of the Negev (https://venus.bgu.ac.il/venus/, accessed on 21 February 2021). Table 2 lists the overlapping spectral bands of the Sentinel-2 and VENµS sensors used in this study to derive vegetation indices. The LAI and $K_c$ estimation models were derived based on three seasons, and crop height models were based on four seasons. An inventory of the Sentinel-2 and VENµS images used in the present study can be found in Table 3, alongside the number of LAI and height measurements taken during each season and used for model derivation.
Table 2. Central wavelengths and bandwidths (nm) of Sentinel-2 and VENµS equivalent bands used in this study.

| Band     | Sentinel-2A | Sentinel-2B | VENµS   |
|----------|-------------|-------------|---------|
|          | Central Wave- | Central Wave- | Central Wave- |
|          | length (nm)  | length (nm)  | length (nm)  |
| Blue     | 492.4       | 492.1       | 491.9    |
| Green    | 559.8       | 559.0       | 555.5    |
| Red      | 664.6       | 664.9       | 666.2    |
| Red Edge | 704.1       | 703.8       | 741.1    |
|          | 740.5       | 739.1       | 741.1    |
| NIR      | 832.8       | 832.9       | 861.1    |
|          | 864.7       | 864.0       | 40       |

Table 3. Imagery inventory from which processing tomato Kc, LAI, and height models were derived.

| Site       | Satellite | Tomato Kc Models Period * | Number of Images | Tomato LAI Models Period * | Number of Images | Tomato Height Models Period * | Number of Images |
|------------|-----------|----------------------------|------------------|----------------------------|------------------|-------------------------------|------------------|
| Gadash 2018| Sentinel-2 | 16 May 2019 20 Jul 2019   | 8–9 **           | 21 May 2019 25 Jul 2019   | 8–9 **           | 16 May 2019 25 Jul 2019   | 9–10 **          |
| Gadash 2018| VENµS     | 11 May 2019 24 Jul 2019   | 28               | 17 May 2019 24 Jul 2019   | 25               | 03 May 2019 24 Jul 2019   | 30               |
| Gadot 2019 | Sentinel-2 | 01 May 2019 14 Aug 2019   | 13–14 **         | 21 May 2019 14 Aug 2019   | 12–13 **         | 21 May 2019 14 Aug 2019   | 12–13 **         |
| Gadot 2019 | VENµS     | 01 May 2019 13 Aug 2019   | 39               | 17 May 2019 13 Aug 2019   | 34               | 17 May 2019 13 Aug 2019   | 34               |
| Gadot 2020 | Sentinel-2 | 20 May 2020 03 Aug 2020   | 14               | 20 May 2020 19 Jul 2020   | 11               | 20 May 2020 03 Aug 2020   | 14               |
| Gadot 2020 | VENµS     | 11 May 2020 03 Aug 2020   | 29               | 21 May 2020 20 Jul 2020   | 22               | 13 May 2020 03 Aug 2020   | 28               |

* Period indicating the start and end date of the experiment. ** A defective red edge band in a Sentinel-2 image acquired on 10 June 2019 prevented the derivation of red edge-based vegetation indices for that date.

2.4. Vegetation Indices and Model Validation

All Sentinel-2 and VENµS bands were resampled to 10 m spatial resolution. After that, thirteen vegetation indices (Appendix A) were derived based on the Sentinel-2 and VENµS imagery, including transformed VENµS imagery that utilised a corrective transformation (Table 4) derived for collection 1 VENµS imagery [23]. Since the radiometric processing of VENµS was improved in collection 2, the applicability of the transformation functions to the re-calibrated VENµS imagery was studied by comparing the performance of models based on the imagery transformed for all seasons against the models based on transformed imagery for 2018–2019 seasons (collection 1) and not transformed for 2020 (collection 2). The performance of the former was found to be better than the latter. Therefore, the transformed VENµS imagery models were applied to all seasons. Overall, three types of tomato estimation models were derived: models based on Sentinel-2; models based on Sentinel-2/non-transformed VENµS; models based on the Sentinel-2/transformed VENµS imagery. Hereafter the combined Sentinel-2/transformed VENµS models
will be referred to as S2/V_T, and combined Sentinel-2/non-transformed VENµS models will be referred to as S2/V_NT.

Table 4. Coefficients for the linear transformation from VENµS to Sentinel-2 surface reflectance (after [23]).

| Bands (Central Wavelength) | Slope  | Intercept |
|---------------------------|--------|-----------|
| 10 m                      |        |           |
| Blue (490 nm)             | 1.0307 | 0.0194    |
| Green (560 nm)            | 1.0035 | 0.0271    |
| Red (665 nm)              | 0.9588 | 0.0287    |
| NIR (842 nm)              | 0.8082 | 0.0768    |
| 20 m                      |        |           |
| Red edge 1 (705 nm)       | 0.9589 | 0.0481    |
| Red edge 2 (740 nm)       | 0.8632 | 0.0648    |
| Red edge 3 (783 nm)       | 0.8347 | 0.0796    |
| NIR (865 nm)              | 0.7841 | 0.0980    |

Linear regression models were derived for the time series of field-measured K_c, LAI, height, and each spectral index time series. Each model was based on all available field measurements of each vegetation variable collected during all seasons when the variable was measured. For every model, the R² and root mean square error (RMSE) values were calculated. RMSE was calculated for each model based on all available data and also for each field experiment separately. In addition to vegetation index-based models, an LAI estimation from the ESA SNAP 7.0 biophysical processor for Sentinel-2 imagery was also produced [42].

The S2/V_T and S2/V_NT models were compared, and the Steiger variation [47] of the two-tailed Fisher's Z-score tests [48] was performed to determine whether the difference in the models' R² is significant ($\alpha \leq 0.05$). The same test was also performed to determine whether the difference in R² of the LAI Biophysical processor and DVI was significant.

The field-measured processing tomatoes LAI and height measured in Gadash 2019 and Gadot in 2019 and 2020 were used to calibrate prediction models for K_c as was done previously [49].

3. Results

Figure 2 presents the experiments' measured LAI and crop height, field measured K_c, the smoothed K_c, and the standard K_c table of the Israeli Extension Service. Figure 2A–D shows height values measured during four experiments and LAI values measured during three experiments. Figure 2E–G shows the three types of the aforementioned variations of the K_c associated with three experiments conducted in Israel. The standard K_c recommendation differs from the measured K_c values. Early in the season, during the crop vegetative development, the standard table recommendation is slightly higher than the measured water consumption. In Gadot 2019, the standard recommendation and measured water consumption are about the same at the peak. In Gadot 2020 and Gadash 2019, the standard recommendation’s peak is higher than the measured water consumption. However, from the mid-late season, the measured water consumption drops below the standard recommendation. Interestingly, in Gadash 2019, the crop height and LAI and the K_c were lower compared to the other seasons. Moreover, the changes in LAI and height in Gadash 2019 were different compared to other seasons. These discrepancies in behavior between tomato variables and differences in the variables' values from season to season demonstrate the variance in crop development and water consumption between seasons. Therefore, real-time estimations of those variables are advantageous over the use of standard tables.
Figure 2. Processing tomato experiments data: measured height, measured LAI, and Sentinel-2 and VENµS satellite image acquisition dates: (A) Gadash 2018; (B) Gadash 2019; (C) Gadot 2019;
GEMI and WDVI were found to be the best VIs for the tomato $K_c$, crop height, and LAI estimation. These results repeated in all three types of models: Sentinel-2-based, S2/VNT, and S2/VT. Tables 5–7 show Sentinel-2, S2/VNT, and S2/VT-based $K_c$, crop height, and LAI estimation models based on the five best-performing VIs: DVI, GEMI, WDVI, SAVI, and MSAVI. The best combined Sentinel-2/VENμS models in the present study are presented in Figure 3. The data points in Figure 3 are not clustered by sensors or experiments, which is indicative of the models’ generality. Therefore, both sensors used in the study can be employed interchangeably. The tomato $K_c$, height, and LAI estimation models’ performance is based on eight other VIs (NDVI, MTCI, IPVI, IRECI, S2REP, REIP, GNDVI, and TNDVI), which can be found in Appendices B–D. Table 5 shows that the RMSE of LAI derived from the biophysical processor is higher and the $R^2$ is lower than VIs such as GEMI, DVI, WDVI, SAVI, and MSAVI. The biophysical processor’s $R^2$ was found significantly lower than the $R^2$ of DVI ($p = 0.016$). It was found that the majority of S2/VT and S2/VNT models do not present significant differences in performance and that the transformation of VENμS imagery is mostly beneficial for the red edge VIs such as MTCI and S2REP (Appendix E). Table 8 shows the difference in performance between S2/VT models and S2/VNT models of the best performing VIs (DVI, GEMI, WDVI, SAVI, and MSAVI). Appendix E shows the difference in performance between S2/Vt models and S2/VNT models for eight additional VIs (NDVI, MTCI, IPVI, IRECI, S2REP, REIP, NDVI, and TNDVI).
Figure 3. Vegetation Index linear regression models based on Sentinel-2 and VENµS imagery: (A) \( K_c \)-GEMI Sentinel-2 and non-transformed VENµS images acquired during three processing tomato growing seasons; (B) Vegetation height (dm)–WDVI Vegetation Index regression model based on Sentinel-2 and transformed VENµS images acquired during four processing tomato growing seasons; (C) Vegetation LAI–WDVI Vegetation Index regression model based on Sentinel-2 and transformed VENµS images acquired during three processing tomato growing seasons.

