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Remote Sensing Monitoring of Durum Wheat under No Tillage Practices by Means of Spectral Indices Interpretation: A Preliminary Study

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Abstract: Due to its advantages, remote sensing monitoring has been used in various applications and made noteworthy contributions to understanding soil and plant processes, as well as in the agriculture sector. The aim of the work is to compare the return of durum wheat crops in conservative agricultural practices in Mediterranean climate conditions by analysing the data from the Sentinel2 satellite through three spectral indices. The analysed spectral indices have different interpretations and therefore have been studied in different periods: (i) NDVI (normalized difference vegetation index) for the evaluation of the vegetative vigour from January to June; (ii) NDWI (normalized difference water index) for the moisture of covered soil from January to June and of bare soil after harvesting from June to August; and (iii) NMDI (normalized multi-band drought index) for the variability of bare soil moisture from June to August. With reference to the machines used in cultivation practices, a further purpose of the study is to investigate the effects of automatic guidance versus manual guidance on production yields and on the spectral indices considered. The first results show that the NDVI follows crop phenological stages by reaching the maximum values in correspondence with the stem elongation and booting stages. Additionally, the NDWI showed the same trend as the NDVI during the current crop. After harvesting, the NDWI showed higher values in the plots cultivated under conservation tillage practices. In the same period, the NMDI showed the same results as the NDWI and a positive correlation, confirming that tillage practices could imply a lower ability to retain water in drought time.

Keywords: no tillage; NDVI; NDWI; NMDI; satellite images; water use; conservation tillage

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1. Introduction

Durum wheat (*Triticum durum* L.), a tetraploid species of wheat, is the 10th most important and commonly cultivated cereal worldwide and a strategic cereal crop in the Mediterranean region. It is used as one of the main components of a variety of meals, such as couscous, bulgur, pasta, etc. Durum wheat production represents about 5% of total wheat production, with a planting area of 13.5 million hectares (Mha) globally [1]. In Italy, the southern regions are slowly regaining the lead in production. Only a tiny portion of the total production is exported, and the majority is farmed for domestic uses [2]. The intricate interplay among environmental factors, yield characteristics, and technical prerequisites accounts for the overall quality of durum wheat. In this case, although genotype has a significant role, all the complicated relationships between water and nitrogen accessibility and temperature regime have an impact [3–6]. A deficiency of water resources is one of the most important limiting factors for agricultural development in the world that can seriously challenge food security [7–9].

The climate in the Mediterranean area is exceptionally unpredictable, with scorching, dry summers and chilly, rainy winters. The previous ten years have seen a rise in climate variability, particularly extreme drought occurrences, leading to significant large crop losses [10].

In order to tackle such problems, adopting an appropriate strategy for sustainable production is essential. Conventional tillage systems in crop production turned out to be the main cause of severe water losses, soil erosion, and desertification in many developing countries, thus destroying approximately 40% of the world's land [11]. Differently, conservation agriculture (CA) has been presented as an adaptable series of crop management strategies ensuring improved sustainable agricultural output, decreasing soil degradation, and promoting the resilience of agricultural systems to climate change [12,13]. This approach aims to achieve sustainable and profitable production based on minimal mechanical soil disturbance, permanent soil cover, and crop diversification through the rotation or intercropping methods that are mainly used in rainfed farming systems, especially in Mediterranean conditions [14]. A number of studies have suggested that agricultural conservation principles could well enhance soil fertility and water infiltration and nutrient cycles and help increase yields, farm profitability, and reduce input requirements [15–18].

Conservation tillage increases water availability for wheat by improving soil water absorption capacity and also reducing evapotranspiration [19]. Conservation tillage reduces soil disturbance, retains crop residues on the soil surface, and effectively reduces wind erosion, water erosion, and soil bulk density [20]. Additionally, it increases the soil's total porosity and saturated water conductivity, boosting soil water holding capacity and rainfall penetration while decreasing soil evaporation and thereby benefiting crop growth, yield and water use efficiency [21]. Peng et al. [22] reported that no-tillage systems significantly increased soil water potential in the 0–10 cm soil depth at the seedling and jointing stages of wheat compared to tillage systems. Sowing on minimally or no-tilled soil represents, in fact, a technique that allows the reduction of the evaporation of the water contained in the soil, and therefore, it is able to ensure the more efficient use of water resources and the adequate productivity of the crop. Overall, CA represents one of the best systems able to contribute to climate change mitigation by reducing energy consumption and atmospheric greenhouse gas concentration [23,24].

Remote sensing techniques have become valuable tools for precision (precise) agriculture (PA) and can help farmers to practice more sustainable agriculture through the evaluation of the crop and soil responses in different cultivation practices. Satellite data are important for the development of sustainable solutions at the field level [25]. The significant improvement in spatial, temporal, and spectral resolutions in satellite data can support the development of sustainable production, particularly yield and water use efficiency in relation to the agronomic techniques adopted [26,27]. In order to enhance water consumption and efficiency in agriculture, significant improvements can be made by using accurate spatial and temporal information on crops and soil conditions [28]. Monitoring the water status is, thus, crucial in the present water scarcity to optimize crop yield and quality [29].

The use of remote sensing techniques can play a key role in monitoring accurate information about plant biophysical parameters. In recent years, spatial, temporal and spectral resolution in satellite data has improved significantly [30]. The use of satellite images allows the identification of the within-field variability of crop development and yield with a resolution of 10×10 m and the definition of homogeneous management zones [31–33], which is limited by the ongoing growing season. Several multispectral indices have been used to analyse crop variability and soil moisture content. The latter affects plant growth, nutrient absorption, microorganisms' presence, matter degradation speed and weathering processes [34]. Among many available optical indices, the normalized difference vegetation index (NDVI) and normalized difference water index (NDWI) have been commonly used for estimating vegetation water content [35–39]. The NDVI helps to determine vegetation status by using drought as an indicator of soil moisture; the NDWI is used for determining the vegetation's hydric index [34]. Jackson et al. [35] demonstrated that the NDWI is superior to the NDVI in retrieving the vegetation water content of corn and soybean fields. Indeed, the NDVI data have been exploited to study crop conditions, estimate crop biomass at different growth stages, predict grain yield and also to point out the amount of green vegetation in one area [40]. For these reasons, many scientists have asserted that the NDVI is the best estimator for light interception, although its values fluctuate during the crop cycle [41].

The Sentinel-2 satellite, providing 13 spectral bands in various frequencies, has a wide range of applications and is used for both crop monitoring and modelling [42,43], and it can monitor and predict drought and its effects on the Earth's surface [44]. Pezzuolo et al. [45] tested the possibility of monitoring the evolution of the vegetation index and modulating the agricultural operations depending on soil features and soil tillage technique management on soft wheat thanks to the study of the relationship between resistivity and the NDVI index. They showed that there was an increase in NDVI from conventional tillage to minimum tillage and no-tillage (NT). Varghese et al. [46] reported that they used Sentinel-2 to investigate the plant responses to different soil moisture conditions and variations in canopy water levels at regional and field levels. As a drought indicator, soil moisture can be obtained from land surface model simulations or satellite estimates. Sentinel-2 outperformed Landsat-8 and showed a significant correlation with soil moisture (<30 cm depth) but a poor correlation with less vegetated areas [47].

