Impact of climate change on vegetation growth trends in a citrus farmland in the south-eastern Sicily

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Abstract

The environmental repercussions of climate change triggered substantial alterations in existing ecosystem balances leading to a gradual reduction in biodiversity and the increasing degradation of soil and the built environment. This has a direct effect on agricultural production in particular, leading to increased crop water requirements, the spread of new pests and pathogens that are difficult to manage, and, thus, a general reduction in productivity. Through the analysis of multispectral data remotely sensed with latest generation of optical sensors (RGB, thermal, NIR and multi-spectral cameras), it is possible to recognize the health status and growth stages of crops. In fact, in relation to the amount of radiation reflected in the different bands it is possible to calculate spectral indices, or vegetation indices. The main vegetative indices are NDVI, SAVI, MSAVI2, GNDVI and NDRE, which are calculated by differentially combining the ultraviolet spectrum, the visible range, and the near and mid-infrared band.

In this paper the outcomes of a multi-year monitoring of a citrus grove field near Rosolini (Syracuse), in south-eastern Sicily-Italy, are presented. This monitoring activity was conducted to highlight areas of productive greenery under stress, on which to act as a priority with specific agronomic interventions. In parallel with the direct monitoring phases of the citrus grove, the trend of average monthly and annual temperature and precipitation values over the past 24 years was also studied to more specifically contextualize the possible presence of significant variations in climatic trends and relate them to the results returned by the calculation of the indices.

1.Introduction

According to the Intergovernmental Panel on Climate Change (IPCC), the climate changes observed over the last 150 years have been mainly caused by the increase in anthropogenic emissions, which have caused an increase in the global concentration of carbon dioxide (the main greenhouse gas) by 50% compared to pre-industrial values and a rise in the global temperature by approximately 1.1°C compared to 1880 (Masson-Delmotte et al., 2018). The environmental repercussions have triggered substantial alterations of existing ecosystem balances leading both to a gradual reduction in biodiversity and an increasing degradation of soil and built environment (Dong et al., 2022; Pörtner et al., 2022). Heat waves, drought periods, hailstorms, tornadoes, and violent rainfall are increasingly frequent extreme phenomena whose effects are directly reflected on agricultural production, leading, in particular, to the increase in crop water requirements, the spread of new weeds and pathogens that are difficult to manage, the ever decreasing availability of water about lower rainfall and rising sea levels (with the associated salinization of water resources) and, therefore, to a general reduction in productivity (Piao et al, 2019; EEA, 2024). Even in relation to the recent increases in food prices and the reduction of stocks, as well as the irreversible deterioration of natural resources, erroneously considered unlimited and inexhaustible, it is evident how the primary sector faces major challenges to be able to guarantee, in the coming decades, the satisfaction of the food needs of all humanity. This assumes even greater relevance in relation to recent studies on world demographic projections. According to analyses conducted by the United Nations, even though the growth rate has fallen below 1% per year, the world population could grow to around 8.5 billion in 2030 and over 9.7 billion in 2050 (United Nations, 2022). While agriculture constitutes one of the most vulnerable sectors to the impacts of climate change, it can also play a strategic role in its mitigation: gross primary productivity (GPP) plays a crucial role in maintaining the surface energy balance through photosynthesis activity (Zhang et al., 2023; Sun et al., 2020), as it contributes to carbon uptake in terrestrial ecosystems. In addition, an efficient fertilizer use can reduce nitrous oxide (N2O) concentrations in the atmosphere, promoting the uptake of key crop nutrients through rational use of available water resources (Iizumi et al., 2018).

In recent years, numerous studies have been conducted to highlight the intrinsic relationship between vegetation and bioclimatic variables (Buehler et al., 2021; Chen et al., 2021; Khikmah et al., 2024), with particular attention to the role of new technologies in making the primary sector more productive and sustainable through a rational and targeted management of production factors to the benefit of farmers' income and the environment (Deng et al., 2022). In this regard, to achieve this goal, a fundamental contribution could come from the large-scale application of the Precision Farming (PF), developed in the 1970s in the USA with technologies derived from control centres, and later implemented with the introduction of microprocessors and GPS in the 1990s (Zhang et al., 2023; Pierpaolia et al., 2013).

Precision Farming represents that set of technologies and tools applied to agricultural production processes aimed at improving production and yield by reducing processing times and the use of resources (such as water, pesticides, fertilizers, etc.), to sustainably raise quality standards, minimizing environmental damage (Bongiovanni et al., 2004; Gebbers et al., 2010; Sishodia et al., 2020). It is an integrated approach that combines an integration of scientific knowledge, next-generation sensing, and satellite and digital technologies, with the acquisition, processing, and interpretation of spatial, physical, environmental, and crop information datasets to modulate agronomic interventions sustainably and reduce pressure on the environment and health (Say et al., 2018; Weiss et al, 2020).