Table 5. Performance statistics of newly developed Sentinel-2-based LAI, Height, \( K_c \) models for the best performing VIs, and the SNAP biophysical processor LAI estimation algorithm’s performance. Performance statistics of additional VIs can be found in Appendix B.

| Vegetation Index | Dataset            | LAI R^2 | LAI RMSE | Height R^2 | Height RMSE (cm) | \( K_c \) R^2 | \( K_c \) RMSE |
|------------------|--------------------|---------|----------|------------|------------------|---------------|--------------|
| GEMI             | Sentinel-2 Gadash 2018 | 0.7444  | 1.3      | 0.651      | 9                | 0.7424        | 0.0855       |
|                  | Sentinel-2 Gadash 2019 | 1.3     | 11       | 0.0727     |                  |               |              |
|                  | Sentinel-2 Gadash 2019 | 1.2     | 6        | 0.1102     |                  |               |              |
|                  | Sentinel-2 Gadot 2019 | 1.3     | 9        | 0.0576     |                  |               |              |
|                  | Sentinel-2 Gadot 2020 | 1.4     | 4        | 0.1122     |                  |               |              |
|                  | All seasons         | 1.3     | 6        | 0.0705     |                  |               |              |
| DVI              | Sentinel-2 Gadash 2018 | 8       |          |            |                  |               |              |
|                  | Sentinel-2 Gadash 2019 | 1.1     | 9        | 0.0705     |                  |               |              |
|                  | Sentinel-2 Gadot 2019 | 1.4     | 4        | 0.1122     |                  |               |              |
| Vegetation Index | Dataset          | LAI | Height | Kc  |
|------------------|------------------|-----|--------|-----|
|                  | R²               | RMSE| R²     | RMSE| R²  | RMSE |
| GEMI             | Sentinel-2 Gadash 2018 | 9   |        |     |     |      |
|                  | VENµS Gadash 2018 |     |        |     |     |      |
|                  | Sentinel-2 Gadash 2019 | 1.2 | 11     | 0.638|     |      |
|                  | VENµS Gadash 2019 | 1.1 | 10     | 0.732|     |      |
|                  | Sentinel-2 Gadot 2019 | 1.3 | 6      | 0.1094|     |      |
|                  | VENµS Gadot 2019 | 1.4 | 6      | 0.1031|     |      |
|                  | Sentinel-2 Gadot 2020 | 1.3 | 9      | 0.0734|     |      |
|                  | VENµS Gadot 2020 | 1.1 | 6      | 0.0801|     |      |
|                  | **All seasons** | **0.7544** | **1.2** | **0.7033** | **8** | **0.8215** | **0.0880** |
| DVI              | Sentinel-2 Gadash 2018 | 9   |        |     |     |      |
|                  | VENµS Gadash 2018 |     |        |     |     |      |
|                  | Sentinel-2 Gadash 2019 | 1.0 | 9      | 0.568|     |      |
|                  | VENµS Gadash 2019 | 0.9 | 9      | 0.0795|     |      |
|                  | Sentinel-2 Gadot 2019 | 1.5 | 4      | 0.1155|     |      |
|                  | VENµS Gadot 2019 | 1.3 | 6      | 0.1161|     |      |
|                  | Sentinel-2 Gadot 2020 | 1.4 | 9      | 0.0864|     |      |
|                  | VENµS Gadot 2020 | 1.0 | 6      | 0.0963|     |      |
|                  | **All seasons** | **0.776** | **1.2** | **0.7681** | **7** | **0.7756** | **0.0984** |
| WDVI             | Sentinel-2 Gadash 2018 | 8   |        |     |     |      |
|                  | VENµS Gadash 2018 |     |        |     |     |      |
|                  | Sentinel-2 Gadash 2019 | 0.7 | 7      | 0.0718|     |      |
|                  | VENµS Gadash 2019 | 1.2 | 10     | 0.0887|     |      |
|                  | Sentinel-2 Gadot 2019 | 2.1 | 9      | 0.1622|     |      |
|                  | VENµS Gadot 2019 | 1.2 | 5      | 0.1087|     |      |
|                  | Sentinel-2 Gadot 2020 | 0.9 | 6      | 0.0674|     |      |

Table 6. Performance statistics of newly developed S2/VNT-based LAI, Height, Kc models for the best performing VIs models. Performance statistics of additional VIs can be found in Appendix C.
| Vegetation Index | Dataset                | LAI R² | RMSE | Height R² | RMSE (cm) | Kc R² | RMSE |
|------------------|------------------------|--------|------|-----------|----------|-------|------|
|                  |                        |        |      |           |          |       |      |
|                  | **GEMI**               |        |      |           |          |       |      |
|                  | Sentinel-2 Gadash 2018 |        |      |           |          |       |      |
|                  | VENµS Gadash 2018      |        |      |           |          |       |      |
|                  | Sentinel-2 Gadash 2019 | 1.6    | 13   |           |          | 0.0798|      |
|                  | VENµS Gadash 2019      | 0.9    | 9    |           |          | 0.0714|      |
|                  | Sentinel-2 Gadot 2019  | 1.0    | 6    |           |          | 0.0944|      |
|                  | VENµS Gadot 2019       | 1.5    | 7    |           |          | 0.1183|      |
|                  | Sentinel-2 Gadot 2020  | 1.5    | 10   |           |          | 0.1120|      |
|                  | VENµS Gadot 2020       | 1.0    | 7    |           |          | 0.0713|      |
|                  | **All seasons**        | **0.7502** | **1.3** | **0.7101** | **8** | **0.7956** | **0.0942** |
|                  |                        |        |      |           |          |       |      |
|                  | **DVI**                |        |      |           |          |       |      |
|                  | Sentinel-2 Gadash 2018 |        |      |           |          |       |      |
|                  | VENµS Gadash 2018      |        |      |           |          |       |      |
|                  | Sentinel-2 Gadash 2019 | 1.3    | 10   |           |          | 0.0609|      |
|                  | VENµS Gadash 2019      | 0.8    | 8    |           |          | 0.0868|      |
|                  | Sentinel-2 Gadot 2019  | 1.3    | 4    |           |          | 0.0996|      |
|                  | VENµS Gadot 2019       | 1.4    | 7    |           |          | 0.1266|      |
|                  | Sentinel-2 Gadot 2020  | 1.3    | 8    |           |          | 0.1225|      |
|                  | VENµS Gadot 2020       | 1.0    | 6    |           |          | 0.0832|      |
|                  | **All seasons**        | **0.7731** | **1.2** | **0.7725** | **7** | **0.755** | **0.1028** |
|                  |                        |        |      |           |          |       |      |
|                  | **WDVI**               |        |      |           |          |       |      |
|                  | Sentinel-2 Gadash 2018 |        |      |           |          |       |      |
|                  | VENµS Gadash 2018      |        |      |           |          |       |      |
|                  | Sentinel-2 Gadash 2019 | 0.9    | 8    |           |          | 0.0531|      |
|                  | VENµS Gadash 2019      | 0.6    | 7    |           |          | 0.1038|      |
|                  | Sentinel-2 Gadot 2019  | 1.6    | 6    |           |          | 0.1286|      |
|                  | VENµS Gadot 2019       | 1.3    | 5    |           |          | 0.1167|      |
|                  | Sentinel-2 Gadot 2020  | 0.9    | 4    |           |          | 0.0901|      |
|                  | VENµS Gadot 2020       | 1.2    | 8    |           |          | 0.1161|      |

**Table 7.** Performance statistics of newly developed S2/Vt-based LAI, Height, Kc models for the best performing VIs. Performance statistics of additional VIs can be found in Appendix D.
All seasons 0.7883 1.2 0.81 7 0.7214 0.1096
SAVI  
Sentinel-2 Gadash 2018 7  
VENµS Gadash 2018 10  
Sentinel-2 Gadash 2019 1.7 12 0.0843  
VENµS Gadash 2019 0.8 8 0.0791  
Sentinel-2 Gadot 2019 1.2 4 0.0774  
VENµS Gadot 2019 1.6 8 0.1255  
Sentinel-2 Gadot 2020 1.4 9 0.1195  
VENµS Gadot 2020 1.0 6 0.0742  
All seasons 0.7383 1.2831 0.7317 8 0.7765 0.0982
MSAVI  
Sentinel-2 Gadash 2018 6  
VENµS Gadash 2018 9  
Sentinel-2 Gadash 2019 1.6 12 0.0755  
VENµS Gadash 2019 0.8 8 0.0846  
Sentinel-2 Gadot 2019 1.3 4 0.0865  
VENµS Gadot 2019 1.6 7 0.1290  
Sentinel-2 Gadot 2020 1.4 9 0.1238  
VENµS Gadot 2020 1.0 6 0.0787  
All seasons 0.7484 1.3 0.7456 8 0.7585 0.1020