Regarding the spectral reflectance differences of moisture absorption properties, various drought indices using the backscatter energy from near-infrared (NIR) and shortwave-infrared (SWIR) channels have been formulated for estimating vegetation water content using satellite remote sensing, such as the normalized multi-band drought index (NMDI) [48]. The potential of the NMDI has been deeply rooted in its application in different research topics, such as drought monitoring in the Henan province of China [49]. The results show that there is a significant correlation between NMDI and soil moisture. The application of remote sensing for the assessment of agricultural drought-vulnerable areas is very effective for early warning systems as well as drought mitigation processes.

In order to monitor the dynamics of the crop examined (durum wheat, cv. Antalis) and the water content, the study of multispectral Sentinel-2 satellite images was carried out by using three indices, the NDVI, the NDWI and the NMDI, on an experimental field that is representative of an agricultural water stress area.

The aim is to compare the responses of durum wheat crops cultivated with no tillage practices with those cultivated under minimum tillage practices in areas characterized by a Mediterranean climate and in water stress conditions. The correlation between the indices considered (the NDVI, NDWI, and NMDI) provided a further element of study to relate the water content with the current crop and to offer further insight into the preservation of water and food systems. A further purpose was to investigate the effects of the automatic driving of tractors versus non-automatic driving in cultivation practices on production yields and on the indices considered. Unfortunately, no specific studies regarding these issues have been dealt with yet. Therefore, the study was carried out in order to determine the correlation between the indices and the yield of durum wheat cultivar under no-tillage practices with dual objectives: to determine the best performing cultivation practices and the best driving method. In this regard, the paper suggests an innovative application of commonly used spectral indices in order to compare the return of different agricultural practices and different driving methods of the tractor in poor water resource conditions.

Furthermore, the present research also aims to provide a contribution of current interest for the public decision-maker who is called to intervene with appropriate regulatory instruments to favour an efficient and sustainable use of water resources. Another objective is to develop a methodology aimed at monitoring the water content of soil and crops by remote sensing and to compare the data with those from ground base platforms in order to contribute to improving agricultural water use management

2. Materials and Methods

2.1. Field Test Description

The experimental study was carried out in the November 2020–June 2021 period during a growing season in collaboration with a local farmer who gave an availability of a 1.4 ha test field that was cultivated with durum wheat (DW). Moreover, the farmer made agricultural machinery available to perform the experimental campaign.

The study area (Figure 1) is located at 260 m a.s.l. in the territory of Aidone (Enna province) (37°26′25.4″ N 14°36′24.4″ E), which is part of Enna province (South Italy) in a typical Mediterranean climate area according to the Köppen climate classification [50].

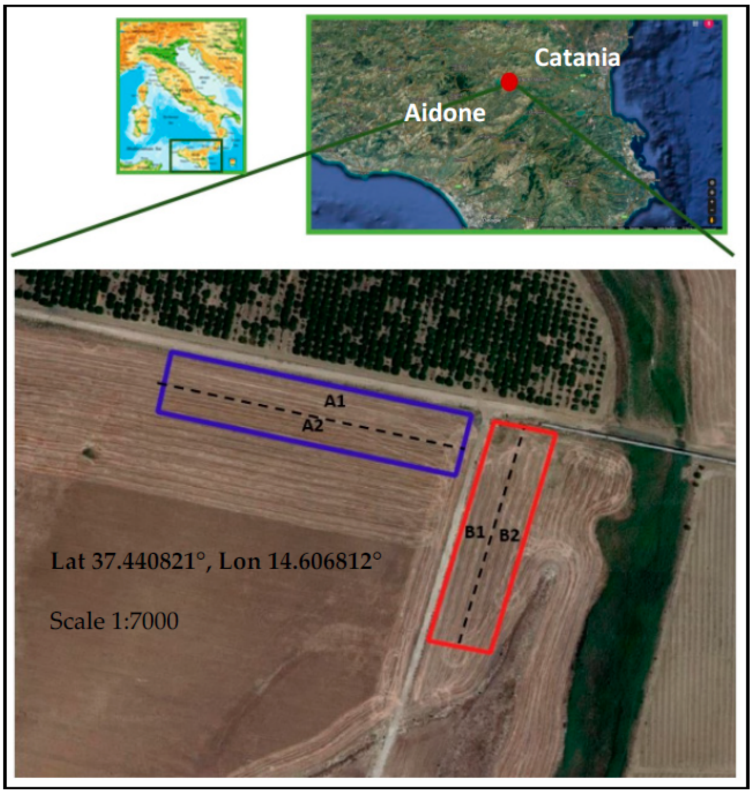

Figure 1. Geographical location of the experimental plots.

The experimental field consists of four plots, two of which are 20 m × 200 m each on flat ground (A1, A2) and two of which are 20 m × 150 m each on land with a slope of 4% (B1, B2) (Figure 1). Another plot, 2500 m from the experimental field, was taken as a control test (CT) because it is managed according to minimum tillage techniques for seedbed preparation (Figure 2).

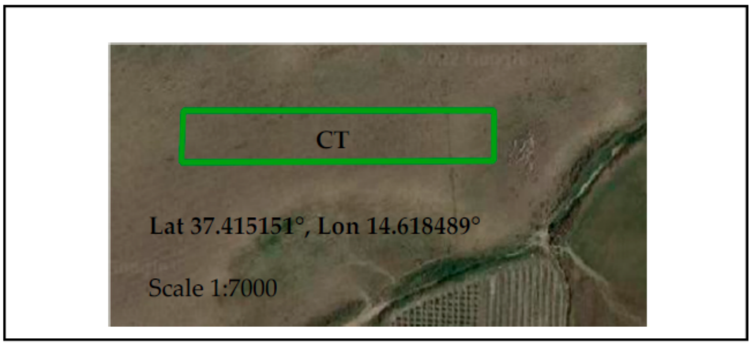

Figure 2. Geographical location of the control plot (CT).

For the characterization of the experimental fields (A1, A2, B1, B2 and CT), soil samplings were carried out following a standardized methodology [51], and the samples were subsequently analysed in a specialized laboratory (Envisep srl).

The physical-chemical soil properties of the different plots are shown in Table 1.

Table 1. Physical-chemical characteristics of the soil in the experimental plots (A1, A2), (B1, B2), (CT).