From an operational point of view, the PF is essentially based on the interpretation of multispectral spatial information datasets acquired by remote sensing techniques both from satellite, in particular from the latest nanosatellite constellations designed to overcome previous limitations associated with the spatial, spectral, and temporal resolution of satellite images (Navrozidisa et al., 2018; Sidike et al., 2019), and from platforms UAV (Unmanned Aerial Vehicles). The latter are essentially based on the use of drones equipped with latest generation of optical sensors, particularly using high-resolution multispectral and thermal cameras. These UAV platforms represent, net of the extension of the acquisition coverage, a preferable solution compared to conventional satellite remote sensing solutions especially about the location of areas where to provide pesticide and herbicide treatments (Ayyappa Reddy et al., 2023; Mahajan et al., 2016; Xue and Su, 2017; Harsh et al., 2021). Through the interpretation of the acquired data and the identification of different spectral signatures, it is possible to distinguish the different land uses, classify crops, highlight hydrological and climatic parameters, and carry out monitoring and estimates of water requirements, thus recognizing the agronomic stress of a crop, i.e. one of the main factors influencing the decision-making and management processes aimed at increasing production. In fact, PF makes it possible to plan variable-intensity cultivation interventions, accurately scheduling the intensity of interventions on the soil, and the distribution of fertilizers and pesticides (Pillosu, 2020).

This paper presents the outcomes of a multi-year monitoring of a field of citrus groves near Rosolini (SI), in southeastern Sicily-Italy, conducted using drone-mounted multispectral cameras. The work is part of a strand of studies, started in 2016 by the research team in collaboration with PhD students, research fellows, collaborators, and producing farms that also provided technological support, to carry out field experiments in different Italian regions (Southern Lazio, Sicily, Campania). The research, on a variety of case studies, aims to evaluate the growth trends of different crops in relation to the climatic conditions recorded in different Italian regions and to highlight areas of productive green under stress, on which to act as a priority with specific agronomic interventions.

2. Precision Farming and vegetation indices

The contribution made by precision farming in recognizing the health and growth stages of crops derives from the analysis of data obtained by remote sensing, the application of which is essentially based on the concept of spectral signature, i.e. the energy absorbed and reflected by surfaces. In fact, by observing how the interaction between the incident energy of a source and different natural surfaces varies, in relation to the different wavelengths of the electromagnetic spectrum, each surface can be characterized by a specific 'fingerprint' (called 'spectral signature'), which distinguishes it from the spectral responses of other materials.

When analyzing vegetation, it is evident that reflectance properties are complex and related to many biophysical and climatic factors, including, for example, vegetative species, leaf age, nutrient stress in relation to soil biochemical parameters, plant health (disease, vigor, etc.), temperature trends, and rainfall rate. The study of the reflectance of electromagnetic waves of leaves, obtained using passive sensors, is mainly based on the analysis of the following light spectra: the ultraviolet range (with wavelengths between 10 and 380nm); the visible spectrum, consisting of the wavelength regions of blue (450-495 nm), green (495-570 nm) and red (620-750 nm); and the near and mid-infrared band (850-1700nm) (Xue et al., 2017).

Concerning the percentage amounts of reflected radiation in the different bands, it is in fact possible to calculate spectral indices, i.e. algebraic combinations of spectral values measured at specific wavelengths. These indicators, also known as vegetation indices, transform the multispectral data in numerical values that describe the state of crop vigor, biomass and chlorophyll content, while also being able to mitigate the noise caused by different aspects that influence the multispectral data in a negative way (different light/shadow gradient, geometrical features of vegetation, etc.) (Orlando et al., 2023; D'Urso et al., 2018; McKinnon et al., 2017).

Of the many vegetation indices, the NDVI, Normalised Difference Vegetation Index, is certainly the most widely used to assess plant health and can be expressed as:

$$NDVI = \frac{(\rho_{NIR} - \rho_{RED})}{(\rho_{NIR} + \rho_{RED})} \tag{1}$$

where ρ_{NIR} is the reflectance in the near-infrared band and ρ_{RED} the reflectance in the red band. Being a normalized index, NDVI values are between -1 and +1, where values between 0.4 and +1 correspond to a presence of vegetation (the higher the value, the higher the plant vigor), values around 0-0.4 indicate soil with poor vegetative cover, while low values (around -1 to 0) correspond to areas with non-vegetative cover (water or urbanized areas). This is easily understandable since the photosynthetically active leaf region absorbs most of the red light of the electromagnetic spectrum and reflects near-infrared light, while, on the contrary, water-stressed vegetation reflects much more red light and absorbs near-infrared light.