Table 8. Difference in performance statistics between newly developed S2/V$_T$ and S2/V$_{NT}$-based LAI, Height, $K_c$ models for the best performing VIs. Positive $R^2$ and negative RMSE indicate the superior performance of the S2/V$_T$ model compared to the equal parameter of the S2/V$_{NT}$ model. Significant differences are marked with (*). Performance statistics of the difference of additional VIs can be found in Appendix E.

| Vegetation Index | Dataset | LAI | R$^2$ | RMSE | Height | R$^2$ | RMSE (cm) | $K_c$ | R$^2$ | RMSE |
|------------------|---------|-----|-------|------|--------|-------|----------|------|-------|------|
| GEMI             | Sentinel-2 Gadash 2018 | -2 |       |       |       |       |          |      |       |      |
|                  | VENµS Gadash 2018      | 1  |       |       |       |       |          |      |       |      |
|                  | Sentinel-2 Gadash 2019 | 0.4|       | 2     | -0.1  | 0     | 0.0159   |      |       |      |
|                  | VENµS Gadash 2019      | -0.2|      | -2    | -0.018| 0     | -0.0151  |      |       |      |
|                  | Sentinel-2 Gadot 2019  | -0.3|      | 0     | -0.015| 1     | 0.0152   |      |       |      |
|                  | VENµS Gadot 2019       | 0.1 |      | 1     | 0.0386| 0     | 0.0088   |      |       |      |
|                  | Sentinel-2 Gadot 2020  | 0.2 |      | 1     | 0.0088| 0     | 0.0088   |      |       |      |
|                  | VENµS Gadot 2020       | -0.1|      | 0     | -0.0259| * | 0.0062   |      |       |      |
|                  | **All seasons**        | -0.0042| 0.0 | 0.0068| 0     | -0.0044|       |      |       |      |
| DVI              | Sentinel-2 Gadash 2018 | -2 |       |       |       |       |          |      |       |      |
|                  | VENµS Gadash 2018      | 1  |       |       |       |       |          |      |       |      |
|                  | Sentinel-2 Gadash 2019 | 0.3|       | 2     | -0.1  | -1    | 0.0041   |      |       |      |
|                  | VENµS Gadash 2019      | -0.1|      | -1    | 0.0073| 0     | -0.0158  |      |       |      |
|                  | Sentinel-2 Gadot 2019  | -0.2|      | 0     | -0.015| 1     | 0.0105   |      |       |      |
|                  | VENµS Gadot 2019       | 0.1 |      | 1     | 0.0360| 0     | -0.0131  |      |       |      |
|                  | Sentinel-2 Gadot 2020  | -0.2|      | -1    | 0.0360| 0     | -0.0131  |      |       |      |
|                  | VENµS Gadot 2020       | 0.0 |      | 0     | -0.0206| 0 | 0.0044   |      |       |      |
|                  | **All seasons**        | -0.0029| 0.0 | 0.0044| 0     | -0.0029|       |      |       |      |
| WDVI             | Sentinel-2 Gadash 2018 | -3 |       |       |       |       |          |      |       |      |
|                  | VENµS Gadash 2018      | 0  |       |       |       |       |          |      |       |      |
|                  | Sentinel-2 Gadash 2019 | 0.2|       | 2     | -0.1  | -3    | -0.0187  |      |       |      |
|                  | VENµS Gadash 2019      | -0.6|      | -3    | 0.0151| -3    | -0.0336  |      |       |      |
|                  | Sentinel-2 Gadot 2019  | -0.5|      | -3    | 0.0080| 0     | 0.0227   |      |       |      |
|                  | VENµS Gadot 2019       | 0.1 |      | 0     | 0.0227| -2    | 0.0080   |      |       |      |
|                  | Sentinel-2 Gadot 2020  | 0.0 |      | -2    | 0.0227| 0     | 0.0080   |      |       |      |
| Method          | Year        | Season | VENµS Gadot 2020 | All seasons | SAVI | MSAVI |
|-----------------|-------------|--------|------------------|-------------|------|-------|
|                 |             |        |                  |             |      |       |
| SAVI            | Sentinel-2 Gadash 2018 | All seasons | 0.0465 | -0.1 | 0.0473* | -1 | -0.0217 | 0.0044 |
|                 | VENµS   Gadash 2018 |         | 0.1          | 1           | 0.0122 |
|                 | Sentinel-2 Gadash 2019 |         | 0.5          | 3           | 0.0216 |
|                 | VENµS   Gadash 2019 |         | -0.2         | -1          | 0.0113 |
|                 | Sentinel-2 Gadot 2019 |         | -0.3         | 0           | -0.0244 |
|                 | VENµS   Gadot 2019 |         | 0.2          | 1           | 0.0166 |
|                 | Sentinel-2 Gadot 2020 |         | 0.4          | 2           | 0.0477 |
|                 | VENµS   Gadot 2020 |         | -0.1         | -1          | -0.0144 |
| **All seasons** |             |        |                |             | -0.0254 | 0.1 | -0.012 | 0 | -0.0373* | 0.0086 |
| MSAVI           | Sentinel-2 Gadash 2018 | All seasons | 0.0255 | 0.1 | -0.0156 | 0 | -0.0347* | 0.0076 |
|                 | VENµS   Gadash 2018 |         | 0.1          | 1           |        |
|                 | Sentinel-2 Gadash 2019 |         | 0.5          | 3           | 0.0165 |
|                 | VENµS   Gadash 2019 |         | -0.2         | -1          | 0.0109 |
|                 | Sentinel-2 Gadot 2019 |         | -0.3         | 0           | -0.0222 |
|                 | VENµS   Gadot 2019 |         | 0.2          | 1           | 0.0154 |
|                 | Sentinel-2 Gadot 2020 |         | 0.4          | 2           | 0.0501 |
|                 | VENµS   Gadot 2020 |         | -0.1         | -1          | -0.0160 |

Figure 4 shows data acquired during two experiments in 2019 and one experiment in 2020. Figure 4A shows LAI and height measurements (in dm; to fit them to the same Y-axis) recorded during three field campaigns in 2019 and 2020. Interestingly, in Gadot 2019, height continued to increase in the middle of the season, while LAI has already started to decrease. In the other fields measured in this study, LAI and height varied simultaneously. Figure 4B shows the smoothed measured $K_c$ curve, the standard $K_c$ table values provided by the Israeli Extension Service (IES), and the estimated $K_c$ values based on the S2/VNIR GEMI model. The field measured $K_c$ varied from season to season, and in Gadash 2019, the measured $K_c$ showed the most considerable difference from the recommended curve, especially in the middle part of the season (approximately 60 days after planting). Moreover, the measured $K_c$ increase, especially during experiments in 2019, does not match the timing of the $K_c$ increase provided by the IES. This demonstrates the significance of using $K_c$ values estimated for a specific field at a specific season for efficient irrigation. The low values of $K_c$, LAI, and height in Gadash 2019 might be explained by the high amount of weeds present in the field during the experiment.
Figure 4. Data associated with three field experiments: Gadash 2019, Gadot 2019, Gadot 2020. (A) LAI and height measurements; (B) Measured, Recommended (IES), and an estimated $K_c$ (S2/VNT GEMI model).

The performance of processing tomato height and LAI-based $K_c$ estimation models using field measurements is shown in Table 9.

Table 9. $K_c$ prediction models based on field measurements of processing tomatoes height and LAI.

|               | $K_c$ Prediction by Height | $K_c$ Prediction by LAI |
|---------------|---------------------------|-------------------------|
| Measurements  | 24                        | 21                      |
| $R^2$         | 0.7467                    | 0.6629                  |
| RMSE          | 0.0948                    | 0.1024                  |

4. Discussion

The field experiments conducted in Israel in 2018–2020 showed that $K_c$, LAI, and crop height in processing tomato differ from season to season but can be estimated correctly in near-real-time from satellite remote sensing imagery. Consequently, agricultural decisions, including the irrigation dose determination, can rely on remote sensing data rather than standard tabular recommendations until late in the season. During the last stage of the season, deficit irrigation is applied according to the percentage of ripe fruit (the ratio of red to green tomatoes on the plant) to delay ripening or expedite it according to the desired harvest schedule [50]. Thus, the irrigation dose at the end of the season cannot be estimated using the remote sensing approach described here.

The field-measured $K_c$ in this study yielded high correlations with VIs from Sentinel-2 and VENµS. Consequently, this study paves the way for more precise $K_c$, LAI, and crop height estimations on a local and global scale based on the freely available optical satellite imagery. These crop variable estimations could be used for better irrigation and fertilization management [51], as well as for early detection of crop disease [52,53], waterlogging [54,55], pest management, and biological control [56].