		Plot		
Properties	**Unit**	**(A1–A2)**	**(B1–B2)**	**(CT)**
Sand	%	48.32	56.58	49.85
Silt	%	26.27	22.42	42.30
Clay	%	25.42	21.00	7.85
Total Lime	% $CaCO_3$	16.33	16.00	9.00
Active Lime	% $CaCO_3$	7.00	5.67	7.00
pH	pH	8.18	8.20	8.10
Conductivity	µS cm^{-1} a 20 °C	520.33	495.00	299.00
N	N%°	1.27	1.74	1.40
P	P_2O_5, mg kg^{-1}	10.40	10.27	15.00
K	K_2O, mg kg^{-1}	677.33	560.33	830.70
Organic matter	%	2.17	1.91	2.01
CEC	meq 100 g^{-1}	38.13	32.30	15.41
Exchangeable K	K, meq 100 g^{-1}	1,45	1.18	1.76
Na	Na, meq 100 g^{-1}	7.65	8.82	1.09
Ca	Ca, meq 100 g^{-1}	22.07	21.20	11.80
Mg	Mg, meq 100 g^{-1}	1.42	1.09	0.79
Fe	Fe, ppm	9.10	52.65	8.50
Zn	Zn, ppm	1.20	1.88	2.00
Mn	Mn, ppm	21.00	27.10	16.80

With reference to the average data shown in Table 1 and according to the USDA classification [52], the soil of plots A1-A2 and B1-B2 is classified as sandy clay loam; the soil of the CT is classified as loam. According to the soil analyses of the plots, the soil appears moderately alkaline, as the pH is around 8, and quite fertile, with a percentage ranging from 1.7 to 2.03% of organic matter. As concerns macronutrients, the plots are well equipped in nitrogen with percentages ranging from 1.2% to 2.6%; the average assimilable phosphorus is scarce with 10.27 mg $kg^{-1,}$ while they are very rich in exchangeable potassium. The soil appears to be moderately endowed with micronutrients, especially iron, zinc and manganese. The climate is typically Mediterranean, rainy in the winter and very arid in the summer. The weather-climatic trend of the year 2020–2021 from sowing (December) to harvest (June) is graphically represented in Figure 3. The data come from the near "Ramacca Giumarra" enabled weather station of SIAS (Sicilian Agrometeorological Information Service) [53] and are subsequently processed to obtain daily average temperatures (°C) and total rainfall (mm).

In general, the minimum temperatures appeared lower than long-term averages, ranging from 6.8 °C in December to 19.9 °C in June, while the maximums have been higher, passing from 12.4 °C during the sowing time to 33 °C during the harvest. The average temperatures remained below 13 °C from December to April, and then they quickly climbed up to harvest, exceeding 25 °C on average.

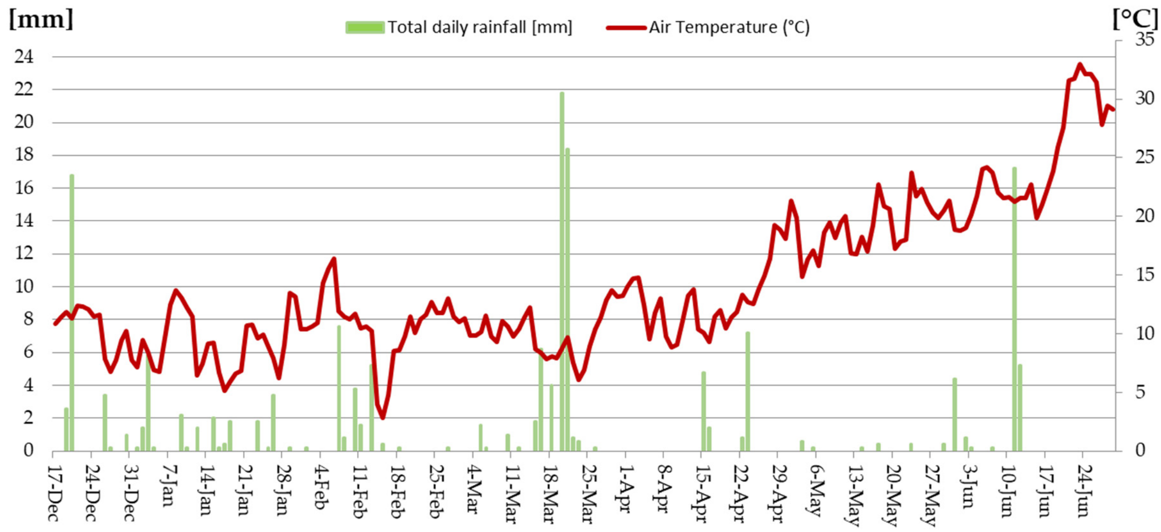

Figure 3. Daily average air temperature and rainfall from December 2020 to June 2021 in the experimental site.

The total rainfall for the area considered was similar to the multi-year averages, but the rains were concentrated in the spring (March), reaching almost the same quantities recorded in the December-February period; then, they unexpectedly reappeared at the end of the cycle during the graining vegetative phase.

The sowing carried out in December made use of the right soil humidity, and the seedlings' emergency was optimal thanks to some rain that fell in January. During the period from January to June, the very low amount of rain has, in some measure, compromised production, only partially supported by the rainfall that occurred in March (57 mm); this led to the closure of the crop cycle with productions slightly below farm averages.

In the period following the wheat harvest (29 June 2021), some rainfall occurred (Figure 4); this intensified at the beginning of July, reaching maximum values of 32.4 mm on 12 July. Overall, about 109 mm rained in 12 days from the harvest to the peak day of rainfall (12 July 2021).

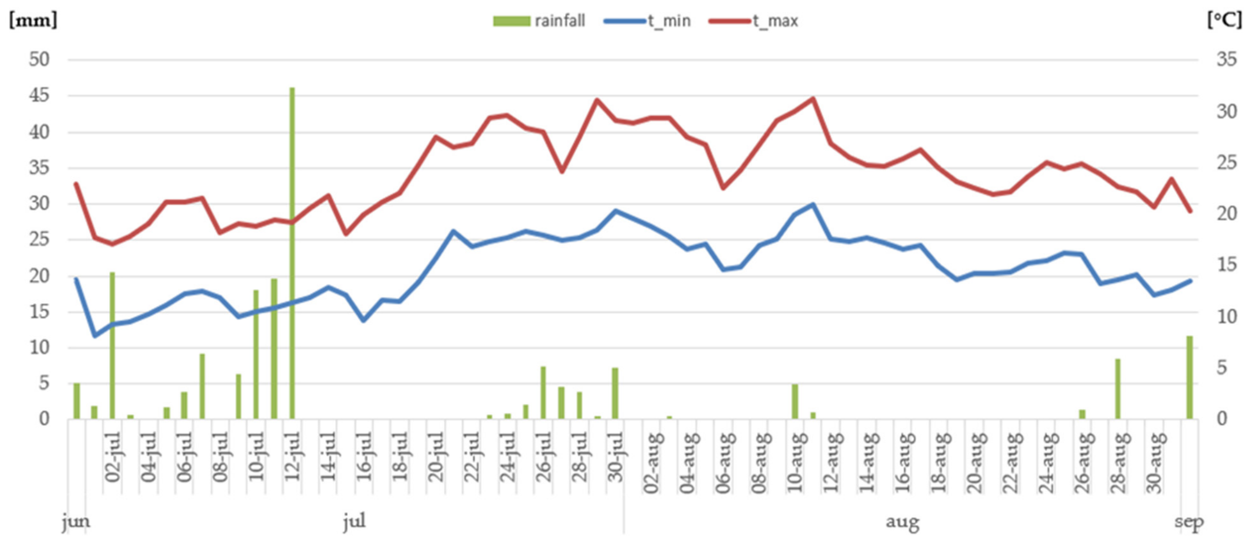

Figure 4. Weather trends from June 2021 to September 2021.