Although it is very useful because it only requires spectral measurements, NDVI is very sensitive to environmental context factors such as general brightness, the shade of vegetation canopies, and the background brightness of the soil. In other words, a directly proportional correspondence between an increase in background brightness and an increase in the index value has been observed, which may alter the understanding of the true vigor index of greenery.

To minimise the backscattering of radiation transmitted by vegetation and reflected by the soil, another spectral index was developed called the SAVI Soil-Adjusted Vegetation Index (Huete, 1988), which can be expressed as follows:

$$SAVI = \frac{(\rho_{NIR} - \rho_{RED})\,(1 + L)}{(\rho_{NIR} + \rho_{RED} + L)} \tag{2}$$

where ρ_{NIR} and ρ_{RED} are the same reflectances used for the NDVI calculation, while the parameter L is the soil conditioning index, which improves the sensitivity of NDVI to the soil background. In real-life applications, the values of L are determined in relation to specific environmental conditions: if the level of vegetation cover is high, L is close to 1 (i.e. the influence of soil has no effect on the extraction of vegetation information); whereas when L is 0, the value of SAVI is equal to NDVI. Being a function of various factors (such as soil moisture, organic content, mechanical composition, iron content, etc.), the parameter L is rather difficult to estimate accurately, and therefore an average value of 0.5 is usually used.

To reduce the approximations of the soil adjustment factor, the SAVI index was modified several times until Richardson and Wiegand, in 1977, succeeded in deriving the L-parameter by means of recursive formulas, resulting in a new, more precise parameter, depending only on the two main spectral bands of analysis (red and infrared):

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$$MSAVI2 = 0.5 * \left[(2\,\rho_{NIR} + 1) - \sqrt{(2\,\rho_{NIR} + 1)^2 - 8\,(\rho_{NIR} - \rho_{RED})} \right] \quad (3)$$

Another vegetation index similar to the NDVI is the Green NDVI (GNDVI), which is mainly used to identify the 'greenness' of vegetation, i.e. active photosynthetic activity. Algebraically, the GNDVI is calculated as follows:

$$GNDVI = \frac{(\rho_{NIR} - \rho_{GREEN})}{(\rho_{NIR} + \rho_{GREEN})} \quad (4)$$

i.e. using the same formula as NDVI, substituting the green region for the red band. Mainly used to determine the uptake of water and nitrogen in the crop canopy, this indicator is more sensitive to chlorophyll variation than NDVI and has a higher saturation point and can therefore be used in the presence of dense vegetation or at a more advanced stage of development (on the other hand, NDVI is more suitable for estimating crop vigor in the early stages of growth/maturation). Again, being a normalized index, the range of possible values is between -1 and 1: values below 0 indicate areas without vegetative cover, while the closer the values are to 1, the more intense the green, i.e. the more vigorous the vegetative cover.

Another particularly useful indicator for identifying the vigor of a plant is the NDRE - Normalised Difference Red Edge, expressed by the following formula:

$$NDRE = \frac{(\rho_{NIR} - \rho_{REDEdge})}{(\rho_{NIR} + \rho_{REDEdge})} \quad (5)$$

Using the RedEdge region, the NDRE index is particularly sensitive to the concentration of chlorophyll at the leaf level, thus making it possible to recognize different stages of vegetation development and maturation, as well as the presence of any pathologies or infestations within the field, to intervene in a targeted and precise manner, avoiding waste and optimizing the health of the entire area. Unlike NDVI, in fact, NDRE presents a linear trend in all advanced growth phases, thus this index does not depend on the biomass content.

The study of these vegetative indicators, combined with the many other indices obtained by differentially combining the multiple multispectral bands available, makes it possible to significantly improve knowledge of the state of growth and health of crops in a totally non-invasive manner, allowing the concept of sustainable intensification of agricultural production through innovation to be fully achieved. The precision introduced by these technologies, in fact, makes it possible to carry out a targeted distribution of the main factors of production (water, fertilizers, plant protection products) only where they are needed and in the quantity corresponding to the real needs of the crop being grown. In addition, the use of sensors also allows real-time monitoring of the health of crops, controlling for example the onset of phytopathogens or unfavourable environmental conditions or rationalizing agronomic practices that, if not well calibrated, could induce pathogenesis in the plants themselves. The advantages brought by PF are recognized internationally and also in Italy, since 2017, such practices have been recognised and regulated by the D.M. 33671 of 22/12/17 "Guidelines for the development of Precision Farming in Italy".

