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Climate change impacts on agricultural suitability and yield reduction in a Mediterranean region

Sameh K. Abd-Elmabod[a,b,c,*], Miriam Muñoz-Rojas[d,e], Antonio Jordán[b], Mariá Anaya-Romero[f], Jonathan D. Phillips[g], Jones Laurence[h], Zhenhua Zhang[c,i], Paulo Pereira[j], Luuk Fleskens[k], Martine van der Ploeg[k], Diego de la Rosa[l]

[a] Soil and Water Use Department, Agricultural and Biological Research Division, National Research Centre, Cairo 12622, Egypt
[b] MED_Soil Research Group, Department of Crystallography, Mineralogy and Agricultural Chemistry, Seville University, Seville 41012, Spain
[c] Institute of Agricultural Resources and Environment, Jiangsu Academy of Agricultural Sciences, Nanjing 210014, China
[d] Centre for Ecosystem Science, School of Biological, Earth and Environmental Sciences, University of New South Wales, Sydney 2052, NSW, Australia
[e] School of Biological Sciences, The University of Western Australia, Perth 6009, WA, Australia
[f] Evenor-Tech, SLU ICT for land evaluation, Seville, Spain
[g] Earth Surface Systems Program, Department of Geography, University of Kentucky, Lexington, KY 40506-0027, USA
[h] Centre for Ecology & Hydrology (CEH-Bangor), Environment Centre Wales, Deiniol Road, Bangor LL57 2UW, UK
[i] School of Agriculture and Environment, The University of Western Australia, Crawley, WA 6009, Australia
[j] Environmental Management Centre, Mykolas Romeris University, Ateities, Vilnius LT-08303, Lithuania
[k] Wageningen University and Research, Soil Physics and Land Management Group, 6700 AA Wageningen, The Netherlands
[l] Earth Sciences Section, Royal Academy of Sciences, Seville 41012, Spain

A R T I C L E I N F O

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A B S T R A C T

Climate change impacts are a serious threat to food provisioning, security and the economy. Thus, assessing agricultural suitability and yield reduction under climate change is crucial for sustainable agricultural production. In this study, we used two sub-models of the agro-ecological decision support system MicroLEIS (Terraza and Cervatana) to evaluate the impacts of climate change on land capability and yield reduction or wheat and sunflower as major rainfed crops in different Mediterranean soil types (in Andalucia, Southern Spain). The Terraza sub-model provides an experimental prediction for the bioclimate deficiency and yield reduction, while the Cervatana sub-model predicts the general land use suitability for specific agricultural uses. Sixty-two districts in Southern Spain were modeled and mapped using soil data and the A1B climate scenario (balanced scenario) for three 30-year periods ending in 2040, 2070 and 2100, respectively. Our results showed that the majority of agricultural soils were suitable for wheat production, and less for sunflowers, especially under projected climate change scenarios. Extreme impacts of climate change were observed in the soil types Typic Xerofluvents and Calcic Haploxerepts, where the land capability was reduced from *Good* and *Moderate* classes to the *Marginal* class. This was especially observed in sunflower crops by 2100. Yield reduction of sunflower was much higher than the reduction for wheat, especially under the projected climate periods, where the results for 2100 showed the severest effect on crop yields with about 95% of the sunflower area showing yield reductions. This high variability of the evaluation results demonstrates the importance of using soil factors, climate and crop information in conjunction in decision-making regarding the formulation of site-specific soil use and management strategies.

1. Introduction

An increase in global food demand is expected in future decades, and the next 50 years pose huge challenges for the sustainability of agriculture and food production (Tilman et al., 2002). This demand will place pressure on soil functions, and provisioning and regulation of ecosystems services. In this context it is important to find sustainable practices to mitigate the impacts of climate change and human pressure on soil resources (DeFries et al., 2016; Untenecker et al., 2017; Pereira et al., 2018; Aggarwal et al., 2019).

Climate change and the increasing population are threatening the global food security (Hanjra and Qureshi, 2010; Poppy et al., 2014;

* Corresponding author at: Soil and Water Use Department, Agricultural and Biological Research Division, National Research Centre, Cairo 12622, Egypt.
E-mail address: sk.abd-elmabod@nrc.sci.eg (S.K. Abd-Elmabod).

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Fanzo et al., 2018). Climate change is expected to increase the humans affected by food insecurity, where from 5 to 170 million people at risk of hunger by 2080 (Rosegrant et al., 2008; Schmidhuber and Tubiello, 2007). Predicted changes in temperature, precipitation, carbon dioxide, and the frequency and severity of extreme events, are expected to have profound effects on soil water availability, carbon storage, and yields (Cox et al., 2018). Recent studies suggest that droughts will intensify in some seasons in areas such as the Mediterranean region and Africa (Smith et al., 2016; Muñoz-Rojas et al., 2017).

Agriculture in the Mediterranean region is inextricably linked to soil quality and water supply (Zalidis et al., 2002). Climate change predictions in the Mediterranean area show that agricultural productivity is projected to decrease (Carsan et al., 2014; Anaya-Romero et al., 2015; Keesstra et al., 2016; Muñoz-Rojas et al., 2017; Jat and Bijay-Singh, 2018). On the other hand, productivity could increase in some locations if farmers adapt to the future climate conditions. In situations where farmers do not adapt a decrease in this productivity is expected (Moore and Lobell, 2014; Rahimi-Moghaddam et al., 2018). Also, the influence of soil properties and available water must be considered to sustain crop production (Kang et al., 2009; Hondebrink et al., 2017). Several studies have investigated the effects of soil physio-chemical characteristics and precipitation on yield variability for major crops, such as corn, soybean and wheat (Si and Farrell, 2004; Bekele et al., 2017; Jarecki et al., 2018; Jourgholami et al., 2019). According to Kitchen et al. (2003) and Whetton et al. (2018) multiple factors affect agricultural land suitability. The relationship between yield, topography and soil properties can be nonlinear and other factors may interact with these three (Juhos et al., 2016). Evaluation of the relationships between climate change and crop productivity depend on a combination of modelling and measurement (Challinor et al., 2009).

Suitability of land for agricultural production is affected by complex interactions between topography, soil properties, climate conditions and management practices (Jaynes et al., 2003; Kravchenko et al., 2005; Jaisli et al., 2018; Juhos et al., 2019; Akbari et al., 2019), and can be determined by land evaluation, which is the process of assessing the potential use of land on the basis of its characteristics (Rossiter, 1996). Land evaluation modeling is a useful approach to identify the most adequate agricultural land use resulting from the interaction between topography, soil properties, climate and agricultural practices (Shahbazi et al., 2009). Detecting environmental limits in sustainable farming is an important stage in the process of land use planning (Bandyopadhyay et al., 2009). Land use planning relates major land uses to soil capability and suitability for each particular site, and is an important prerequisite for achieving environmental sustainability. Any agricultural practice will have negative impacts when applied on a land with low suitability for that agricultural use. For example, in some areas of the Mediterranean region, the use of marginal agricultural land is one of the primary causes of soil degradation (De la Rosa et al., 2009; Anaya-Romero et al., 2015). Climate change affects crop production directly and indirectly (Yang et al., 2017; Tebaldi and Lobell, 2018; Neset et al., 2018; Dong et al., 2018), thus to achieve adequate predictions for the future scenarios, there is an essential need to consider soil properties. Land capability is expected to decrease under climate change, and summer crops are expected to be more sensitive to climate change than winter crops (California Department of Food and Agriculture, 2013).