No noteworthy rain events occurred subsequently. In this way, through the analysis of the indicated indices, it was possible to study what happened in the bare soil in terms of water content in the three tests compared (A, B and CT).

The temperatures of the post-harvest period were typical of summer, with an overall average temperature of 26.5 °C, a maximum peak of 44.7 °C and a minimum of 11.6 °C.

2.2. Machines and Practices for DW Cultivation

In plots A1, A2, B1, and B2, the following cultivation practices were carried out: pre-sowing weeding, sod-seeding, fertilisation, spring weeding, and harvesting. In the CT plot, minimum tillage was carried out with a cultivator at a depth of 20–25 cm instead of pre-sowing weeding. Weeding was carried out twice, with the first at the end of August 2020 and the second in November 2020, with a non-selective herbicide based on glyphosate at a dose of 2 L ha^{-1} using a mechanical pulverisation sprayer with a working width of 15 m. The sprayer was towed by a Fendt 716 (120 kW) 4WD tractor. The sowing of the DW Antalis cultivar (195 kg ha^{-1}) was carried out on 17 December 2020 according to the no-till seeding practice, using a row seeder with a pneumatic distribution SiderMan model Newton, 5.10 m wide with 34 furrows and a wheelbase of 15 cm, having a mass of 1350 kg. The sowing depth averaged 7–8 cm. In particular, the Antalis cultivar is especially suitable even for the most difficult environments of Italian dry farming due to its qualities of rusticity and tolerance to plant diseases. It also has a slow ripening with excellent grain filling and interesting quality characteristics for the milling industry. The seeder was connected to a Fendt 930 Vario 4WD tractor (year 2019), 217 kW of power and 11.3 t of mass. With the tractor, the automatic guide to be compared with the manual one was activated both in the flat parcel and in the sloping parcel. In January 2021, urea-based fertilization was carried out in an amount equal to 100 kg ha^{-1} with a double centrifugal fertilizer spreader with a working width of 33 m. At the end of February 2021, weeding was carried out based on MCPA 60% with a dose of 1 L ha^{-1} by means of a mechanical boom sprayer of 15 m working width. The fertilizer spreader and boom sprayer were connected to the Fendt 716 (120 kW) 4WD tractor.

On 29 June 2021, the harvesting was carried out for a single test thesis with the latest generation New Holland model CX7.90 combine harvester, 275 kW, and a 10,000 L tank whose fill level is controllable by the IntelliView IV monitor installed in the cab, which is able to display and monitor all functions and parameters of the combine harvester. On the top of the tank is the antenna able to receive DGPS signals and GLONASS signals. The harvester has an automatic cutting height adjustment system in addition to the hydraulic adjustment cylinders of the header, as well as some sensors mounted in the lower part of the header that allows it to follow the profile of the ground and, at the same time, to hydraulically adjust its position to maintain a uniform cutting height. After pre-setting the driving paths, the machine was driven automatically thanks to the fully integrated New Holland IntelliSteer (Delta, BC, Canada) automatic steering system, which can use three different levels of accuracy, such as EGNOS (20 cm), RTX (4 cm) and RTK (2 cm). The machine is also equipped with grain moisture sensors and high-precision weight sensors (whatever the type, variety or moisture content of the grains) that are functional to map production.

2.3. The Experimental Design

As shown in Table 2, the experiment was carried out in no-tillage conditions on the plots described before (A and B). Only the CT was carried out on the plot cultivated according to minimum tillage practices. The tests are five in total, including the CT.

Table 2. The factors of the experiment.

Practices	Plot Position	Driving Method
No tillage (NT)	On flat ground (A)	Automatic (A1)
		Manual (A2)
	On a slope (B)	Automatic (B1)
		Manual (B2)
Control test (CT)	On flat ground (CT)	Automatic

Two different positions of the plots, on flat ground (A) and on a slope (B), and two different driving methods were considered (A1 and A2; B1 and B2).

The comparison between the different tests was assessed by means of the study of NDVI, NMDI, NDWI and grain yield (Mg ha^{-1}).

2.4. The Image Analysis Methodology

Satellite information was derived from available Sentinel-2 satellite products. Level-2° products representing bottom-of-atmosphere reflectance in cartographic geometry were extracted from the "Copernicus Open Access Hub" of the ESA (European Space Agency) website [54].

Products are a compilation of elementary granules of fixed size, along with a single orbit. A granule is the minimum indivisible partition of a product (containing all possible spectral bands).

Of the 12 available wavelength bands, 6 have been processed in this study: B3 (green: 560 nm), B4 (red: 665 nm), B8 (visible and near-infrared–VNIR: 842 nm), B8a (visible and near-infrared–VNIR: 865 nm), B11 (short-wave infrared–SWIR: 1610 nm), B12 (short-wave infrared–SWIR: 2190 nm). From these bands, three spectral indices were calculated for each pixel of the images relating to the plots under study: NDVI (1), NDWI (2) and NMDI (3), the formulas of which are reported below:

$$\mathrm{NDVI} = \frac{R_{842\mathrm{nm}} - R_{665\mathrm{nm}}}{R_{842\mathrm{nm}} + R_{665\mathrm{nm}}} \tag{1}$$

$$\mathrm{NDWI} = \frac{R_{560\mathrm{nm}} - R_{842\mathrm{nm}}}{R_{560\mathrm{nm}} + R_{842\mathrm{nm}}} \tag{2}$$

$$\mathrm{NMDI} = \frac{R_{865\mathrm{nm}} - (R_{1610\mathrm{nm}} - R_{2190\mathrm{nm}})}{R_{865\mathrm{nm}} + (R_{1610\mathrm{nm}} - R_{2190\mathrm{nm}})} \tag{3}$$

The distribution map files of the reflectance values of the selected bands from the Sentinel-2 satellite databases were processed by R software. The processing involved the following phases: (i) opening the .tif files with the *raster* package and viewing them using the "spplot" function to check for the presence of clouds; (ii) cropping the pixels relating to the observed plots and the control test with the "crop" function; and (iii) transformation into a data-frame first and subsequently into a data table using the function "as.data.frame" of the *base* package and "write.table" of the *utils* package.