3. Geographic and climatic framework of the case study

The described analytical method was applied on a test area of approximately 7.30 hectares located near Rosolini (locality Bivio, 36°51'28.00" N - 15° 00' 33.05" E) in the province of Syracuse in south-eastern Sicily (Fig.1). This is a historic family-run company that produces only biological citrus fruits and that, in order to face the challenges of increasingly competitive and demanding markets, has rationalized and improved its business management by sharing the principles of Precision Farming through the use of the most modern agronomic and marketing techniques, and exclusively cultivating the varieties of citrus fruits that are best suited to its soils, such as Naveline, New Hall and Lane Late oranges.

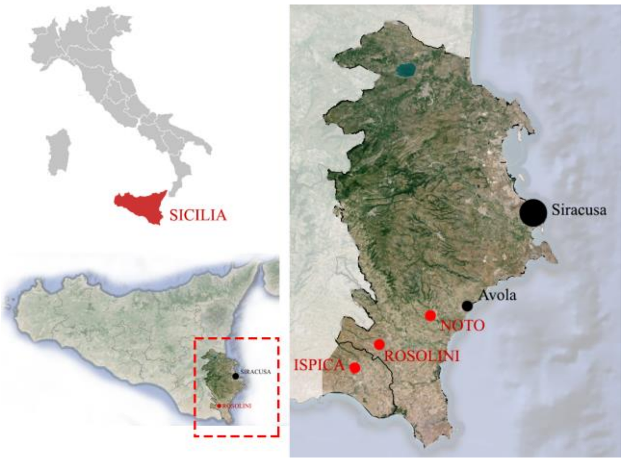

Fig. 1 – Territorial framework

From an orographical point of view, the field is located in what is commonly known as the Vallo di Noto, a geographically complex area due to the presence of many torrents and gorges, which stretches mainly between the provinces of Ragusa and Syracuse, and which became famous in 2002, when many historical centres of the region's late Baroque towns became a UNESCO World Heritage Site. The regular and flat morphology of the Wall is characterized by the presence of the Hyblean mountains, reliefs geologically made up of sedimentary layers, and outcrops of prehistoric lavas related to volcanic phenomena linked, to a certain extent, to the geological instability of the area (at the northern boundary of the Wall, in fact, lies the contact line between the Eurasian and North African plates). The presence of the reliefs and the distance from the sea favor a welcoming and mild climate, sunny and with temperatures that, in winter, are around 10°C while in summer they reach a maximum of 40°C, depending on the different exposure to the winds. These climatic conditions make the area particularly suitable for the cultivation of citrus groves and vineyards (the Nero D'Avola wine, for example, is well-known). Due to global warming and rising sea levels, however, in 2018 the Vallo di Noto, along with several other UNESCO sites in the Mediterranean area, was classified as an area at high risk of erosion, i.e. of land consumption due to natural agents such as water or wind, in relation to the distance from the coast (Reimann et al., 2018). It is evident how this risk factor, a direct consequence of the ongoing climate change, can also have negative repercussions on the agricultural productivity of the area.