Land evaluation models are increasingly being used to assess the impacts of climate change on land capability and land degradation, planning of land use and designing suitable soil management systems (Anaya-Romero et al., 2011, 2015; Akbari et al., 2019). One of such tools is the MicroLEIS DSS, an agro-ecological decision support system that was developed to help decision-makers to evaluate specific agro-ecological problems (De la Rosa et al., 2004). It was designed as a knowledge-based approach, which incorporates a set of information tools, linked to each other. Thus, custom applications can be performed on a wide variety of problems related to land productivity and land degradation (De la Rosa et al., 2009; Abd-Elmabod et al., 2017). Several agroecological or crop models have been developed and applied in different areas in recent studies to assess land suitability or capability for wheat (El Baroudy, 2016). Other crops such as sunflower are by far less studied, despite their importance in Mediterranean regions and their potential for cultivation in marginal lands (Chiaramonti and Panoutsou, 2019). One of the few examples is the research developed by Rabati et al (2012) in Iran, who used MicroLEIS to assess land suitability for sunflower and maize.

Despite advances in the foreseen impacts of a changing climate in the Mediterranean region (Malek et al., 2018), and an increasing number in modelling approaches for predicting crop yields (Iizumi et al., 2018), several gaps remain at local and regional scales. For example, many studies do not consider edaphic factors for evaluation of land suitability and there is lack of spatial analyses reflecting model outputs (Abd-Elmabod et al., 2017). MicroLEIS DSS presents several advantages such as the integration of multiple databases and models (13 land evaluation models), which combined can, among other applications, assess land capability, predict yield increases or reductions of relevant crops, and identify land management strategies for climate adaptation, i.e. reducing the salinity and exchangeable sodium percentage or improving the drainage (Anaya-Romero et al., 2015). Further advantages in comparison to other modelling approaches are its integrated tool for data spatialization and the requirement of inputs that are practical to obtain in field surveys (Muñoz-Rojas et al., 2013). MicroLEIS has been widely used over the last 30 years for different purposes, mostly in the Mediterranean region. Focusing on agricultural land use, planning, and management for soil protection purposes under current environmental conditions (De la Rosa et al., 2009; Abd-Elmabod et al., 2019a). Recent developments of Micro LEIS allow that some of the integrated models, can be run under different hypothetical scenarios of climate and agriculture management (Muñoz-Rojas et al., 2015, 2017; Lozano-García et al., 2017; Abd-Elmabod et al., 2017).

In this study the MicroLEIS DSS model was applied to evaluate the impacts of climate change on land capability and yield reduction for wheat and sunflower as major rainfed crops in different Mediterranean soil types. Specifically, we present a study in the Andalusian region (Southern Spain) under different climate change scenarios. These future projected scenarios covered three time periods, e.g. 2011–2040 (2040, near-future), 2041–2070 (2070; mid-future) and 2071–2100 (2100 far-future) under the A1B socio-economic scenario (medium emissions scenario) (IPCC, 2014; Agencia Estatal de Meteorología, www.aemet.es).

2. Material and methods

2.1. Study area

The Andalusia region extends over the southern part of Spain between latitudes 36° 00′ and 38° 44′ N and longitudes 1° 30′ and 7° 45′ W (Fig. 1). This region covers an area of approximately 87,600 km^2 and comprises 62 districts that are grouped into eight provinces (Almeria, Cadiz, Cordoba, Granada, Huelva, Jaen, Malaga, Sevilla).

The topography and land use are shown in Fig. S1-A. The topography ranges from the lowlands of the Guadalquivir basin to the mountain ranges in the Baetic Cordillera and Sierra Morena (Benet, 2006; Gutiérrez et al., 2013). According to Vera (1994), there are three main geological units (Fig. S1-C) in this region. First, the northern part consists of Sierra Morena, a crystalline massif which is very ancient (Paleozoic), and was part of the Armorica continent. The second unit is represented by the Neogene tectonic basin of the Guadalquivir (formed from the Middle Miocene (Langhian) until present day). The third geological feature (in the south-east) is the Baetic cordillera (Triassic-Lower Miocene), which is the westernmost part of the European Alpine chain. In Andalusia, there are four main river basins, Guadalquivir in central Andalusia, Guadiana in the northwest, Sur in the south and

Fig. 1. Top left location of Andalusia region in Spain. Bottom right provinces (8) and natural regions (62).

Segura in the southeast. The most important river is the Guadalquivir and its main tributaries: Guadalimar, Guadiana Menor, and Genil (Fig. S1-D).

According to the climate calculations using the CDBm climate database integrated in MicroLEIS DSS, the Huércal Overa station (AL02) in Almería, is the most arid location in the study area (Fig. S1-E and S1-F), with an annual rainfall of 275 mm, a mean temperature of 17 °C, potential evapotranspiration (ET_0) of 883 mm, and an average of 10 arid months (in which the ET_0 exceeds the actual precipitation) per year. Conversely, the most humid area is Gaucín (MA05) in Málaga, with an annual rainfall of 1170 mm, a mean temperature of 14.9 °C, an ET_0 of 772 mm, and an average of 5 arid months per year. Excluding these two extreme cases (arid and humid), the rest of the study area typically has a Mediterranean climate with an annual precipitation average of 586 mm, mean annual temperate of 14.7 °C, and average ET_0 of 830 mm.

Approximately half of the Andalusia region is occupied by natural vegetation areas (mostly forest) while most of the remainder is occupied by agricultural land. Less than 5% of the region is urban or water bodies (Bermejo et al., 2011). Agriculture in Andalusia has conventionally been based on systems integrating wheat crops, olive trees and vineyards, but in recent decades, traditional systems have been replaced with intensive and extensive monocultures e.g., wheat, sunflower, rice, cotton and sugar beet (Muñoz-Rojas et al., 2011).

Major changes in land use/land cover occurred within the region between 1956 and 2007 as permanent crops increased to occupy 20% (17,234 km^2, in 2007) of the study area instead of 15% (13,324 km^2, in 1956) (Anaya-Romero et al., 2011) Also, heterogeneous agricultural land increased to cover 13% (11,421 km^2) of Andalusian total area in 2007 instead of 12% (10,450 km^2) in 1956 (Muñoz-Rojas et al., 2011). These increases in cultivated land are directly related to crop types and their production.