In total, 48 images were processed from January 2021 to August 2021; 26 of these were useful for obtaining the indices. Atmospheric corrections were applied to the images coming from the satellites by applying the Sen2Cor algorithm through the sen2r package in the R software.

In this way, a dataset for each spectral index was obtained, and it was organized in such a way as to have the information relating to longitude, latitude, day and the calculated index value for each row.

Therefore, after observing the distribution of the data and verifying the normality and uniformity of the variability between the observed data groups, any presence of outliers was verified.

The processing provided, for the three indices studied (NDVI, NMDI and NDWI), the verification of the descriptive characteristics of the values collected for each observed condition. Then, ANOVA (analysis of variance) was carried out to study the possible significance between the averages of the conditions compared. In cases of significance, post hoc tests were applied to analyse significant differences.

The differences between the test were studied through the NDVI and NDWI in the period from January (one month after sowing) to June (just before harvest) to verify any differences in the vegetative phases of the crop and in the soil moisture. The NMDI index, dedicated to the observation of soil moisture, was studied in the summer after the wheat was harvested.

Meteorological data relating to the temperature and the rainfall of the period were compared with spectral indices (NMDI and NDWI) data with the aim of explaining the results, especially in terms of water content.

3. Results and Discussion

3.1. Vegetation Index NDVI and Grain Yield

The NDVI spectral index showed an initially increasing trend (Figure 5) coinciding with the growth of the current crop with a plateau in the spring period, in which values greater than 0.9 are reached for all tests (A, B and CT) in correspondence of high photosynthetic activity of the crop in the stem elongation and booting. The CT showed particularly higher values of the NDVI than the other two conditions (A ad B). This trend corresponds to that found in the NDVI studies on wheat fields [33,55–57]. The average of the NDVI values was statistically higher (p-value < 0.05) among the plots in the plain conditions (A and CT) with a value of 0.70 and 0.71, respectively, compared to those placed on a slope (B), which had a mean value of 0.66. Due to reduced photosynthetic activity at the beginning of plant development, the lowest values (0.4) were recorded in January for all tests (A, B and CT). At the end of the cycle (dry ripening), very low values (0.21) were recorded for the test control, while values of 0.30 were recorded for tests A and B. Other authors [58] reported that the NDVI ranged from 0.26 to 0.57 during the seedling stage of durum wheat due to a low amount of accumulated biomass and LAI values, as well as the difficulties of indices to distinguish between vegetation and soil. At the tillering stage, NDVI values ranged between 0.34 and 0.86; at the anthesis stage, the values ranged from 0.53 to 0.88. Ali et al. [41] found that in the five growth stages ranging from the beginning of stem elongation to heading, the mean values ranged from 0.29 to 0.66.

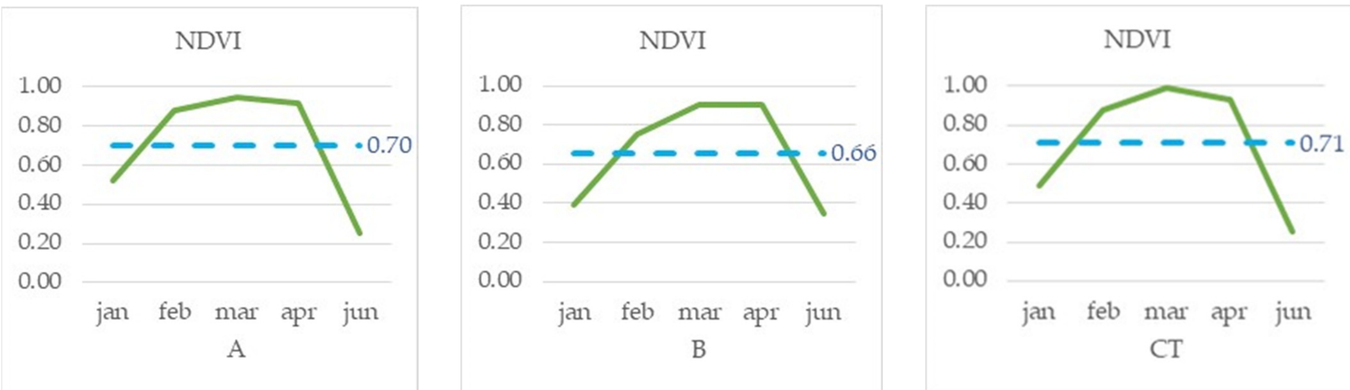

Figure 5. NDVI trend from sowing to harvesting in the different tests.

As concerns the grain yield (Table 3), the test showed less yield on the slope (B) than on flat (A) tests. Additionally, the mean NDVI confirmed higher values for the flat test than on the slope, with high mean values on the CT field (Figure 5). More particularly, looking at Figures 6 and 7, the spatial variability of crop traits is highly evident, and an area with less vegetation index (with more pixels in red colour) is always evident in test B (on the slope) and in CT.

Table 3. The grain yield in the tests.

Practices	Plot Position	Driving Method	Grain Yield (Mg ha^{-1})
No tillage (NT)	On flat ground (A)	Automatic (A1)	4.5
		Manual (A2)	2.5
		mean	3.5
	On a slope (B)	Automatic (B1)	2.9
		Manual (B2)	2.6
		mean	2.7
Control test (CT)	On flat ground (CT)	Automatic	3.0