This study’s most important result was the demonstration of effectively joining Sentinel-2, and VENµS imagery for agricultural monitoring suggested before the launch of
those missions [38]. This was possible because of the close resemblance of Sentinel-2 and VENμS spectral response functions and a good radiometric and atmospheric correction. Application of corrective transformation functions [23] improved the performance of VIs based on the red edge bands (MTCI, S2REP, and REIP), while for the other VIs, the transformation was found unnecessary or provided only marginal performance improvement.

Many VIs showed good Kc estimation performance; the best performing Kc estimation was achieved with the GEMI S2/VNT model ($R^2 = 0.82$, RMSE = 0.09). In an earlier study, a canopy cover-based Kc estimation model achieved $R^2 = 0.96$ [27]. In that study, the canopy cover was calculated using cameras installed in the field. Unlike this approach that relies on in-field sensors, the approach suggested in this paper, based on satellite remote sensing, facilitates the estimation of vegetation variables over more extensive areas at a low cost. This study shows that Kc estimation from optical satellite remote sensing can serve as a reliable source for irrigation decisions and potentially for other agricultural activities throughout the whole growing season of processing tomato. The best performing LAI estimation models showed promising results (S2/V: WDVI LAI estimation model: $R^2 = 0.79$, RMSE = 1.2). This result agrees with a previous study that found WDVI, which takes soil reflectance into account, as a good indicator of LAI [57]. In comparison to the newly-obtained processing tomato LAI models, multi-crop models derived in previous studies demonstrated lower performance, e.g., $R^2 = 0.62$ [58], $R^2 = 0.66$ [59], $R^2 = 0.72$ [60]. A tomato LAI model from previous work [28] showed a lower coefficient of determination ($R^2 = 0.69$) and lower RMSE = 0.56 compared to this study. However, this model was based on only four days of field measurements. Moreover, that work [28] did not include LAI measurements in the final stage of a growing season, while the LAI models in the present study were based on three full growing seasons. Consequently, the processing tomato LAI estimation models developed in the present study are suitable for general use in precision agriculture applications throughout the growing season. Additionally to LAI estimation based upon the VIs, the performance of the SNAP biophysical processor LAI estimation algorithm was studied ($R^2 = 0.53$, RMSE = 2.3) and found to be significantly less accurate compared to the empirical model based on DVI, which was found to be the most accurate Sentinel-2-based VI for LAI estimation.

Similar to Kc and LAI estimation models, the tomato height estimation models were found to perform well throughout the processing tomato growing season. The S2/V: WDVI-based height estimation model ($R^2 = 0.81$, RMSE = 7 cm) was found to be the best, and this approach shows great promise for agricultural crop monitoring. The obtained results confirmed the previously found conclusion that WDVI is a well-suited VI for crop LAI and height estimations [33].

Kc, LAI, and height estimation models based solely on Sentinel-2 data were as accurate as the combined Sentinel-2/VENμS models. Subsequently, a pooled time-series of imagery from both sensors increases the available satellite imagery’s temporal resolution. In cloudy regions, either sensor could fill gaps in the acquisitions of the other, and either sensor can efficiently monitor crop development when imagery from the other sensor is not available. For example, during both experiments in 2019, many VENμS images filled in a long gap in Sentinel-2 data in April–May, and one Sentinel-2 image filled a gap in VENμS images in May–June.

Additionally to the Kc estimation based on the remote sensing data, Kc estimation models based on the field measured LAI and height were derived. These models’ performance was similar to the remote sensing-based models and might be used on the local scale in the absence of remote sensing imagery. The Kc-height model is of particular interest from a practical viewpoint since farmers can easily and routinely take plant height measurements.

While this study provided useful results from thirteen VIs (including VIs based on the red edge bands and soil adjusted VIs) to estimate Kc, LAI, and height in the processing tomato using Sentinel-2 and VENμS imagery, there is merit in future studies on other crops. Future efforts could follow the procedure suggested in this paper to empirically
calibrate and test prediction models for different indices and identify those that achieve the best performance. Studies based on two or more different sensors should make sure to perform a radiometric calibration between sensors.

5. Conclusions

This work demonstrates the conjoint use of Sentinel-2 and VENµS imagery for estimating \( K_o \), LAI, and height of processing tomato. It was found that red edge VIs should be based on Sentinel-2 and transformed VENµS imagery. At the same time, other VIs can be derived directly from imagery obtained by both systems, and no corrective transformation is required to match the two sensors. In addition, models based solely on Sentinel-2 showed similar performance as the joint Sentinel-2 and VENµS imagery models. The \( K_o \), LAI, and height estimation models derived empirically using field measurements show good performance and are ready for application. The LAI estimation performance from the SNAP biophysical processor was also studied and found inferior to the VI-based LAI estimation models. The irrigation in the early and middle parts of the processing tomato growing season can rely on remote sensing-based models rather than standard table values to best match the actual crop development and capture within-field variability.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Vegetation indices used in the present study.

| Index Name                          | Formula                                                                 | Reference |
|-------------------------------------|-------------------------------------------------------------------------|-----------|
| Normalised Difference Vegetation Index (NDVI) | \[
\frac{(NIR - RED)}{(NIR + RED)} \]
| 1                                   |                                                                         | [61]      |
| Global Environmental Monitoring Index (GEMI) | \[
\eta \times (1 - 0.25 \times \eta) - \frac{[(RED - 0.125)]}{(1 - RED)}
\]
\[
where \ \eta = \frac{2 \times (NIR2 - RED2) + 1.5 \times NIR + 0.5 \times RED}{(NIR + RED + 0.5)}
\]
| 2                                   |                                                                         | [62]      |
| Weighted Difference Vegetation Index (WDVI) | \[
NIR - S \times RED
\]
\[
where: S is the slope of the soil line.
\]
| 3                                   |                                                                         | [63]      |
| Green Normalized Difference Vegetation Index | \[
\frac{(NIR - GREEN)}{(NIR + GREEN)}
\]
| 4                                   |                                                                         | [64]      |
Appendix B

Table A2. Performance statistics of newly developed Sentinel-2-based LAI, Height, $K_c$ models, and the performance of the SNAP biophysical processor LAI estimation algorithm. Performance statistics of better performing VIs can be found in Table 5.

| Vegetation Index | Dataset                  | LAI $R^2$ | RMSE | Height $R^2$ | RMSE (cm) | $K_c$ $R^2$ | RMSE |
|------------------|--------------------------|-----------|------|--------------|-----------|-------------|------|
| NDVI             | Sentinel-2 Gadash 2018   | 1.5       | 11   | 1.5          | 5         | 0.0919      |      |
|                  | Sentinel-2 Gadash 2019   | 1.2       | 9    |              |           |             |      |
| All seasons      | 0.6594                   | 1.4       | 0.6387 | 9           | 0.7524 | 0.0826     |      |
| MTCI             | Sentinel-2 Gadash 2018   | 2.0       | 11   |              |           | 0.1608      |      |
|                  | Sentinel-2 Gadash 2019   | 2.6       | 11   | 2.1          | 8         | 0.0724      |      |
| All seasons      | 0.16                     | 2.3       | 0.5216 | 10          | 0.2653 | 0.1433     |      |
| IPVI             | Sentinel-2 Gadash 2018   | 1.5       | 11   | 1.5          | 5         | 0.0919      |      |
|                  | Sentinel-2 Gadash 2019   | 1.2       | 9    |              |           | 0.0558      |      |
| All seasons      | 0.6594                   | 1.4       | 0.6387 | 9           | 0.7524 | 0.0826     |      |
| IRECI            | Sentinel-2 Gadash 2018   | 1.5       | 11   | 1.5          | 5         | 0.0919      |      |
|                  | Sentinel-2 Gadash 2019   | 1.2       | 9    |              |           | 0.0558      |      |
| All seasons      | 0.6594                   | 1.4       | 0.6387 | 9           | 0.7524 | 0.0826     |      |
|          | S2REP   | All seasons | 1.4 | 0.7688 | 7   | 0.4636 | 0.1233 |
|----------|---------|-------------|-----|--------|-----|--------|--------|
|          | 2018    |             | 11  |        |     |        |        |
| Sentinel-2 Gadash 2018 | 2.1     | 12          | 0.1619 |
|          | 2019    |             | 2.5 | 10     | 0.1750 |
|          | 2020    |             | 2.1 | 9      | 0.0730 |
|          | All seasons |          | 2.3 | 0.559  | 10  | 0.2893 | 0.1411 |
| S2REP    |         |             |     |        |     |        |        |
|          | 2018    |             | 16  |        |     |        |        |
| Sentinel-2 Gadash 2018 |         |             |     |        |     |        |        |
|          | 2019    |             | 2.1 | 14     | 0.1619 |
|          | 2020    |             | 2.1 | 10     | 0.0730 |
|          | All seasons |          | 2.3 | 0.3176 | 12  | 0.2893 | 0.1411 |
| REIP     |         |             |     |        |     |        |        |
|          | 2018    |             | 10  |        |     |        |        |
| Sentinel-2 Gadash 2018 |         |             |     |        |     |        |        |
|          | 2019    |             | 1.6 | 12     | 0.1138 |
|          | 2020    |             | 1.4 | 9      | 0.0660 |
|          | All seasons |          | 1.5 | 0.6314 | 9   | 0.6048 | 0.1059 |
| GNDVI    |         |             |     |        |     |        |        |
|          | 2018    |             | 9   |        |     |        |        |
| Sentinel-2 Gadash 2018 |         |             |     |        |     |        |        |
|          | 2019    |             | 1.6 | 12     | 0.0955 |
|          | 2020    |             | 1.3 | 9      | 0.0538 |
|          | All seasons |          | 1.5 | 0.6222 | 9   | 0.7572 | 0.0818 |
Appendix C