2.2. Description of the MicroLEIS decision support system (DSS)

MicroLEIS DSS is able to predict the optimum land use and management practices for each soil type. Additionally, it is able to assess the optimum biomass productivity, the minimum environmental vulnerability and through a recent update, the maximum capacity for soil C sequestration (Muñoz-Rojas et al., 2013, 2015, 2017). MicroLEIS includes three databases; soil (SDBm), climate (CDBm) and management (MDBm) and 13 models (Abd-Elmabod et al., 2017). In this study, two of those models, *Terraza* and *Cervatana,* were run under different climate scenarios for wheat and sunflower crops in order to evaluate soil productivity as bioclimate deficiency/yield reduction, and general land suitability, respectively.

2.2.1. Soil database (SDBm)

The soil database (SDBm plus) (De la Rosa et al., 2002) includes detailed information of 1103 soil profiles in Andalusia inculding site information, morphological descriptions and detailed soil physio-chemical analyses. In this study, we selected the most representative soil profiles, based on dominant soil types, for each natural region of Andalusia (total of 62 soil profiles) (Fig S2). Table 1 shows the ranges

Table 1
Ranges and dominant values of land characteristics of the 62 benchmark soils for Andalusia. (*) Soil parameters measured within the soil section 0 to 50 cm. Source: adapted from De la Rosa et al. (2002).

Land characteristics, Unit		(Range) Dominant
Site-related characteristics	Landform	(plan-mountain), hill
	Slope gradient, %	(0.7– > 30), 2
	Elevation, m asl	(1–2080), 490
Soil-related characteristics	Useful depth, cm	(0–260), 150
	Drainage	(poor-excessive), well
	Particle size distribution*	(sand-clay), clay
	Superficial stoniness	(nil–abundant), nil
	Organic matter, * %	(0.1–4.3), 1.6
	pH*	(5.1–8.7), 7.4
	Cation exchange capacity, * meq/100 g	(2.5–50.4), 17.5
	Sodium saturation, * %	(0.2–11.9), 2.7

and dominant values of land characteristics of the 62 benchmark soils for Andalusia.

Soil profiles were classified to the sub-group level of USDA Soil Taxonomy (USDA, 2014), resulting in 31 soil units that were included in seven soil orders. Table S1 shows the area coverage for existing soil orders in Andalusia region which comprise Alfisols (18,361 km^2; 21%), Aridisols (2450 km^2; 3%), Entisols (18,564 km^2; 21%), Inceptisols (22,518 km^2; 26%), Mollisols (6269 km^2; 7%), Ultisols (3748 km^2; 4%) and Vertisols (15,691 km^2; 18%). The three major soil sub-groups (comprising 13% of the surface area) are Typic Haploxererts, Typic Haploxerults, and Lithic Haploxerepts that represents 5.0, 4.3 and 3.6% of the area, respectively (Fig. S2 and Table S1). Several soil characteristics have been used in this research, including organic matter, pH, calcium carbonate content, exchangeable sodium percentage, texture, drainage class and depth.

2.2.2. Climate database (CDBm)

Current climate variables, mainly precipitation and temperature (1960–2010), were obtained from the CDBm climate database which is one of the main components of MicroLEIS DSS. Climate observations from 62 climate stations distributed throughout the eight provinces of the Andalusia region were considered as a pool from which to draw eight stations with the most accurate representation of the local climate and the spatial variation for scenario modelling. To do this, in each province, one representative climate station (among others) was selected. For instance, in the case of precipitation, the spatial variation can vary within the same province, and in many provinces the station with the highest annual precipitation receives more than double the amount of rainfall of the lowest reported value for the same province. Therefore, the most representative climate stations from each province were selected, e.g. those with climate values closest to the average for each province. The monthly climate parameters of the eight representative climate stations from 62 station of Andalusia were calculated for different climate change scenarios; the current situation, and projections for future 30-year periods ending in 2040, 2070 and 2100 respectively.

2.2.3. Climate change scenarios

In this research, the average values of 18 regional climate change models for the SRES scenario A1B (balanced) for three time periods 2011–2040, 2041–2070 and 2071–2100 besides current climate situation were used (Agencia Estatal de Meteorología, www.aemet.es). Fig. 2 shows decreasing precipitation and increasing minimum and maximum temperature under the different projected time periods of climate change compared with the current situation for the different seasons of the year. In this figure, the y-axis represents the cumulative values of precipitation or the mean values of temperature for the four seasons under each time periods.

2.2.4. Climate indices

Different climate indices that are related to crop productivity were calculated based on CDBm, including humidity, aridity and precipitation concentration indices. The Humidity index (HU_i) is used to estimate the general availability of water to plants. It is also often used to anticipate the needs of artificial drainage and/or irrigation in an area (FAO, 1996). The humidity index can be calculated based on Eq. (1) as:

$$HU_i = \frac{P}{ET_0} \tag{1}$$

where, P is the precipitation and ET_0 is the reference evapotranspiration (calculated according to Thornthwaite's method). The Aridity index (ARi) is a simple procedure to estimate the general climate aridity and is calculated as the number of months of the year when the ET_0 exceeds the precipitation. According to Oliver (1980), the precipitation concentration index (PC_i) was proposed to estimate the seasonality of rainfall from the temporal variability of monthly rainfall. It is expressed as a percentage, according to Eq. (2) as:

$$PC_i = \frac{\sum_{i=1}^{12} p_i^2}{(\sum_{i=1}^{12} p_i)^2} \times 100 \tag{2}$$

where p_i is the monthly precipitation in month i.

2.2.5. Yield reduction and land capability models

The Terraza and Cervatana models can evaluate soil productivity as bioclimatic deficiency, and general land capability respectively. The choice of land components (site/soil, climate, and crop/management factors) as input variables or diagnostic indicators for the predictive models is a basic part of the land capability analysis (De la Rosa et al., 2004, 2009). Fig. 3 shows a conceptual scheme of the Terraza and Cervatana models that link site, soil, climate and crop factors with soil quality. The calculations of the Terraza and Cervatana models are empirical, formulated and calibrated using expert knowledge. These models have been previously calibrated and validated in the field under management practices, soil types, climate, and time scales like those used in this study (De la Rosa, 1974; De la Rosa et al., 1981, 1992; De la Rosa et al., 2004). Indeed, the models were calibrated in the study area (Andalusia) (De la Rosa and Moreira, 1987; Anaya-Romero et al., 2015) during the modelling development phase, where validation included calculation of standard errors, root mean square error, slope and intercept of regression, and correlation of observed vs. predicted results.