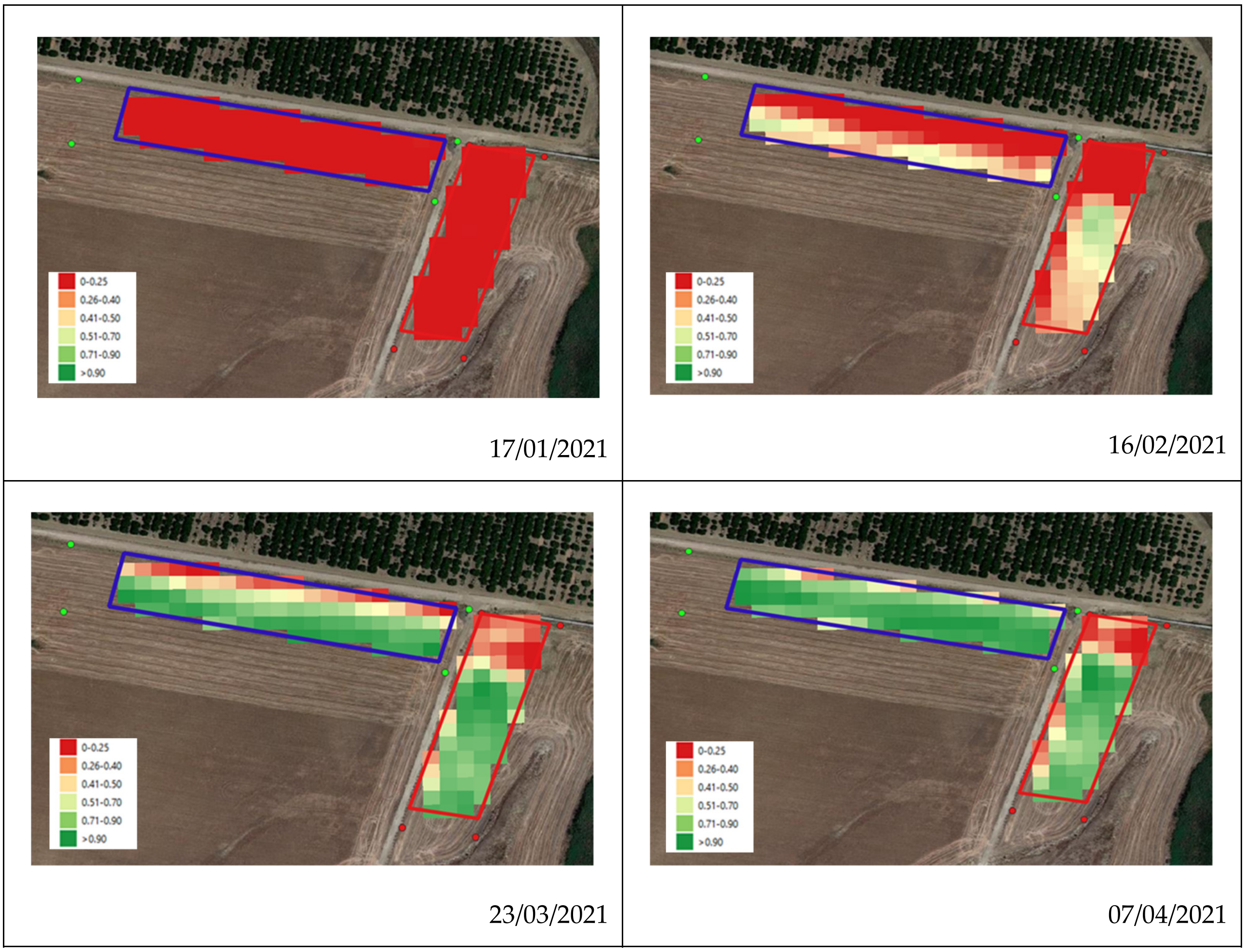

Figure 6. Trend of NDVI in the plots on different dates.

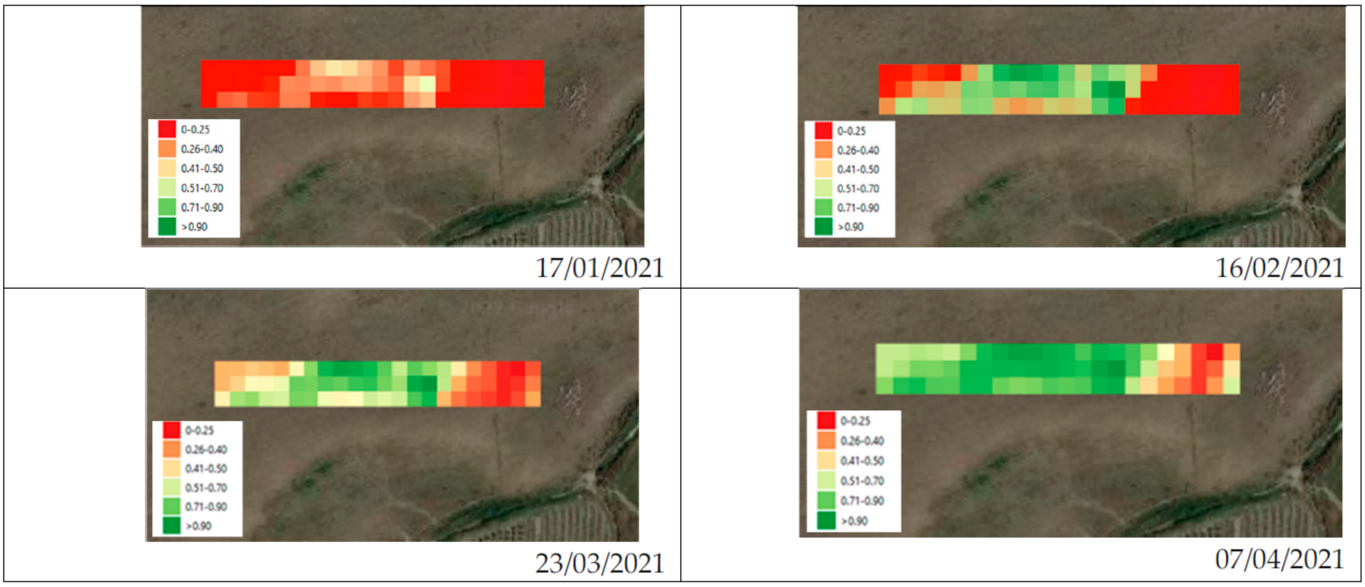

Figure 7. Trend of NDVI in the control plot (CT) in different dates.

Moreover, a higher yield in the automatic driving method (A1 and B1) than the manual one (A2 and B2) is recorded (Table 3). This is due to the greater regularity of sowing with the automatic guide in parallel rows, which allows respecting the distance between the rows and reduces the competition between the seeds and plants, in line with what Polishchuk [59] expressed on wheat sowing tests with automatic guided machines. On the contrary, the NDVI is always lower in automatic driving methods than in manual ones (A2 vs. A1 and B2 vs. B1) (Table 4). The values of the NDVI spectral indices are shown in Table 4, which also indicates the minimum and maximum values recorded in the experiment as a whole. The automatic satellite driving system showed NDVI values lower than manual driving both in the entire cultivation period (Jan–Jun) and in the period of greatest vigor (Mar–Apr). The table also shows the result of Tukey's post hoc test. The manual driving method indicates higher mean values of NDVI that are statistically different from the automatic driving method in the first period (0.48 vs. 0.41) and in the second one (0.79 vs. 0.68). This could be caused by a possible overlapping of the sowing rows and a consequent and involuntary higher sowing density. More years of experimentation will be useful to validate these results.

Table 4. NDVI in different driving methods.

	Driving Method	NDVI (January–June)	NDVI (March–April)
Mean value	Manual	0.48 a	0.787 a
	Automatic	0.41 b	0.683 b
Minimum value	Manual	0.02	0.237
	Automatic	0.12	0.346
Maximum value	Manual	0.99	0.997
	Automatic	0.93	0.935

Means followed by different letters, reported in superscript, are significantly different according to the Tukey's test.

3.2. NMDI and NDWI Water Content Indexes

Due to their different meaning, the indexes NMDI and NDWI were analysed in distinct periods: (i) the first index was during the summer period (from June to August) on bare soil; (ii) the second index was from January to August during the vegetation stage and after the harvesting in the summer period (from June to August). Both indices showed a good correlation with water potential; even though the NMDI is generally considered an advantageous water index as it incorporates two water bands, it showed a weaker correlation with water potential compared to the NDWI [60].