Table A3. Performance statistics of S2/VNIR-based LAI, Height, Kc models. Performance statistics of better performing VIs can be found in Table 6.

| Vegetation Index | Dataset | LAI $R^2$ | RMSE | Height $R^2$ | RMSE (cm) | $K_c$ $R^2$ | RMSE |
|------------------|---------|----------|------|--------------|-----------|-------------|------|
| NDVI             | Sentinel-2 Gadash 2018 | 9       |      | 11           | 0.0939    |             |      |
|                  | VENµS Gadash 2018 | 9       |      | 10           | 0.0718    |             |      |
|                  | Sentinel-2 Gadash 2019 | 1.5     | 11   | 10           | 0.0887    | 8            | 0.1115 |
|                  | VENµS Gadot 2019 | 1.6     | 8    |              |           | 9            | 0.0700  |
|                  | Sentinel-2 Gadot 2020 | 1.2     | 9    |              |           | 8            | 0.0844  |
|                  | VENµS Gadot 2020 | 1.2     | 8    |              |           |              |        |
|                  | All seasons | 0.8099  | 1.4  | 0.6885       | 0.7009    | 0.0905      |      |
| MTCI             | Sentinel-2 Gadash 2018 | 17      |      |              |           |             |      |
|                  | VENµS Gadash 2018 | 11      |      |              |           |             |      |
|                  | Sentinel-2 Gadash 2019 | 1.6     | 6    |              |           | 13           | 0.1439  |
|                  | VENµS Gadash 2019 | 2.1     | 14   |              |           | 10           | 0.2325  |
|                  | Sentinel-2 Gadot 2019 | 2.8     | 8    |              |           | 10           | 0.1845  |
|                  | VENµS Gadot 2019 | 2.8     | 10   |              |           | 9            | 0.0869  |
|                  | Sentinel-2 Gadot 2020 | 2.4     | 10   |              |           | 11           | 0.1559  |
|                  | VENµS Gadot 2020 | 2.1     | 11   |              |           |              |        |
|                  | All seasons | 0.0804  | 2.4  | 0.4062       | 0.2945    | 0.1750      |      |
| IPVI             | Sentinel-2 Gadash 2018 | 9       |      |              |           |             |      |
|                  | VENµS Gadash 2018 | 9       |      |              |           |             |      |
|                  | Sentinel-2 Gadash 2019 | 1.5     | 11   |              |           | 10           | 0.0939  |
|                  | VENµS Gadash 2019 | 1.0     | 10   |              |           | 5            | 0.0718  |
|                  | Sentinel-2 Gadot 2019 | 1.5     | 5    |              |           | 8            | 0.0887  |
|                  | VENµS Gadot 2019 | 1.6     | 8    |              |           | 10           | 0.1114  |
|                  | Sentinel-2 Gadot 2020 | 1.2     | 9    |              |           | 8            | 0.0701  |
|                  | VENµS Gadot 2020 | 1.2     | 8    |              |           |              | 0.0841  |
|                  | All seasons | 0.7012  | 1.4  | 0.687        | 0.8103    | 0.0904      |      |
| IRECI            | Sentinel-2 Gadash 2018 | 10      |      |              |           |             |      |
|                  | VENµS Gadash 2018 | 9       |      |              |           |             |      |
|                  | Sentinel-2 Gadash 2019 | 1.0     | 7    |              |           | 7            | 0.0964  |
|                  | VENµS Gadash 2019 | 0.9     | 7    |              |           | 10           | 0.1378  |
|                  | Sentinel-2 Gadot 2019 | 1.8     | 7    |              |           | 6            | 0.1753  |
|                  | VENµS Gadot 2019 | 1.7     | 6    |              |           | 5            | 0.1605  |
|                  | Sentinel-2 Gadot 2020 | 1.0     | 5    |              |           | 9            | 0.1493  |
|                  | VENµS Gadot 2020 | 1.7     | 9    |              |           |              |        |
|                  | All seasons | 0.661   | 1.5  | 0.7684       | 0.5179    | 0.1447      |      |
| S2REP            | Sentinel-2 Gadash 2018 | 12      |      |              |           |             |      |
|                  | VENµS Gadash 2018 | 10      |      |              |           |             |      |
|                  | Sentinel-2 Gadash 2019 | 1.9     | 9    |              |           | 11           | 0.1456  |
|                  | VENµS Gadash 2019 | 2.0     | 11   |              |           | 15           | 0.1538  |
|                  | Sentinel-2 Gadot 2019 | 2.8     | 15   |              |           | 9            | 0.2199  |
|                  | VENµS Gadot 2019 | 2.7     | 9    |              |           | 10           | 0.1752  |
|                  | Sentinel-2 Gadot 2020 | 2.1     | 8    |              |           | 9            | 0.0790  |
|                  | VENµS Gadot 2020 | 2.0     | 10   |              |           |              | 0.1514  |
|                  | All seasons | 0.1541  | 2.3  | 0.5588       | 0.4066    | 0.1616      |      |
Table A4. Performance statistics of S2/V$_T$-based LAI, Height, $K_c$. Performance statistics of better performing VIs can be found in Table 7.

| Vegetation Index | Dataset          | LAI $R^2$ | LAI RMSE | Height $R^2$ | Height RMSE (cm) | $K_c$ $R^2$ | $K_c$ RMSE |
|------------------|------------------|-----------|----------|--------------|-----------------|-------------|------------|
| NDVI             | Sentinel-2 Gadash 2018 | 0.623     | 1.5      | 0.6156       | 0.743           | 0.1053      |
|                  | VENµS Gadash 2018  |           | 1.5      |              |                 |             |
|                  | Sentinel-2 Gadash 2019 | 2.0       | 14       | 0.1223       |                 |             |
|                  | VENµS Gadash 2019  | 1.0       | 9        | 0.0665       |                 |             |
|                  | Sentinel-2 Gadot 2019 | 1.2       | 5        | 0.0662       |                 |             |
|                  | VENµS Gadot 2019  | 2.0       | 10       | 0.1461       |                 |             |
|                  | Sentinel-2 Gadot 2020 | 1.4       | 10       | 0.0926       |                 |             |
|                  | VENµS Gadot 2020  | 1.2       | 8        | 0.0863       |                 |             |
|                  | **All seasons**   | **0.623** | **1.5**  | **0.6156**   | **0.743**       | **0.1053**  |
| MTCI             | Sentinel-2 Gadash 2018 | 2.1       | 12       | 0.1649       |                 |             |
|                  | VENµS Gadash 2018  |           | 1.5      | 6            | 0.1368          |             |
|                  | Sentinel-2 Gadash 2019 | 2.6       | 10       | 0.1802       |                 |             |
|                  | VENµS Gadash 2019  | 2.7       | 11       | 0.1823       |                 |             |
|                  | Sentinel-2 Gadot 2019 | 2.0       | 9        | 0.0906       |                 |             |
|                  | VENµS Gadot 2020  | 2.0       | 12       | 0.1561       |                 |             |
|             | IPVI            | IRECI           | S2REP          | REIP            | GNDVI          | TNDVI          |
|-------------|----------------|----------------|----------------|----------------|----------------|----------------|
|             | 0.2094 2.2 0.5212 11 | 0.646 1.5 0.6454 9 | 0.6527 1.5 0.7349 8 | 0.1992 2.3 0.5893 10 | 0.1446 2.3 0.4117 12 | 0.5782 1.6 0.6342 9 |
| All seasons | 0.4222 0.1583  | 0.7233 0.1092  | 0.5139 0.1453  | 0.5709 0.1366  | 0.4658 0.1529  | 0.6596 0.1216  |
| IPVI        | Sentinel-2 Gadash 2018 | VENµS Gadash 2018 | VENµS Gadash 2018 | VENµS Gadash 2018 | VENµS Gadash 2018 | VENµS Gadash 2018 |
|             | Sentinel-2 Gadash 2019 | 2.1 14 0.1253  | Sentinel-2 Gadash 2019 | 1.4 10 0.0916  | Sentinel-2 Gadash 2019 | 2.8 22 0.2433  |
|             | VENµS Gadash 2019 | 0.7 7 0.1394  | VENµS Gadash 2019 | 0.8 7 0.1394  | VENµS Gadash 2019 | 1.6 7 0.1249  |
|             | Sentinel-2 Gadot 2019 | 1.2 5 0.0635  | Sentinel-2 Gadot 2019 | 1.4 6 0.1527  | Sentinel-2 Gadot 2019 | 2.4 10 0.1658  |
|             | VENµS Gadot 2019 | 1.9 8 0.1713  | VENµS Gadot 2019 | 1.9 8 0.1713  | VENµS Gadot 2019 | 2.7 10 0.1556  |
|             | Sentinel-2 Gadot 2020 | 1.9 11 0.1588 | Sentinel-2 Gadot 2020 | 1.9 11 0.1588 | Sentinel-2 Gadot 2020 | 2.1 11 0.1208  |
|             | VENµS Gadot 2020 | 1.3 5 0.1125  | VENµS Gadot 2020 | 1.3 5 0.1125  | VENµS Gadot 2020 | 2.1 10 0.1563  |
| All seasons | 0.2094 2.2 0.5212 11 | 0.646 1.5 0.6454 9 | 0.6527 1.5 0.7349 8 | 0.1992 2.3 0.5893 10 | 0.1446 2.3 0.4117 12 | 0.5782 1.6 0.6342 9 |
Table A5. Difference between performance statistics of S2/V₃ and S2/VNT-based LAI, Height, Kc models. If R² is positive and RMSE is negative, it means that this parameter performance of the combined S2/V₃ model is higher than the equal parameter of the S2/VNT model. Significant differences are marked with (*). Performance statistics of better performing VIs can be found in Table 8.