The bioclimatic deficiency model (Terraza) depends in its calculations mainly on climate and crop parameters (Fig. 3). The climate change models predict climatic parameters that can be entered into the Terraza model to study the impact of climate change on the bioclimate deficiency. Predicted climate parameters values under different future periods such as temperature and precipitation can be entered into the Terraza model to study the impact of climate change on the bioclimate deficiency. The average values of 18 regional climate change models for the A1B scenario and 30-year periods (2040, 2070 and 2100) as well as the current climate were examined by the Terraza and Cervatana models for evaluating yield reduction, and agriculture land suitability, respectively. This work focuses on studying two major rainfed crops (wheat and sunflower), since irrigated areas in Andalusia represent only 10%; the dominant cultivation practices (90%) depend on rainfed agriculture.

In this study, the Terraza model investigates the response of wheat and sunflower productivity, the major crops in the studied region, to climate change. The assessment of expected yield reduction by water shortage was studied for the actual agricultural area, approximately 48,580 km^2 (55.5% of Andalusia), and the model results were grouped into eleven classes ranging from 0 (no yield reduction) to 10 (the yield reduction is between 90 and 100%). Water deficiency and water surplus for wheat and sunflower crops were calculated, then yield reduction for each land unit were calculated.

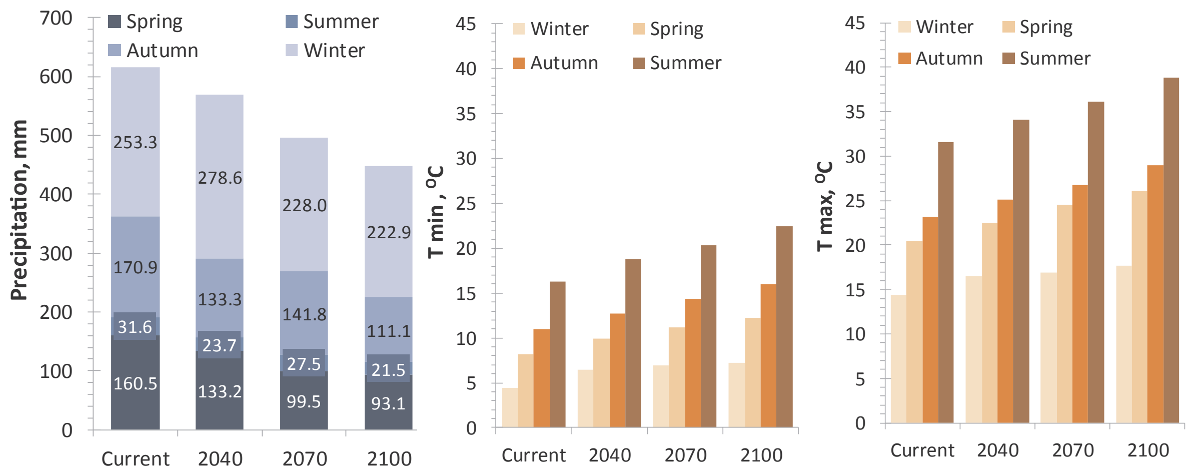

Fig. 2. Variation of climate parameters under A1B climate change scenario for three projected years 2040, 2070 and 2100 during Spring, Summer, Autumn and Winter seasons. Y-axis shows values for precipitation (mm), minimum temperature (Tmin, °C), and maximum temperature (Tmax, °C). Source: Adapted from State Meteorological Agency, 2011.

The Cervatana model predicts the general land capability for specific agricultural uses, depending on information about; topography (t), soil factors (l), erosion risk (r) and bioclimate deficiency (b) (Fig. 3). The model results are grouped into four classes: S1-optimum, S2-good, S3-moderate and N-marginal that are calculated for each specific combination of soils and crops (Fig. S3). Under these four classes, 13 subclasses were categorized based on the number of limiting factors that affect the agricultural use (Fig. S3).

The bioclimate deficiency classes (output from the Terraza model) are established by combining the classes of water deficiency and frost risk based on the criterion of maximum limitation. Bioclimate deficiency calculation starts by determining the monthly ET_0 using the method of Thornthwaite (1948), as explained in Eq. (3);

$$ET_0 = 1.6\left(\frac{10Tm}{I}\right)^a \tag{3}$$

where Tm is monthly mean temperature (°C); I is the annual heat index; and a an empirically determined exponent. I and a are constants for each site, which can be calculated as illustrated in Eq. (4) and Eq. (5), respectively:

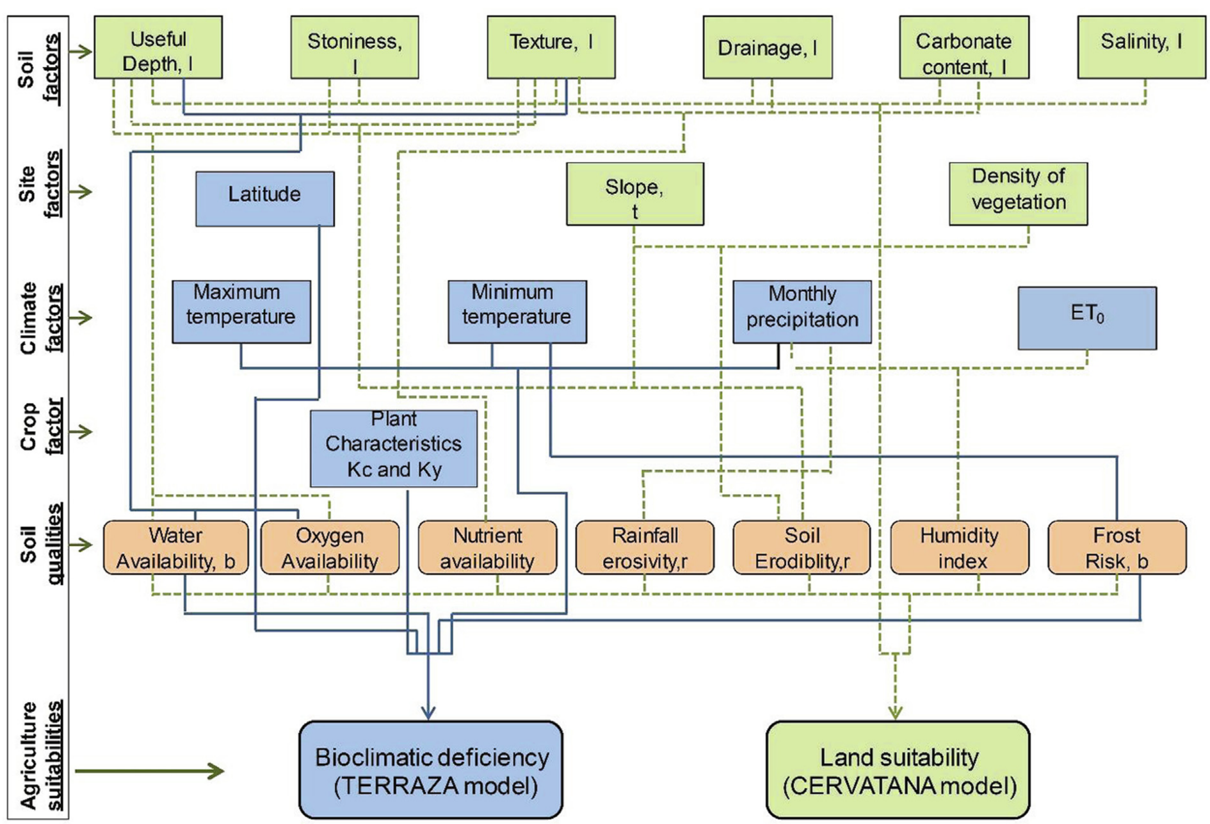

Fig. 3. General scheme of the Terraza and Cervatana models. Green colour is assigned for land suitability model (Cervatana), blue represents the bioclimatic deficiency model (Terraza) and the soil qualities are shown in orange.