The NMDI values showed an increasing trend in the observed period (31 July 2021–10 August 2021) with a minimum value of 0.36 for test A, 0.34 for test B and 0.38 for the CT due to some meteoric events that occurred in the last ten days of July. Subsequently, there was an increase in the NMDI values due to a dry period starting in the second half of July. In general, the reduction in NMDI values corresponded to an increase in soil water content (Figure 8).

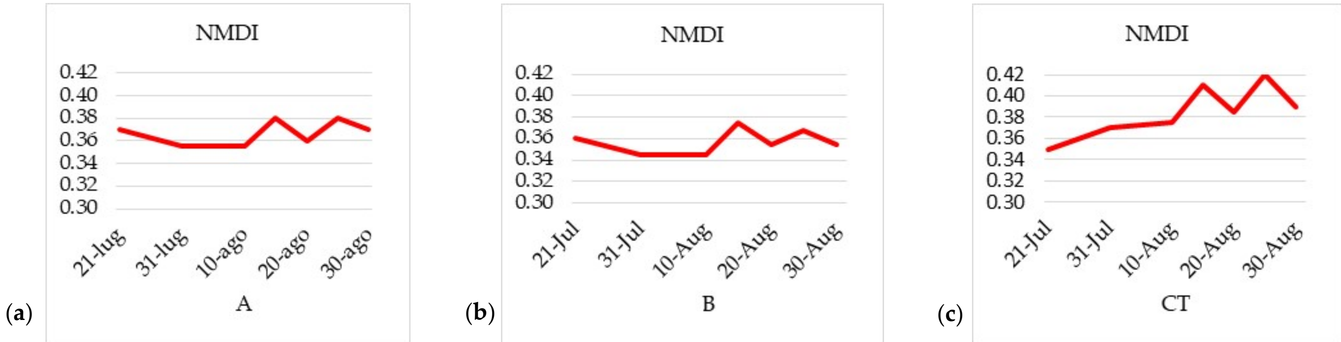

Figure 8. NMDI trend on flat ground (**a**), on a slope (**b**) and on the control plot (**c**).

The comparison of the three graphs shows a difference between the no-tillage test (A and B) and the CT, with higher values in the last one, as well as each date after the rainfall. Most probably, this difference can be attributed to a lower ability of the CT plot, with respect to no-tillage tests, to retain water in the dry period.

The NDWI spectral index showed an initially increasing trend (Figure 9) according to the growth of the crop with a plateau in the spring period. In particular, values greater than 0.35 are reached for test A and the CT in correspondence with the sprouting phase and the keg phase. The values show an excellent vegetative and water state of the crop resulting from rainfall, while, in the same period, test B showed a lower value (0.28) than test A and CT, probably due to the slope of the plot.

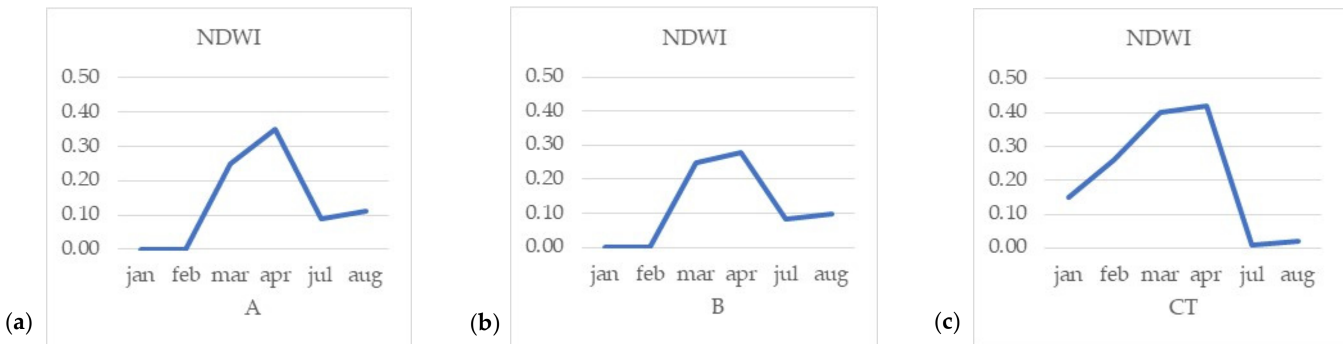

Figure 9. NDWI trend on flat ground (**a**), on a slope (**b**) and on the control plot (**c**).

After April, the values dropped for all the tests as a result of the approach of maturation and of harvesting, similar to what was shown with the NDVI. This shows that the NDWI also represents a suitable index for assessing canopy and crop yields [34].

Moreover, other authors showed that the NDWI better reflected the crop water content based on its sensitivity to vegetation water content, especially during soil drying, exhibiting a non-linear relationship with the vegetation water content [61].

The trend of the NDWI was also studied in the period following harvesting (29 June 2021), and, as also happened for the NMDI values in the summer period, here the difference between the no-tillage tests (A and B) and the control test is evident in favour of no-tillage tests (Figure 10). From these results, it is possible to confirm that both sensing drought indices, the NDVI and the NMDI, can explain soil moisture variability in the experimental plots, although more years and data are needed to corroborate this assumption.

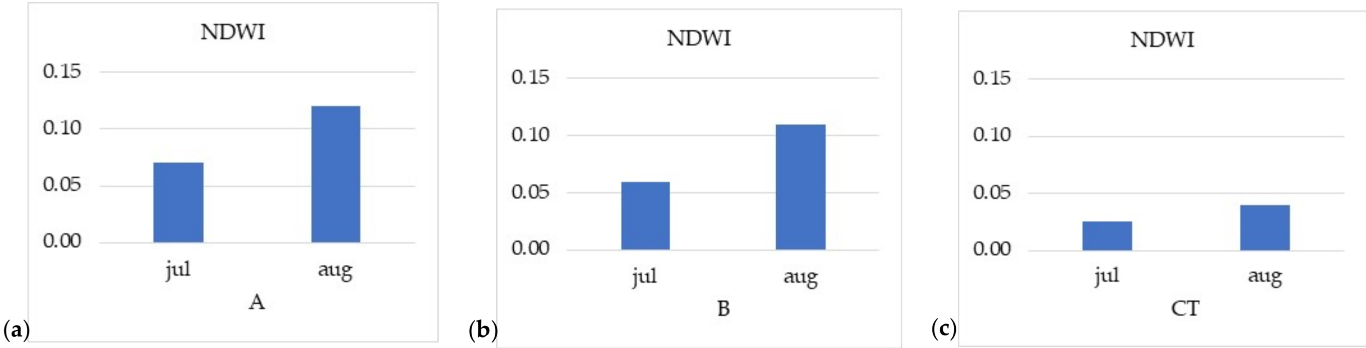

Figure 10. NDWI trend in summer period on flat grond (**a**), on a slope (**b**) and on the control plot (**c**).