| Vegetation Index | Dataset | LAI | Height | Kc |
|------------------|---------|-----|--------|----|
|                  |         | R² | RMSE   | R² | RMSE (cm) | R² | RMSE |
| NDVI             | Sentinel-2 Gadash 2018 | 0.5 | 3 | 0.0284 |
|                  | VENµS Gadash 2018 | 0.0 | 0 | −0.0054 |
|                  | Sentinel-2 Gadash 2019 | −0.3 | 0 | −0.0226 |
|                  | VENµS Gadash 2019 | 0.4 | 2 | 0.0346 |
|                  | Sentinel-2 Gadot 2019 | 0.2 | 1 | 0.0226 |
|                  | VENµS Gadot 2019 | 0.0 | 0 | 0.0019 |
|                  | All seasons | −0.1869 * | 0.2 | −0.0729 * | 1 | 0.0421 * | 0.0147 |
| MTCI             | Sentinel-2 Gadash 2018 | 0.5 | 3 | 0.0210 |
|                  | VENµS Gadash 2018 | 0.0 | 0 | −0.0051 |
|                  | Sentinel-2 Gadash 2019 | −0.6 | −7 | −0.0523 |
|                  | VENµS Gadash 2019 | −0.1 | −5 | −0.0022 |
|                  | Sentinel-2 Gadot 2019 | −0.1 | 1 | 0.0038 |
|                  | VENµS Gadot 2019 | −0.4 | −1 | 0.0002 |
|                  | Sentinel-2 Gadot 2020 | −0.1 | 1 | 0.0000 |
|                  | VENµS Gadot 2020 | 0.0 | 0 | 0.0063 |
|                  | All seasons | 0.129 * | −0.2 | 0.115 * | −1 | 0.1277 * | −0.0166 |
| IPVI             | Sentinel-2 Gadash 2018 | 0.6 | 3 | 0.0314 |
|                  | VENµS Gadash 2018 | −0.4 | −2 | 0.0188 |
|                  | Sentinel-2 Gadash 2019 | −0.3 | 0 | −0.0252 |
|                  | VENµS Gadash 2019 | 0.3 | 2 | 0.0317 |
|                  | Sentinel-2 Gadot 2019 | 0.2 | 1 | 0.0270 |
|                  | VENµS Gadot 2019 | 0.0 | 0 | 0.0063 |
|                  | Sentinel-2 Gadot 2020 | −0.1 | 1 | 0.0000 |
|                  | VENµS Gadot 2020 | 0.0 | 0 | 0.0063 |
|                  | All seasons | −0.0552 * | 0.1 | −0.0416 * | 1 | −0.087 * | 0.0188 |
| IRECI            | Sentinel-2 Gadash 2018 | 0.4 | 3 | −0.0048 |
|                  | VENµS Gadash 2018 | −0.1 | 0 | 0.0016 |
|                  | Sentinel-2 Gadash 2019 | −0.4 | −1 | −0.0225 |
|                  | VENµS Gadash 2019 | 0.2 | 2 | 0.0108 |
|                  | Sentinel-2 Gadot 2019 | −0.4 | −3 | −0.0368 |
|                  | VENµS Gadot 2019 | 0.8 | 7 | 0.0917 |
|                  | Sentinel-2 Gadot 2020 | −0.4 | −3 | −0.0368 |
|                  | VENµS Gadot 2020 | 0.0 | 0 | 0.0006 |
|                  | All seasons | −0.0083 | 0.0 | −0.0335 | 1 | −0.004 | 0.0006 |
| S2REP            | Sentinel-2 Gadash 2018 | 0.5 | 3 | 0.0284 |
|                  | VENµS Gadash 2018 | 0.0 | 0 | −0.0054 |
|                  | Sentinel-2 Gadash 2019 | −0.3 | 0 | −0.0226 |
|                  | VENµS Gadash 2019 | 0.4 | 2 | 0.0346 |
|                  | Sentinel-2 Gadot 2019 | 0.2 | 1 | 0.0226 |
|                  | VENµS Gadot 2019 | 0.0 | 0 | 0.0019 |
|                  | Sentinel-2 Gadot 2020 | −0.1 | 1 | 0.0002 |
|                  | VENµS Gadot 2020 | 0.0 | 0 | 0.0063 |
|                  | All seasons | −0.1869 * | 0.2 | −0.0729 * | 1 | 0.0421 * | 0.0147 |
| Reference | Methodology | Season | VENµS Gdash 2019 | VENµS Gdash 2019 | VENµS Gdash 2019 | VENµS Gdash 2019 | VENµS Gdash 2019 |
|-----------|-------------|--------|------------------|------------------|------------------|------------------|------------------|
| Remote Sens. 2021, 13, 1046 | | | | | | | |
| | REIP | Sentinel-2 Gdash 2018 | 0.5 | 7 | 0.0449 |
| | Sentinel-2 Gdash 2019 | 0.0 | 3 | 0.0196 |
| | Sentinel-2 Gdash 2020 | 0.0 | 3 | 0.0196 |
| | All seasons | 0.0451 | -0.1 | 0.0305 | 0 | 0.1643 | -0.0250 |
| | GNDVI | Sentinel-2 Gdash 2018 | 0.3 | 4 | 0.0414 |
| | Sentinel-2 Gdash 2019 | 0.0 | 3 | 0.0047 |
| | Sentinel-2 Gdash 2020 | 0.1 | 1 | 0.0164 |
| | All seasons | -0.0063 | 0.0 | -0.0698 | 1 | 0.0435 | -0.0062 |
| | TNDVI | Sentinel-2 Gdash 2018 | 1.0 | 6 | 0.0564 |
| | Sentinel-2 Gdash 2019 | 0.4 | 3 | 0.0470 |
| | Sentinel-2 Gdash 2020 | 0.4 | 2 | 0.0464 |
| | All seasons | -0.0695 | 0.1 | -0.0592 | 1 | -0.1035 | 0.0202 |