$$I = \sum_{1}^{12} \left(\frac{Tm}{5}\right)^{1.514} \quad (4)$$

$$a = 0.000000675 \cdot I^3 - 0.0000771 \cdot I^2 + 0.01792 \cdot I + 0.49239 \quad (5)$$

A second step for calculating the yield reduction is to consider the crop characteristics. The crop monthly evapotranspiration (*ETc*) and the monthly real evapotranspiration (*ETa*) are used as crop factors and they are calculated based on Eq. (6) and Eq. (7), respectively, as:

$$ET_c = ET_0 \cdot K_c \quad (6)$$

$$ET_a = ET_c - D \quad (7)$$

where *Kc* is crop coefficient and *D* is the monthly water deficit. If the ET_a is positive, there is a surplus or excess (S) of water; if the ET_a is negative, there is a water deficit (D). All the calculated values in Eq. (6) and Eq. (7) are dependent on the growth stage of each crop.

The monthly reduction of yield (*Ry*) is calculated using Eq. (8):

$$Ry = Ky\left(1 - \frac{ET_a}{ET_c}\right) = 1 - \frac{Ya}{Ym} \quad (8)$$

where *Ky* is the crop coefficient of efficiency, *Ya* is the real crop production and *Ym* is the potential crop production.

The annual reduction in crop production (*Rys*) is calculated by Eq. (9):

$$Rys = Kys\left(1 - \frac{SET_a}{SET_c}\right) \cdot 100 \quad (9)$$

where *SETa* is the sum of the monthly real evapotranspiration and *SETc* is the sum of the monthly evapotranspiration of the crop during its phenological period.

In this study the three coefficients considered to model crop responses were the monthly crop coefficient (*Kc*), the monthly crop coefficient of efficiency (*Ky*), and the coefficient of seasonal reduction (*Kys*). These coefficients were determined using the FAO databases (FAO, 1976, 1986), for wheat and sunflower. The *Kc* and *Ky* for these two crops are presented in Table 2. The *Kys* values are 1.00 and 0.95 for wheat and sunflower, respectively.

Frost risk was estimated according to the criteria of Verheye (1986) and then adapted for the Mediterranean regions. The frost risk was defined as the number of months with minimum average temperature below 6 °C.

2.3. Spatial analyses

The Terraza and Cervatana models' results were integrated in a Geographical Information System (GIS) environment for spatial representation of the land capability classes and yield reduction in the study area. ArcGIS 10.4.1 software was used for data processing of the land resources database to produce the final maps.

Table 2
Kc and *Ky* for Wheat and Sunflower crops according to FAO (1976, 1986).

Months	Crop coefficient (*Kc*)		Coefficient of efficiency (*Ky*)	
	Wheat	Sunflower	Wheat	Sunflower
January	0.75	–	0.20	–
February	0.75	–	0.20	–
March	0.81	0.48	0.20	0.25
April	0.84	0.75	0.33	0.38
May	0.46	1.00	0.52	0.83
June	–	0.88	–	0.80
November	0.35	–	0.20	–
December	0.75	–	0.20	–

3. Results

3.1. Climate data under future climate change

The monthly climate parameters (Tmax, Tmin and P) and the ET_0, ARi, HUi and PCi of eight representative meteorological stations of Andalusia provinces are presented graphically (Fig. 4 and Fig. S4) for the projected years under the A1B scenario (2040, 2070, and 2100) as well as the current situation. Generally, the trend predicts a decrease of precipitation and increase in temperature over time. Specifically, precipitation is expected to decrease in 2070 and 2100 compared with the current situation, whereas a slight increase is projected for 2040. Conversely, the mean temperature is expected to increase during the projected years of 2040, 2070, and 2100 (Fig. 4).

Projections of the annual climate indices are presented in Fig. S4. In general, the ET_0 and ARi are expected to increase in the future as a result of temperature increasing and precipitation decreasing for all the studied meteorological stations. The HUi is predicted to decrease under the projected future climate change in all locations. The PCi index results show a different trend compared with other studied parameters, as there is an increase in 2040 followed by a decrease in 2070 and another increase in 2100 for almost all meteorological stations.

3.2. Soil characteristics

Several soil characteristics have been used in this research, including organic matter, pH, calcium carbonate content, exchangeable sodium percentage, texture, drainage and soil depth. For the soil organic matter, the soil type HU01-Lithic Xerochrepts showed the highest content of 4.3%. Approximately 28% of the area had pH values ranging between 5 and 6.5 (strongly to slightly acidic soils, respectively, Soil Survey Division Staff, 1993). However, around 22% of the study area had pH values above 8. Regarding the carbonate content, the highest percentage (> 40%) was observed in soils that were formed from calcareous parent material, such as the soil type GR07-Calcic Haploxerepts. The lowest cation exchange capacity (CEC = 1.3 meq/100 g) was found for coarse sandy soils (GR03-Typic Xerorthents), while the highest values were observed in the heavy clay soils, where the CEC value reached up to 50.4 meq/100 g (in the soil type CO02-Typic Haploxererts). Soil salinity problems were observed in some natural land use areas (i.e. SE05, HU06 and AL04) with a high concentration of salt. The highest salt concentration (30.8 dS/m) was found in soil type SE05-Typic Fluvaquents. The calcic soils had low exchangeable sodium percentage (ESP) compared with the saline soils which had high ESP values. There was a massive variation in the soil texture within the study area from sandy to clayey soil. The drainage status in the study area can be divided into different classes: good (51% of the total area), moderate (29%), poor (14%), and excessive (6%). Regarding soil depth, shallow soils prevail in the natural land use and forest areas, where the depth does not extend to 50 cm (e.g. GR06-Typic Xerorthents and HU02-Lithic Xerorthents, with a depth of 12 and 9 cm, respectively). The deepest soils were found in GR05-Typic Rhodoxeralfs and SE06-Typic Haploxerults soil types, with 170 and 250 cm depth, respectively.