3.3. Statistical Analysis

The data of the three spectral indices are shown in Table 5. The analysis of variance (ANOVA) for the evaluation of the significance (*p*-value < 0.01) of the average data showed statistically significant differences between the tests in all three spectral indices.

Table 5. Comparisons between the indices in the different tests (A. B, and CT).

	TEST	NMDI (July–August)	NDWI (July–August)	NDWI (January–June)	NDVI (January–June)	NDVI (March–April)
Mean	A	0.37 a	0.09 a	0.11 b	0.46 a	0.77 a
	B	0.36 a	0.08 a	0.09 b	0.44 b	0.70 b
	CT	0.39 b	0.03 b	0.19 a	0.46 a	0.79 a
Minimum	A	0.31	−0.02	−0.27	0.14	0.36
	B	0.31	−0.02	−0.27	0.13	0.24
	CT	0.32	−0.06	−0.26	0.03	0.46
Maximum	A	0.40	0.19	0.52	0.93	0.93
	B	0.40	0.21	0.52	0.93	0.93
	CT	0.52	0.16	0.59	0.91	0.99

Means followed by different letters, reported in superscript, are significantly different according to the Tukey's test.

The analysis of the variation of the spectral indices' values showed a similar trend over time between the two driving conditions, with the Student's t-test not significant (*p*-value > 0.05). This means that the variations over time have been synchronous but of different intensities, especially in the spring observation period.

The results of Tukey's post hoc test for the different averages values showed that the two tests, A and B, are not statistically different for the NMDI (0.37 and 0.36, respectively), for the NDWI on bare soil (0.09 and 0.08, respectively) and for the NDWI on crops (0.11 and 0.09, respectively), while the mean values of the NDVI (0.77 and 0.70, respectively) showed statistically significant differences (Table 5). Moreover, the results showed the CT is significantly different from the other tests (A and B) for NMDI values (0.39), for the NDWI (0.03) and for the NDVI (0.46).

Higher NMDI values and lower NDWI values for CT indicated a lesser presence of surface moisture in the tilled soil. In the summer drought period, the NMDI and NDWI values of CT demonstrated a lower capacity to retain water in comparison with no-tillage tests (A and B).

Overall, the experimentation recorded consistent values of the NMDI and the NDWI, with discriminating capacities against land cultivated with conservation techniques intercepting a lower surface water content during crop cultivation and a higher surface water content on bare soil. Other data are needed to prove these results.

As for the NDVI, the CT, similar to test A, recorded the highest values, indicating a greater photosynthetic activity of the cultivated area on flat land in comparison to test B carried out on slope land.

However, statistically significant correlations between the yield and the indices are not found. The correlation between the NDVI and the yield was calculated (−0.63), as reported in Table 6, and it was not statistically significant. Cabrera-Bosquet et al. [62] have found a strong linear regression between durum wheat and the NDVI. On the contrary, Dalla Marta et al. [63] found completely different results, with no correlations observed between the crop parameters and the indices. These results are in line with those demonstrated by other authors [60] in a study carried out in central Greece on several fields cultivated with durum wheat of different varieties of Thessaly plain for the 2017–2018 and 2018–2019 growing periods. They found there is no correlation between the whole growing period (1 December–31 May) and yield for the NDVI; on the contrary, strong correlations appeared from flowering to the end of the growing period (20 April–31 May) or after the flowering period (6–25 May). Moreover, Toscano et al. [64] showed that a comparison of the NDVI with yield monitoring values reveals significant positive linear relationships (r ranging from 0.5 to 0.7). Similar results were found by Freeman et al. [65]. The results of Tuvdendorj et al. [57] showed that the NDVI, NDWI, and NMDI were positively correlated with spring wheat yield in Mongolia. A positive and significant correlation exists between the NMDI and NDWI (Table 6), and similar results were found by Zhou et al. [61].

Table 6. Correlation between grain yield, NDWI, NMDI and NDVI.

	YIELD	NMDI	NDWI	NDWI_JUL_AUG	NDVI	NDVI_MAR_APR
YIELD	–					
NMDI	−0.397	–				
NDWI	−0.480	0.993 ***	–			
NDWI_(JUL_AUG)	−0.341	−0.304	−0.310	–		
NDVI	−0.634	0.403	0.412	0.698	–	
NDVI_(MAR_APR)	−0.540	0.775	0.756	0.357	0.864	–

Note: *** $p < 0.001$.

Other authors found a negative correlation under critical stress conditions, such as high temperature and drought, during crop growth [66–69].

4. Conclusions

This paper reports some results obtained from a multi-year experimentation, still in progress, aimed at studying agricultural mechanization solutions for herbaceous crops suitable for reducing the use of water resources in Mediterranean environments where the effects of climate change can occur very severely.

To this end, the study aimed to use the images provided by Sentinel-2 for the study of specific vegetation indices (the NDVI) and water content monitoring indices (the NDWI and NMDI), verifying the responses of durum wheat cultivation in no-tillage practices compared to reduced tillage practices. Moreover, the aim is to search, from an agronomic point of view, for any differences between sowing carried out with manual guidance of the tractor and sowing carried out with automatic guidance.

In fact, in water stress conditions, it has been shown that direct sowing on no-tillage soil, a typical practice of conservative agriculture, can bring considerable advantages of an agronomic nature, as well as environmental and economic ones, through energy saving and greater work productivity, with a view to saving water and better exploiting this precious resource.

Through the study of the NDVI index, it was possible to verify the effect of the no-tillage practice on the crop trend during the various phenological phases, demonstrating that there are no statistically significant differences between the test under no-tillage practices on flat ground (A) and the CT under minimum tillage practices, and that the manual driving recorded higher values than the automatic one, probably due to a higher sowing density for the overlapping between the rows.

The NDWI index helps to monitor the evolution of the water content of the crop from sowing to harvesting, demonstrating that there is no statistically significant difference between the test carried out on flat land and those on slopes in terms of the water content during the current crop. Higher and statistically significant values of the NDWI were recorded for the CT, demonstrating a greater water content during crop presence. Thus, the remotely sensed estimation of plant water status using satellite data might have been feasible and useful for monitoring and assessing drought in agricultural areas [61,70].

However, in the summer period, on bare soil, the no-tilled plots showed a statistically significant difference compared to the CT, with a disadvantage for the latter. Even if the NDWI values are very low, this corresponds to low water content and low coverage of the vegetation fraction. In a period of water stress, in fact, the NDWI decreased in all test conditions, indicating that the soil and crop moisture, as well as water content, are very important factors for crop yield [57].

Even the NMDI values on bare soil recorded the same results and showed a very high and positive correlation with the NDWI.

However, in order to obtain more reliable results, it is necessary to carry out further tests over several years of experimentation and to integrate both satellite and ground data for crop yield and moisture content estimation. The integration of remote sensing and field data might be useful to improve plant responses under specific growing conditions and to enhance water management. This would also make it possible to overcome the limits associated with the presence of clouds during the image acquisition period, especially during the winter season.

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