**References**

1. Shtull-Trauring, E.; Cohen, A.; Ben-Hur, M.; Tanny, J.; Bernstein, N. Reducing salinity of treated waste water with large scale desalination. *Water Res.* **2020**, *186*, 116322, doi:10.1016/j.watres.2020.116322.
2. Pimentel, D.; Berger, B.; Filiberto, D.; Newton, M.; Wolfe, B.; Karabinakis, E.; Nandagopal, S. Water resources: agricultural and environmental issues. *Bioscience* **2004**, *54*, 909–918, doi:10.1201/9781420046687.
3. Allen, R.G.; Pereira, L.S.; Dirk, R.; Smith, M. Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-FAO Irrigation and Drainage Paper 56. *FAO Rome* **1998**, *300*, D05109.
4. Pereira, L.; Paredes, P.; Hunsaker, D.; López-Urrea, R.; Shad, Z.M. Standard single and basal crop coefficients for field crops. Updates and advances to the FAO56 crop water requirements method. *Agric. Water Manag.* **2021**, *243*, 106466, doi:10.1016/j.agwat.2020.106466.
5. Beeri, O.; Pelta, R.; Shilo, T.; Mey-Tal, S.; Tanny, J. Accuracy of crop coefficient estimation methods based on satellite imagery. *Precis. Agric.* **2019**, *19*, 9.
6. De Oliveira, T.C.; Ferreira, E.; Dantas, A.A.A. Temporal variation of normalized difference vegetation index (NDVI) and calculation of the crop coefficient (Kc) from NDVI in areas cultivated with irrigated soybean. *Ciência Rural* **2016**, *46*, 1683–1688, doi:10.1590/0103-8478cr20150318.
7. Navarro, A.; Rolim, J.; Miguel, I.; Catalão, J.; Silva, J.; Painho, M.; Vekerdy, Z. Crop Monitoring Based on SPOT-5 Take-5 and Sentinel-1A Data for the Estimation of Crop Water Requirements. *Remote Sens.* **2016**, *8*, 525, doi:10.3390/rs8060525.
8. Johnson, L.F.; Trout, T.J. Satellite NDVI Assisted Monitoring of Vegetable Crop Evapotranspiration in California’s San Joaquin Valley. *Remote Sens.* **2012**, *4*, 439–455, doi:10.3390/rs4020439.
9. Corbari, C.; Ravazzani, G.; Galvagni, M.; Cremonese, E.; Mancini, M. Assessing Crop Coefficients for Natural Vegetated Areas Using Satellite Data and Eddy Covariance Stations. *Sensors* 2017, 17, 2664, doi:10.3390/s17112664.
10. Rozenstein, O.; Haymann, N.; Kaplan, G.; Tanny, J. Estimating cotton crop water consumption using a time series of Sentinel-2 imagery. *Agric. Water Manag.* 2018, 207, 44–52, doi:10.1016/j.agwat.2018.05.017.
11. Park, J.; Baik, J.; Choi, M. Satellite-based crop coefficient and evapotranspiration using surface soil moisture and vegetation indices in Northeast Asia. *Catena* 2017, 156, 305–314, doi:10.1016/j.catena.2017.04.013.
12. Li, H.; Luo, Y.; Zhao, C.; Yang, G. Remote sensing of regional crop transpiration of winter wheat based on MODIS data and FAO-56 crop coefficient method. *Intell. Autom. Soft Comput.* 2013, 19, 285–294, doi:10.1080/10798587.2013.824150.
13. Mateos, L.; González-Dugo, M.; Testi, L.; Villalobos, F. Monitoring evapotranspiration of irrigated crops using crop coefficients derived from time series of satellite images. I. Method validation. *Agric. Water Manag.* 2013, 125, 81–91, doi:10.1016/j.agwat.2012.11.005.
14. Rozenstein, O.; Haymann, N.; Kaplan, G.; Tanny, J. Validation of the cotton crop coefficient estimation model based on Sentinel-2 imagery and eddy covariance measurements. *Agric. Water Manag.* 2019, 223, 105715, doi:10.1016/j.agwat.2019.105715.
15. Martínez, L.J. Relationship between crop nutritional status, spectral measurements and Sentinel 2 images. *Agron. Colomb.* 2017, 35, 205–215, doi:10.15446/agron.colomb.v35n2.62857.
16. Flood, N. Continuity of Reflectance Data between Landsat-7 ETM+ and Landsat-8 OLI for Both Top-Of-Atmosphere and Surface Reflectance: A Study in the Australian Landscape. *Remote Sens.* 2014, 6, 7952–7970, doi:10.3390/rs6097952.
17. Sabzchi-Dehkhangharni, H.; Nazemi, A.H.; Sadreddini, A.A.; Majnooni-Heris, A.; Biswas, A. Recognition of different yield potentials among rain-fed wheat fields before harvest using remote sensing. *Agric. Water Manag.* 2021, 245, 106611, doi:10.1016/j.agwat.2020.106611.
18. Research Developments in Saline Agriculture. *Research Developments in Saline Agriculture*; Springer: Berlin/Heidelberg, Germany, 2019, doi:10.1007/978-981-13-5832-6.
19. Singh, R.K.; Khand, K.; Kagone, S.; Schauer, M.; Senay, G.B.; Wu, Z. A novel approach for next generation water-use mapping using Landsat and Sentinel-2 satellite data. *Hydrol. Sci. J.* 2020, 65, 2508–2519, doi:10.1080/02626667.2020.1817461.
20. Ghosh, S.; Behera, D.; Jayakumar, S.; Das, P. Comparison of Sentinel-2 Multispectral Imager (MSI) and Landsat 8 Operational Land Imager (OLI) for Vegetation Monitoring. In *Spatial Modeling in Forest Resources Management*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 175–192.
21. Mourad, R.; Jaafar, H.; Anderson, M.; Gao, F. Assessment of Leaf Area Index Models Using Harmonized Landsat and Sentinel-2 Surface Reflectance Data over a Semi-Arid Irrigated Landscape. *Remote Sens.* 2020, 12, 3211, doi:10.3390/rs12193211.
22. Padró, J.-C.; Pons, X.; Aragonés, D.; Diaz-Delgado, R.; García, D.; Bustamante, J.; Pesquer, L.; Domingo-Marimon, C.; González-Guerrero, O.; Cristóbal, J.; et al. Radiometric Correction of Simultaneously Acquired Landsat-7/Landsat-8 and Sentinel-2A Imagery Using Pseudoinvariant Areas (PIA): Contributing to the Landsat Time Series Legacy. *Remote Sens.* 2017, 9, 1319, doi:10.3390/rs9121319.
23. Manivasagam, V.; Kaplan, G.; Rozenstein, O. Developing Transformation Functions for VENμS and Sentinel-2 Surface Reflectance over Israel. *Remote Sens.* 2019, 11, 1710, doi:10.3390/rs11141710.
24. Harel, D.; Sofer, M.; Broner, M.; Zohar, D.; Gantz, S. Growth-Stage-Specific Kc of Greenhouse Tomato Plants Grown in Semi-Arid Mediterranean Region. *J. Agric. Sci.* 2014, 6, 132–142, doi:10.5599/jas.v6n1p132.
25. Čerkevkin, N.; Todorovic, M.; Snyder, R.L.; Boari, F.; Pace, B.; Cantore, V. Evaluation of the crop coefficients for tomato crop grown in a Mediterranean climate. *Options Méditerranéennes Séries A Mediterr. Semin.* 2010, 94, 91–94.
26. Rosa, R.; Dicken, U.; Tanny, J. Estimating evapotranspiration from processing tomato using the surface renewal technique. * Biosyst. Eng.* 2013, 114, 406–413, doi:10.1016/jbiosystemseng.2012.06.011.
27. Hanson, B.R.; May, D.M. Crop evapotranspiration of processing tomato in the San Joaquin Valley of California, USA. *Irrig. Sci.* 2005, 24, 211–221, doi:10.1007/s00271-005-0020-x.
28. Vanino, S.; Nino, P.; De Micheile, C.; Bolognesi, S.F.; D’Urso, G.; Di Bene, C.; Pennelli, B.; Vuolo, F.; Farina, R.; Pulighe, G.; et al. Capability of Sentinel-2 data for estimating maximum evapotranspiration and irrigation requirements for tomato crop in Central Italy. *Remote Sens. Environ.* 2018, 215, 452–470, doi:10.1016/j.rse.2018.06.035.
29. Williams, J.R. The EPIC Model, Computer Models of Watershed Hydrology. *Water Resour. Publ. Highl. Ranch Colo.* 1995, pp. 909–1000 ISBN 0918334918.
30. Ducharmin, B.; Hadria, R.; Er-Raki, S.; Boulet, G.; Maisongrande, P.; Chehbouni, A.; Escadafal, R.; Ezzahar, J.; Hoedjes, J.C.B.; Kharrou, M.H.; et al. Monitoring wheat phenology and irrigation in Central Morocco: On the use of relationships between evapotranspiration, crops coefficients, leaf area index and remotely-sensed vegetation indices. *Agric. Water Manag.* 2006, 79, 1–27, doi:10.1016/j.agwat.2005.02.013.
31. Sadeh, Y.; Zhu, X.; Dunkelley, D.; Walker, J.P.; Zhang, Y.; Rozenstein, O.; Manivasagam, V.; Chenu, K. Fusion of Sentinel-2 and PlanetScope time-series data into daily 3 m surface reflectance and wheat LAI monitoring. *Int. J. Appl. Earth Obs. Geoinf.* 2021, 96, 102260, doi:10.1016/j.jag.2020.102260.
32. Farg, E.; Abutaleb, K.A.; Arafat, S.M.; El Sharkawy, M.M.; Nabil, M. Assessment of Sentinel-2 data capabilities for vegetation physiological parameters retrieving in the Nile Delta. *Biosci. Res.* 2020, 17, 467–478.
33. Papadavid, G.; Hadjimitisis, D.; Toulios, L.; Michaelides, S. Mapping potato crop height and leaf area index through vegetation indices using remote sensing in Cyprus. *J. Appl. Remote Sens.* 2011, 5, 053526, doi:10.1117/1.3596388.
34. Thenkabail, P.S.; Ward, A.D.; Lyon, J.G. Landsat-5 Thematic Mapper models of soybean and corn crop characteristics. *Int. J. Remote Sens.* 1994, 15, 49–61, doi:10.1080/01431169408954050.

35. Kamble, B.; Kilic, A.; Hubbard, K.G. Estimating Crop Coefficients Using Remote Sensing-Based Vegetation Index. *Remote Sens.* 2013, 5, 1588–1602, doi:10.3390/rs05041588.

36. Jackson, R.D.; Idso, S.B.; Reginato, R.J.; Pinter, P.J. Remotely Sensed Crop Temperatures and Reflectances as Inputs to Irrigation Scheduling; American Association of Agricultural Engineers: New York, NY, USA, 1980; pp. 390–397.