3.3. Land capability

Land capability in Andalusia was evaluated under the current and future climate change scenarios (A1B) based on climatic parameters and soil characteristics. Besides the evaluation of agricultural areas, the land capability assessment was applied on the forest soils too as they occupied approximately 42% of the study area. The land capability classification for the forest areas ranged from moderately capable class (S3tr, moderate land capability with slope and soil erodibility as limiting factors) to marginal class (Ntl, not capable for agricultural use with slope and soil factors as maximum limitations). Accordingly, topography, shallow soil depth, and high erosion risk are the most

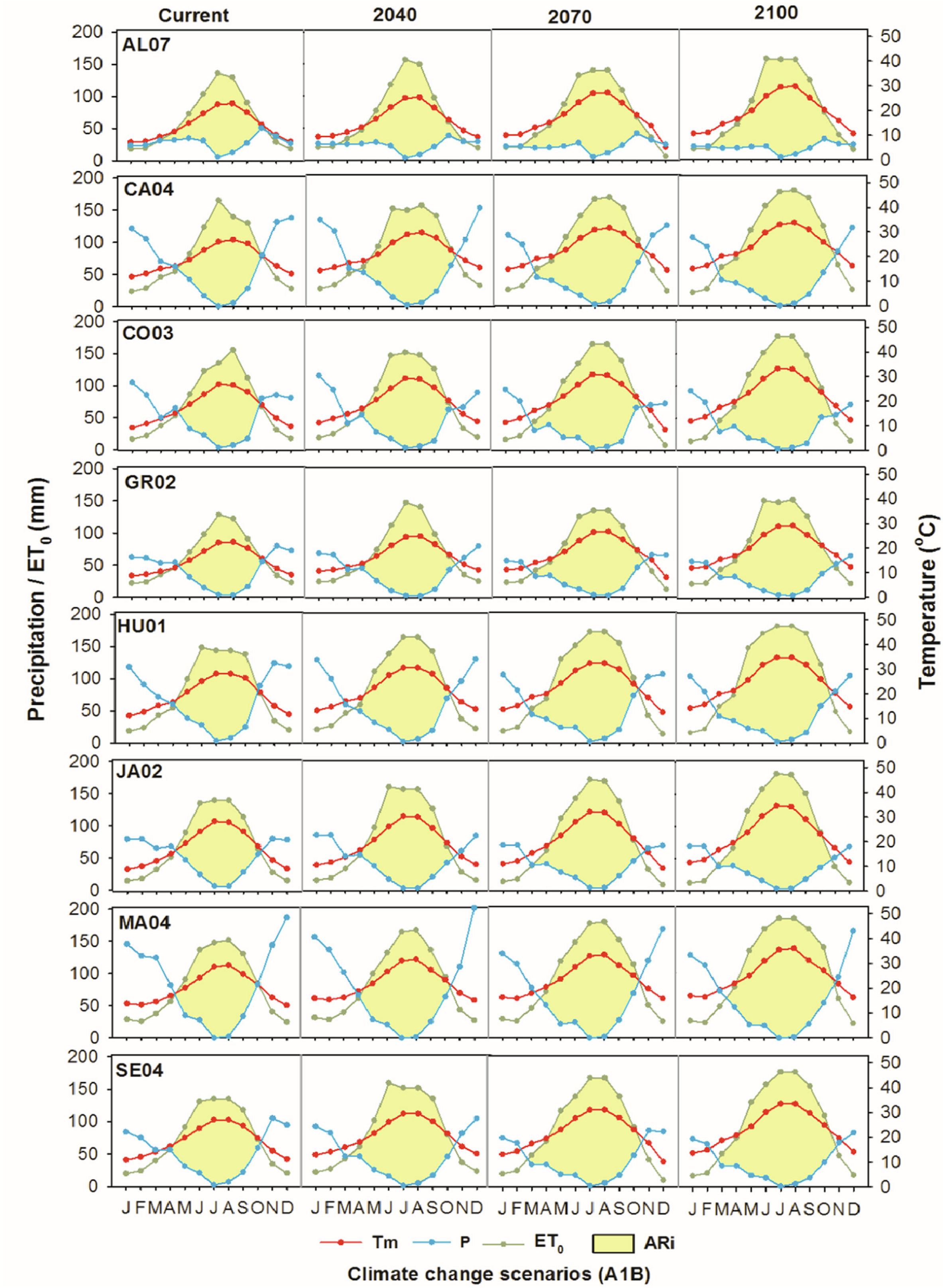

Fig. 4. CDBm output for eight representative metrological stations of Andalusia region under A1B climate change scenario for three projected periods 2040, 2070 and 2100 besides current climate situation. Tm: temperature mean in °C, P: precipitation in mm, ET_0: reference evapotranspiration in mm, ARi: aridity index. X-axis represents the months of the year from January, J to December, D. The two letters symbol (Al, Almeria; CA, Cadiz; CO, Cordoba; GR, Granada; HU, Huelva; JA, Jaen; MA, Malaga and SE, Sevilla) represent the eight provinces of Andalusia region and the two digits represent the number of representative metrological stations. Left hand y-axis shows ET_0 and P, Right hand y-axis shows Tm.