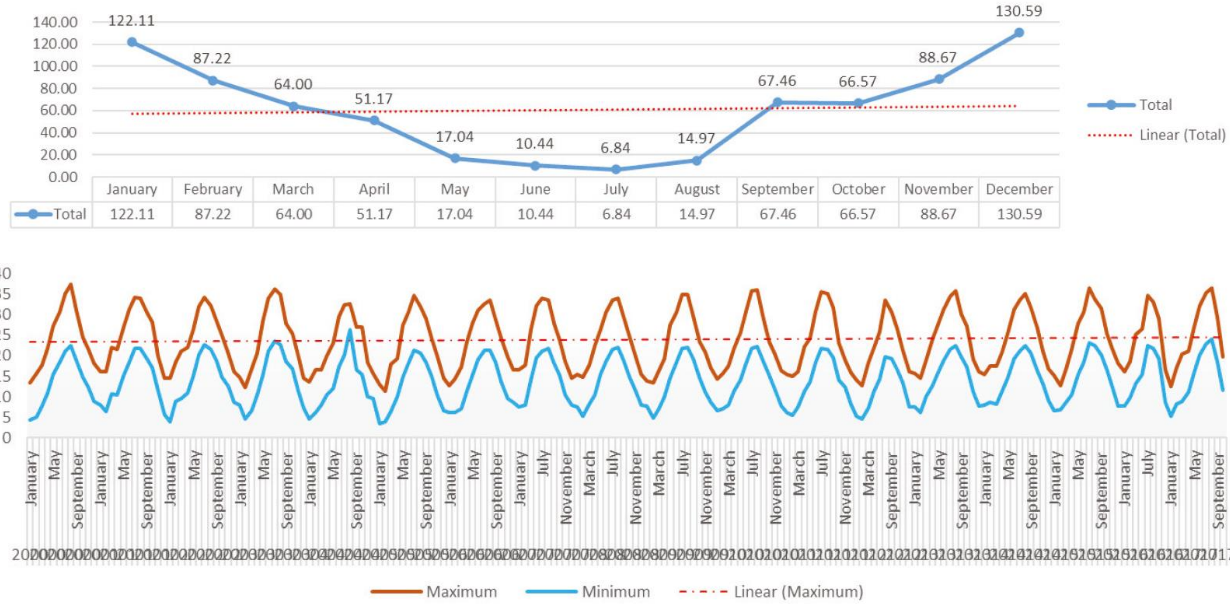

Fig. 2 – Analysis of climate data from 2000 to 2023: average monthly rainfall values (top), max and min temperature trends (bottom).

In light of these findings, in parallel with the direct monitoring phases of the citrus grove, the hydrological annals of the Ispica and Noto meteorological stations, close to the test area, were consulted to study the trend of average monthly and annual temperature and rainfall values over the last 24 years to contextualize, in a more specific manner, the possible presence of significant variations in the recorded climatic trends. Indeed, the collection of agro-meteorological data makes it possible to consider events that help to understand the long-term effects of precipitation and temperature, as well as the correlations with evapotranspiration and its influence on the different development phases of crop species. The trendline reveals that the maximum temperature consistently averages 23.9°C, while the minimum temperature maintains a steady average of 13.66°C. As far as mean rainfall values are concerned, the mean yearly value is about 46.01 mm (Fig.2).

4. Monitoring activities

The monitoring of the growth index of the citrus grove in the Bivio area (Rosolini-SI) was conducted using the technique of precision digital photogrammetric surveying through the use of a UAV platform, equipped with latest-generation multispectral photogrammetric cameras capable of simultaneously acquiring 5 bands (Blue, Green, Red, edge and NIR). As part of this experimentation, four flights were conducted from 2020 to 2022 at different periods (July 2020, March 2021, July 2022, and September 2022) corresponding to different stages of crop maturity, also in relation to the possibility of calculating vegetation indices that saturate at different levels of vegetation growth. The site area of approximately 7.30 hectares allowed the use of UAVs with high flight autonomy, capable of acquiring images for the entire plot of land (Fig. 3). With regard to the acquisition of both RGB images and multispectral bands, a camera equipped with the professional pre-calibrated Micasense RedEdge-M Multispectral sensor with a resolution of 1280 x 980 px, pixel size 3.75 x 3.75 µm and focal length 5.5mm was used.
After the acquisition phase, the multispectral datasets were loaded into the Agisoft photoscan software, thanks to which it was possible to first perform the alignment of the shoots relative to each individual band and, subsequently, generate the dense point cloud, the Digital Terrain Model (DTM) and, finally, the multispectral orthomosaic (Fig.4).

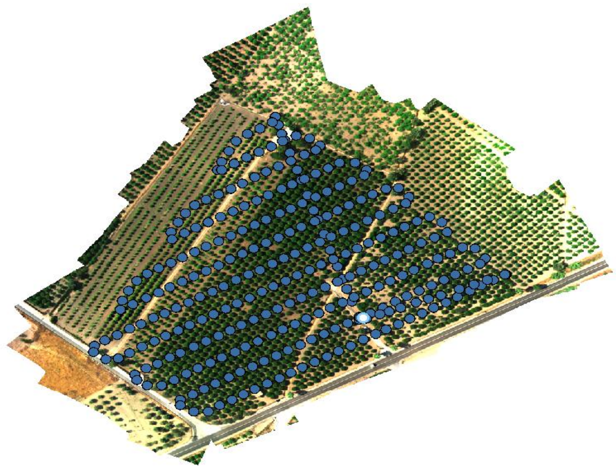

Fig. 3 – Orthomosaic and location of photographic sockets

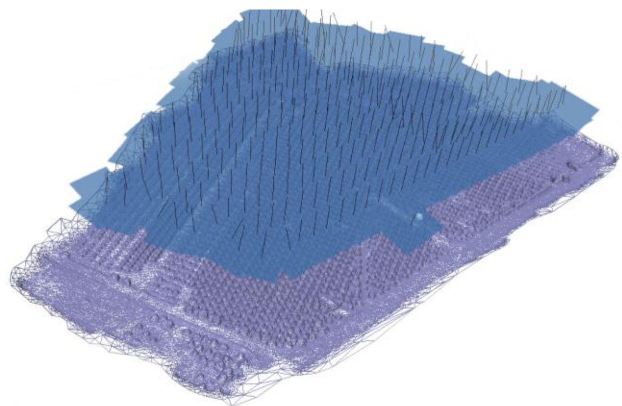

Fig. 4 – Cloud points and photographic shoots

Table 1 summarises the specifications of each acquisition campaign from which useful information can be derived with respect to the number of shoots, flight heights with relative ground resolutions, tie points, and accuracy of the photogrammetric shoots.