37. Ewert, F. Modelling Plant Responses to Elevated CO2: How Important is Leaf Area Index? *Ann. Bot.* 2004, 93, 619–627, doi:10.1093/aob/mch101.

38. Herrmann, I; Pimstein, A.; Kanieli, A.; Cohen, Y.; Alchanatis, V.; Bonfil, D. LAI assessment of wheat and potato crops by VENuS and Sentinel-2 bands. *Remote Sens. Environ.* 2011, 115, 2141–2151, doi:10.1016/j.rse.2011.04.018.

39. Nguy-Robertson, A.L.; Peng, Y.; Gitelson, A.A.; Arkebauer, T.J.; Pimstein, A.; Herrmann, I; Kanieli, A.; Rundquist, D.C.; Bonfil, D.J. Estimating green LAI in four crops: Potential of determining optimal spectral bands for a universal algorithm. *Agric. For. Meteorol.* 2014, 192–193, 140–148, doi:10.1016/j.agrformet.2014.03.004.

40. Heuvelink, E.; Bakker, M.; Elings, A.; Kaarsemaker, R.; Marcelis, L. Effect of leaf area on tomato yield. *Acta Hort.* 2005, 691, 43–50, doi:10.17660/actahortic.2005.691.2.

41. Sun, Y.; Qin, Q.; Ren, H.; Zhang, T.; Chen, S. Red-Edge Band Vegetation Indices for Leaf Area Index Estimation From Sentinel-2/MSI Imagery. *IEEE Trans. Geosci. Remote Sens.* 2020, 58, 826–840, doi:10.1109/tgrs.2019.2940826.

42. Weiss, M.; Baret, F. S2ToolBox Level 2 Products: LAI, FAPAR, FCOVER. Available online: http://step.esa.int/docs/extra/ATBD_S2ToolBox_L2B_V11.pdf (accessed on 21 February 2021).

43. Beeri, O.; Netzer, Y.; Munitz, S.; Mintz, D.F.; Pelta, R.; Shilo, T.; Horesh, A.; Mey-Tal, S. Kc and LAI Estimations Using Optical and SAR Remote Sensing Imagery for Vineyards Plots. *Remote Sens.* 2020, 12, 3478, doi:10.3390/rs12113478.

44. Revill, A.; Florence, A.; MacArthur, A.; Hoad, S.; Rees, R.; Williams, M. Quantifying Uncertainty and Bridging the Scaling Gap in the Retrieval of Leaf Area Index by Coupling Sentinel-2 and UAV Observations. *Remote Sens.* 2020, 12, 1843, doi:10.3390/rs12111843.

45. Richardson, A.J.; Wiegand, C.L. Distinguishing vegetation from soil background information. *Photogramm. Eng. Remote Sens.* 1977, 43, 1541–1552.

46. Dedieu, G.; Kanieli, A.; Hagolle, O.; Jeanjean, H.; Cabot, F.; Ferrier, P.; Yaniv, Y. A Joint Israeli—French Earth Observation Scientific Mission with High Spatial and Temporal Resolution Capabilities. In Proceedings of the 4th ESA CHRIS/Proba Work, 19–21 September 2006; Esrin, Frascati Italy; pp. 19–21.

47. Steiger, J.H. Tests for comparing elements of a correlation matrix. *Psychol. Bull.* 1980, 87, 245–251.

48. Fisher, R.A. On the Probable Error of a Coefficient of Correlation Deduced from a Small Sample. *Metron 1921*, 1, 1–32.

49. Čereković, N.; Todorović, M.; Snyder, R.L. The Relationship Between Leaf Area Index and Crop Coefficient for Tomato Crop Grown in Southern Italy. *Euroinfvent* 2010, 1, 3–10.

50. Johnstone, P.; Hartz, T.; LeStrange, M.; Nunez, J.; Miyao, E. Managing Fruit Soluble Solids with Late-season Deficit Irrigation in Drip-irrigated Processing Tomato Production. *HortScience* 2005, 40, 1851–1861, doi:10.21273/hortsici.40.6.1857.

51. Aksic, M.; Gadzic, S.; Deletic, N.; Gadzic, N.; Stojkovic, S. Tomato fruit yield and evapotranspiration in the conditions of South Serbia. *Bulg. J. Agric. Sci.* 2011, 37, 150–157.

52. Huang, W.; Luo, J.; Zhang, J.; Zhao, C.; Wang, J.; Yang, G.; Huang, H.; Huang, L.; Du, L.H.A.S. Crop Disease and Pest Monitoring by Remote Sensing. *Remote Sens. Appl.* 2012, 37–76, doi:10.5772/35204.

53. Gogoi, N.; Deka, B.; Bora, L. Remote sensing and its use in detection and monitoring plant diseases: A review. *Agric. Rev.* 2018, 39, 307–313, doi:10.18805/agr-r-1385.

54. Choubey, V.K. Detection and delineation of waterlogging by remote sensing techniques. *J. Indian Soc. Remote Sens.* 1997, 25, 123–135, doi:10.1007/bf03025910.

55. Hassan, M.S.; Mahmud-ul-islam, S. Detection of Water—Logging Areas Based on Passive Remote Sensing Data in Jessore District of Khulna Division, Bangladesh. *Int. J. Sci. Res. Publ.* 2014, 4, 1–7.

56. Ennouri, K.; Kallel, A. Remote Sensing: An Advanced Technique for Crop Condition Assessment. *Math. Probl. Eng.* 2019, 2019, 1–8, doi:10.1155/2019/9404565.

57. Lanfr, S. Vegetation analysis using remote sensing. *Argent. Spat. Agency Cordoba Natl. Univ. Veg.* 2010, 1–58.

58. Fan, L.; Gao, Y.; Brück, H.; Bernhofer, C. Investigating the relationship between NDVI and LAI in semi-arid grassland in Inner Mongolia using in-situ measurements. *Theor. Appl. Clim.* 2008, 95, 151–156, doi:10.1007/s00704-007-0369-2.

59. Pasqualotto, N.; Delegido, J.; Van Wittenbergh, S.; Rinaldi, M.; Moreno, J. Multi-Crop Green LAI Estimation with a New Simple Sentinel-2 LAI Index (SeLI). *Sensors* 2019, 19, 904, doi:10.3390/s19040904.

60. Xavier, A.C.; Vettorazzi, C.A. Mapping leaf area index through spectral vegetation indices in a subtropical watershed. *Int. J. Remote Sens.* 2004, 25, 1661–1672, doi:10.1080/014311604001620803.

61. Tucker, C.J. Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sens. Environ.* 1979, 8, 127–150, doi:10.1016/0034-4257(79)90013-0.

62. Pinty, B.; Verstraete, M.M. GEMI: A non-linear index to monitor global vegetation from satellites. *Vegetatio* 1992, 101, 15–20, doi:10.1007/bf00319911.

63. Clevers, J. Application of a weighted infrared-red vegetation index for estimating leaf Area Index by Correcting for Soil Moisture. *Remote Sens. Environ.* 1989, 29, 25–37, doi:10.1016/0034-4257(89)90076-x.
64. Gitelson, A.A.; Merzlyak, M.N. Remote sensing of chlorophyll concentration in higher plant leaves. *Adv. Space Res.* **1998**, *22*, 689–692, doi:10.1016/s0273-1177(97)01133-2.
65. Qi, J.; Chehbouni, A.; Huete, A.R.; Kerr, Y.H.; Sorooshian, S. A modified soil adjusted vegetation index. *Remote Sens. Environ.* **1994**, *48*, 119–126, doi:10.1016/0034-4257(94)90134-1.
66. Dash, J.; Curran, P. Evaluation of the MERIS terrestrial chlorophyll index (MTCI). *Adv. Space Res.* **2007**, *39*, 100–104, doi:10.1016/j.asr.2006.02.034.
67. Crippen, R. Calculating the vegetation index faster. *Remote Sens. Environ.* **1990**, *34*, 71–73, doi:10.1016/0034-4257(90)90085-z.
68. Frampton, W.J.; Dash, J.; Watmough, G.; Milton, E.J. Evaluating the capabilities of Sentinel-2 for quantitative estimation of biophysical variables in vegetation. *ISPRS J. Photogramm. Remote Sens.* **2013**, *82*, 83–92, doi:10.1016/j.isprsjprs.2013.04.007.
69. Bosanquet, B. VII.—CRITICAL NOTICES. *Mind* **1898**, *VII*, 101–108, doi:10.1093/mind/vii.25.101.
70. Huete, A. A soil-adjusted vegetation index (SAVI). *Remote Sens. Environ.* **1988**, *25*, 295–309, doi:10.1016/0034-4257(88)90106-x.
71. Deering, D.W.; Rouse, J.W.; Haas, R.H.; Schell, J.A. *Measuring “Forage Production” of Grazing Units From Landsat Mss Data*; Ann Arbor, MI, USA, 1975; Volume 2, pp. 1169–1178.