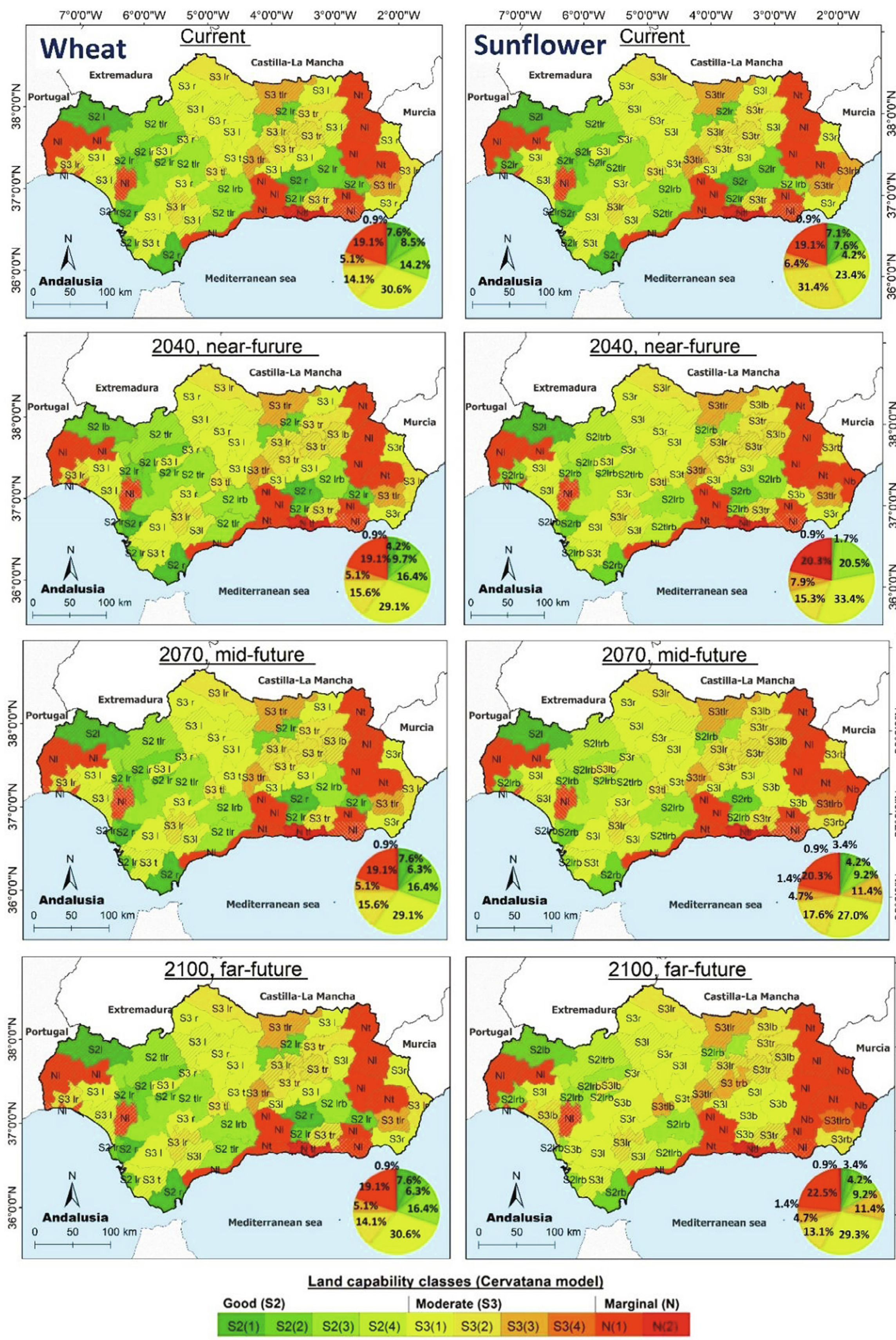

Fig. 5. Land capability (spatial distribution and pie diagram with % area of capabilities classes) for wheat and sunflower in Andalusia under current and future projections (2040, 2070, and 2100) of climate change scenario. Limitation factors; t, topography (slope type and slope gradient); l, soil (useful depth, texture, stoniness/rockiness, drainage, and salinity); r, erosion risk (soil erodibility, slope, vegetation cover, and rainfall erosivity); b, bioclimatic limitation.

limiting factors in the forest areas. Some soils that are currently used for the forests uses, such as JA06-LHXI, have a good capability for agriculture (S2) (Fig. 5).

Regarding the land capability for agricultural areas, land capability for the areas under wheat cultivation, ranged from S2r/S2l (good; CA02-Chromic Haploxererts, CO07-Typic Xerofluvents and SE08-Aquic Haploxeralfs), to Ntl (not capable; GR04-Lithic Haploxerepts). As shown in Fig. 5, 7.6% of the study area has S2 class (good capability) with only one limiting factor (soil erodibility, r or soil factors, I). Currently, 14.2% of the area has S2 class with three limiting factors, but this is expected to increase slightly (to 16.4%) under the projected climatic period (2040, 2070 and 2100) (Fig. 5). Additionally, the results showed that 19.1% of the area is classified as not capable for agricultural use (N) and this percentage does not change under the different climatic periods (Fig. 5). In most cases, under wheat cultivation, land capability class is not expected to change in the future climate, except for some soil types that are in GR01, HU02 and JA01 units. In these regions, slight negative impacts at subclass level are expected, especially under the 2040 scenario.

For sunflower crops, soil units CA03-CRXA, HU05-APXA, JA01-TRXA, SE01-CHXA, SE02-TRXA, SE09-TXFE and CA02-THXV currently have a good land capability subclass (S2lr) but it is expected to decrease to (S2lrb) in 2040, 2070 and 2100 (Fig. 5), mostly at the subclass levels. GR05-TRXA is currently classified as S2lr and is projected to remain as S2lr in 2040 and 2070, but is expected to change to moderately capable for agricultural use (S3b) in 2100 (Fig. 5). On the other hand, extreme changes in land capability for sunflower cropping are observed in the soil unit AL02-CHXI, where the capability class S3lrb will likely change to Nb (not capable) in the future. In addition, land capability of AL08-TXFE is currently S2lrb but is expected to change to S3b in 2040 and 2070, and Nb in 2100. Fig. 5 shows a detailed temporal (current, 2040, 2070 and 2100) and spatial analysis of land capability under sunflower cultivation.

3.4. Yield reduction

The largest yield reductions were found in sunflower, as the expected yield reductions varied between slight (approximately below 10% in GR09, HU03, MA01 and JA04 soil units) to extreme reductions of 80% for AL02, AL05, AL07 and AL08 soil units (Figs. 6 and 7). The climatic periods of 2070 and 2100 had more yield reduction compared with current and 2040 (Fig. 7). Much lower yield reductions are predicted for wheat, which were negligible except in a few regions, like AL02 (Figs. 6 and 7), under the A1B climate change scenario. Water surplus decreased and the water deficit increased in all soil units for all future years (2040, 2070 and 2100) compared to the current situation. Expected yield reduction by water shortage increased systematically in the future years.

Regarding wheat, in 2040, 2070, and 2100, only 2, 6 and 10% of the study area, respectively, experience wheat yield reduction whereas the rest of the Andalusia does not show a reduction in the wheat yield. The observed affected areas are mainly AL02, AL07 and AL08 soil units (all in Almeria province). In the long-term, wheat cultivation will be partly affected by future climate change, as an expected yield reduction to up to 36% between 2040 and 2100 could be observed for the AL02 soil unit.

Conversely, the sunflower crop is highly susceptible to future climate change in 2040, 2070, and 2100. Even under the current conditions, the sunflower crop is threatened by the reduction in its yield, as only 51% of the study area is resistant to yield reduction. About 10% of the rest of the area (49%) is affected by yield reductions between 21 and 80%. In 2040, around 22% of the sunflower-cropped area will be resistant to the climate change effects. In 2070 and 2100, only about 5% of the sunflower area would experience no yield reduction. Conversely, around one fifth of the area showed the highest yield reduction classes between 50 and 80% in 2100. Thus, comparing with the current scenario, all projected future periods (2040, 2070 and 2100) show higher expected yield reduction by water deficit.

4. Discussion

4.1. Climate parameters

A decrease in the total quantity and extent of precipitation is expected in the future as a direct effect of climate change under the A1B scenario. Additionally, the precipitation will tend to be concentrated in a shorter period within a year. Generally, global climate change can accelerate the hydrological cycle, increase air temperature and evaporation. A warmer atmosphere can hold more water vapor; consequently, the precipitation concentration will tend to increase. As a result, extreme precipitation events can become more frequent and intense, which can lead to more severe soil degradation (Shahbazi and Jafarzadeh, 2010; Trenberth, 2008; De La Rosa et al., 1996).