	flight 07.2020	flight 03.2021	flight 07.2022	flight 09.2022
Number of images	1775	1015	1220	1470
Flying altitude	60 m	78.6 m	94.4 m	81.3 m
Ground resolution	4.12 cm/pix	5.38 cm/pix	6.49 cm/pix	5.58 cm/pix
Tie points	1.213.640	665.015	621.119	791.793
Projections	4.791.201	2.731.875	3.012.822	3.457.558
Reprojection error	0.642 pix	0.634 pix	0.649 pix	0.658 pix

Table 1 - Technical specifications of each acquisition campaign

In this regard, in particular, it can be observed that the reprojection error is more or less the same in all four monitors, within a range of 0.634 to 0.658 pixels, therefore, absolutely acceptable against an average ground resolution of 5.39cm/pix and also in agreement with literature data.
Subsequently, all the individual multispectral orthomosaics were exported in GeoTiff format and imported into the QuantumGis software in which, by calibrating the settings of the Raster Calculator and setting the correct algebraic formulas, it was possible to process the graphic outputs of the vegetation indices useful for describing the state of health of the crop.
Specifically, the NDVI, SAVI, MSAVI2, GNDVI, and NDRE indices were calculated for each of the four monitoring sessions carried out, and since all indices were normalized, to facilitate the comparison of results also from a graphical point of view, a scale for displaying the results in false colors was set, from purple (minimum values) to red (maximum values), establishing the same intervals for all vegetation indices. (Fig.5). The mean values of these indices were calculated for each of the four monitoring phases and are shown in Fig.6.

5. Results

From an initial general analysis of the average values of the vegetative indices calculated for each of the four different monitoring sessions, the state of health of the field in September 2022 appears to be little different from that measured in July 2020, with NDVI, MSAVI2 and GNDVI values slightly lower than those of the first monitoring session, but which in any case show a medium/high level of crop vigor ($\Delta NDVI_{2022-2020}$=0.064; $\Delta MSAVI_{22022-2020}$=0.07; $\Delta GNDVI_{2022-2020}$=0.080).
More specifically, it can be seen that the SAVI index, calculated to reduce the effects of soil reflectance, returns somewhat better values, in terms of crop vigor, than those obtained with the NDVI, probably due to the approximation (overestimation) to 0.5 of the soil adjustment factor L. Since a more precise determination of this factor is not possible (lack of further and specific information regarding soil composition and biophysical characteristics), the values calculated by applying the MSAVI2 index seem to be more realistic and reliable, and in fact, represent a sort of average value between those returned by NDVI and SAVI.

Net of the influence of soil reflectance and crop shadows, the numerical values confirm what has already been illustrated with respect to the similarity between NDVI and GNDVI; in fact, the differences found in all the monitoring are less than 4% on average.
What instead clearly emerges, both from the analysis of the mean values of the vegetation indices and from the graphical comparison of the same, is a strong anomaly in the values for the second monitoring, which took place in March 2021. Almost all the indices show a drastic reduction in crop vigor, which cannot be attributed solely to the different ripening phases of the citrus grove compared to the other monitoring. NDVI and MASVI2, in particular, even show very similar negative values (-0.07 and -0.0753), a symptom of stress in the vegetation due to water shortage, nutrient deficiency, and the presence of diseases or pests. Bearing in mind that a very critical period in the ripening phases of orange groves can be precisely the beginning of spring when spring frosts can affect the flowering of crops, these indices were compared with the climatic data recorded by the Ispica meteorological station during the same period and it was observed that the corresponding rainfall rate was particularly high (1 day out of 3 recorded rainfall) and temperatures never exceeded 18°C. Undoubtedly, these atmospheric conditions had a negative influence on the health of the citrus grove, without however justifying such a significant variation in the index values. An analysis of the productivity data provided by the company owning the field and relating to the period in question revealed a decrease in both harvest quantities and turnover. While this confirmed the correctness of the vegetation indicators calculated, it also made it possible to understand how this negative change was due to the spread of a bacterium (called tristeza) which, precisely in that year, affected part of the citrus grove, compromising its agricultural yield. Therefore, the vegetation indices, in addition to describing the level of the vigour of the crops, made it possible to control the nutritional supplements that may be necessary for plants lacking in nutrition. In this context, the use of so-called 'beneficial insects', a valid alternative to classical pesticides, deserves special mention. These are animals, naturally present in the ecosystem, that have the ability to naturally contain and control the action of crop-damaging pests, such as ladybirds.
Lastly, analyzing in more detail the two monitoring reports for the year 2022, it can be seen that all the vegetative indicators referring to the month of September show a general decrease compared to those calculated in July: if the approximately 17% decrease in the NDVI index can be partially overestimated due to the strong influence of soil reflectance (particularly significant in the summer months), a general decrease in vigor of approximately 15% is seen in both the MSAVI2 index and the GNDVI. This significant reduction in photosynthetic activity, and therefore in chlorophyll concentration, estimated at around -30% according to the NDRE index, is probably related to the unhealthy heat waves exceptionally recorded during this period. Comparison with the recorded climatic data, in fact, shows peaks in the maximum temperature values (37°-38°C) combined with an almost total absence of rainfall (only 37mm of rain recorded in a single monthly event). This, in fact, confirms the findings of the Istituto Superiore per la Protezione e la Ricerca Ambientale (SNPA), which indicated 2022 as the least rainy and warmest year since 1961.

6.Conclusions

Precision Farming can help in managing crop production inputs in an environmentally friendly way, and by using site-specific

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knowledge, can contribute in many ways to long-term sustainability of production agriculture, confirming the intuitive idea that PF should reduce environmental loading by applying fertilizers and pesticides only where they are needed, and when they are needed. Climate change play a crucial role in influencing vegetation greenness which is one of the key indicators of vegetation health and the response of the crops to climate variations and adaptability is complex and challenging to accurately simulate.
In this study by using multispectral remote sensing technology different crop indices has been computed with their specific uses and some limiting factors. Therefore, for agronomic applications, the choice of a specific index needs to be made with attention by considering the advantages and the limitations in a specific environment in relation to the climate conditions. In the same approach, in the next future, we think to extend the sperimentation also considering the characteristic of the land, its morphology, shading and moisture and analyzing other climate factors as elevated CO_2 concentration, varying nitrogen deposition rates and other anthropic factors that could influence the vegetation health.

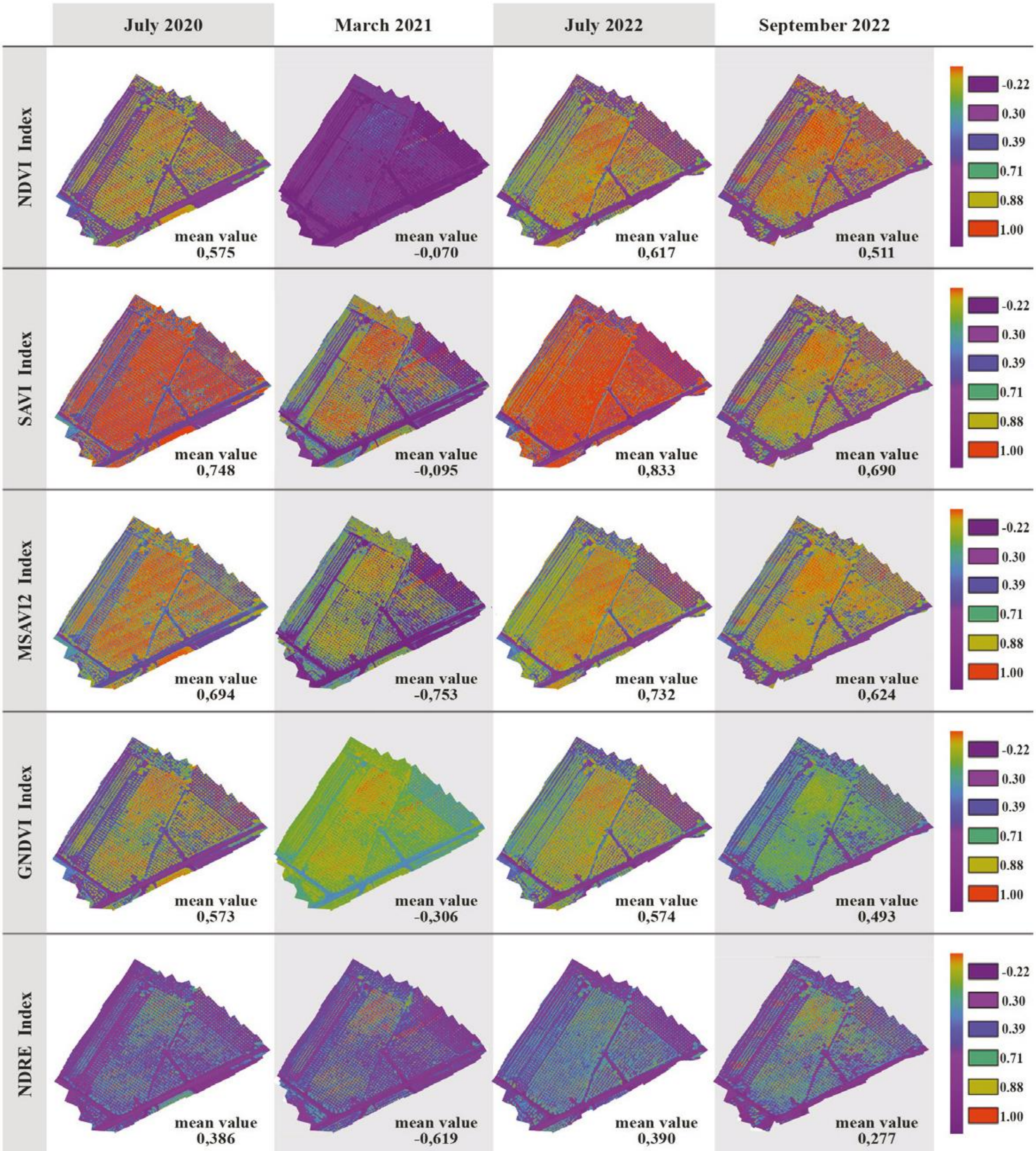
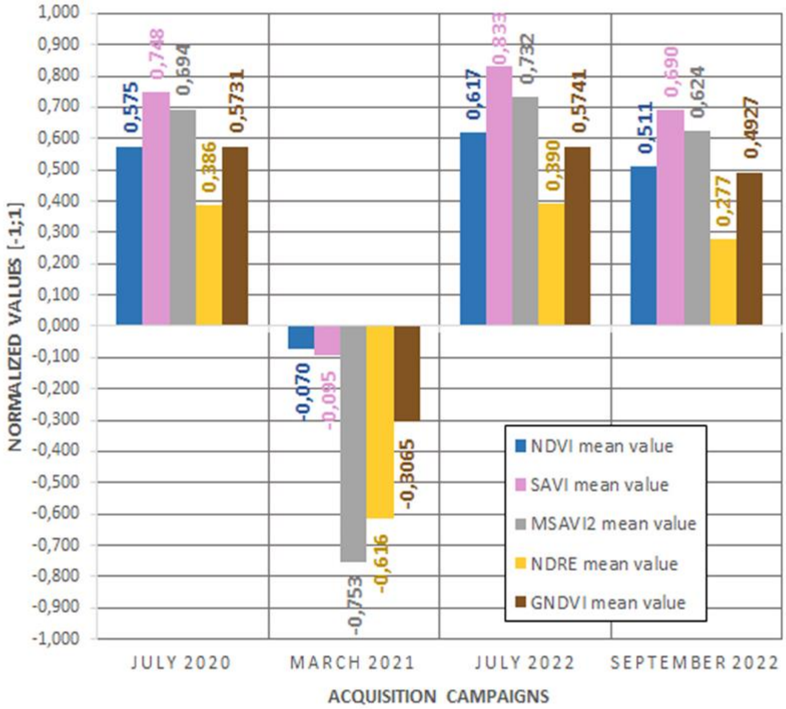


Fig. 5 - NDVI, SAVI, MSAVI2, GNDVI, NDRE vegetation indices calculated for each monitoring (July 2020, March 2021, July 2022, September 2022): graphical comparisons with the same color intervals for all vegetation indices



	flight 07.2020	flight 03.2021	flight 07.2022	flight 09.2022
NDVI medio	0.575	-0.070	0.617	0.511
SAVI medio	0.748	-0.095	0.833	0.690
MSAVI2 medio	0.694	-0.753	0.732	0.624
GNDVI medio	0.573	-0.307	0.574	0.493
NDRE medio	0.386	0.386	0.390	0.277

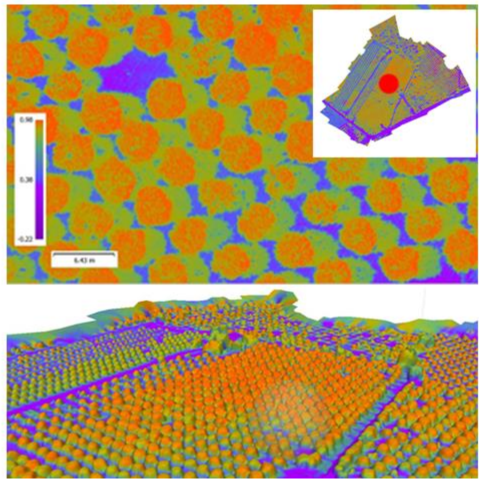


Fig. 6 - NDVI, SAVI, MSAVI2, GNDVI, NDRE vegetation indices calculated for each monitoring (July 2020, March 2021, July 2022, September 2022): summary graph and table of mean values

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