These findings are consistent with Al-Mukhtar and Qasim (2019) and Fonseca and Santos (2019) where the results obtained from this research as the precipitation is predicted to decrease and temperature is predicted to increase in 2040, 2070, and 2100. The studied indices (especially, ET_0 and ARi) are expected to increase in the future with increasing temperature and decreasing precipitation. These findings are consistent with those reported by Anaya-Romero et al. (2015) and De La Rosa et al. (1996).

4.2. Land capability

Overall, the land evaluation models applied in this research can be used to predict the effects of expected future climate change on the agricultural activities through their impact on wheat and sunflower yield reduction, and land capabilities for agricultural practices. Although climate change projections have been used to study impacts on agricultural and natural ecosystems around the world, their influence on the quality of agricultural land has been poorly studied (Mueller and Lotze-Campen, 2012; Luedeling et al., 2014). These general outcomes are consistent with Niknam et al. (2018) who applied the Terraza and Cervatana models to assess the effects of climate change on bio-climatic constraints and land capability classes in the Miandoab Plain, Iran. However, while the Terraza and Cervatana models were used to evaluate chronic effects, the impact of extreme events is not covered, and should be built into crop modeling techniques; otherwise there is a risk of underestimating crop yield reductions, which in turn would result in the application of inappropriate policies for confronting climate change (Moriondo et al., 2011; Reynolds et al., 2016).

As Almeria province is the most arid area in Andalusia (Anaya-Romero et al., 2015; State Meteorological Agency, 2011), Typic Haploxerepts soils (exemplified in AL07), have a low rating in terms of their suitability to agricultural production because they are not resilient to change in their natural land uses. Consequently, the Cervatana outputs showed that the Almeria land capability was dominantly marginal capable for agricultural use even for wheat, and different from other provinces that were not as sensitive to climate-induced yield reduction.

The Cervatana model was applied for the existing land uses/land cover (agriculture, forest, and pasture) in Andalusia. Remarkably, the model showed a good land capability for agriculture in some forest areas. Thus, it may be possible to shift some forested areas into cultivated crops. Nevertheless, this move may adversely affect soil protection (e.g. soil erosion) and consequently decrease land capability in the long term by increasing soil erodibility (r) which is a major limiting factor for land capability in the Andalusia region. This is consistent with Serpa et al. (2015) who indicated a potential negative impact of the expansion of sunflower cultivation for soil protection in drier areas as the replacement of pasture by sunflower (under A1B climate change scenario) led to a sharp increase in soil erosion by +257%.

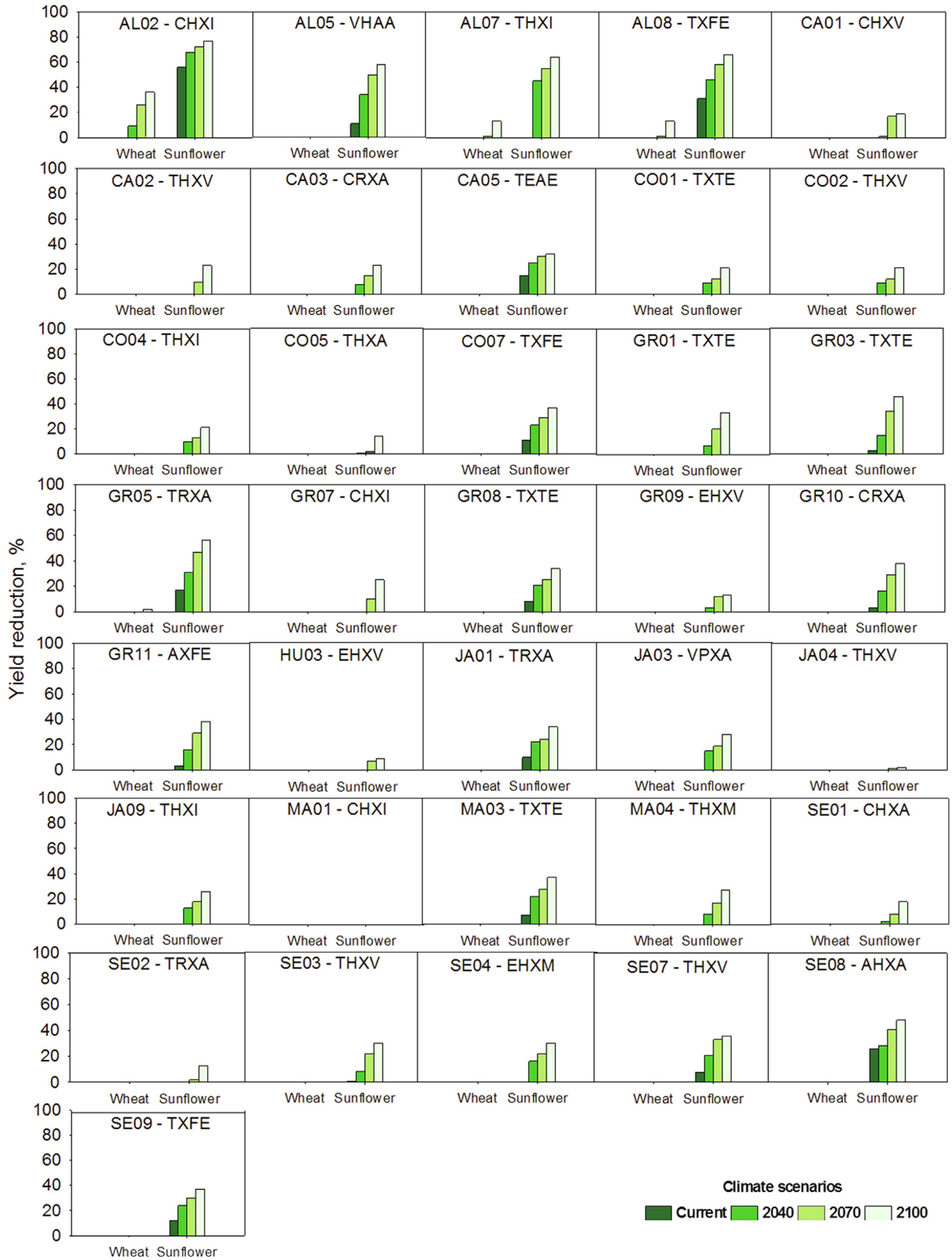

Fig. 6. Wheat and sunflower yield reduction under current and 2040, 2070 and 2100 of A1B climate change scenario.

4.3. Yield reduction

In this study, the application of the Terraza model under the expected climate change showed a notable decrease in sunflower yield and less effect for wheat crop. However, a remarkable yield reduction for both wheat and sunflower are predicted in Almería province (AL02 district). Other soil types in Almería province (AL05, AL07 and AL08 districts) show the highest yield reduction in sunflower crop compared with other province (Figs. 6 and 7), because of the lowest water surplus and highest water deficit. Sunflower cultivation would be significantly

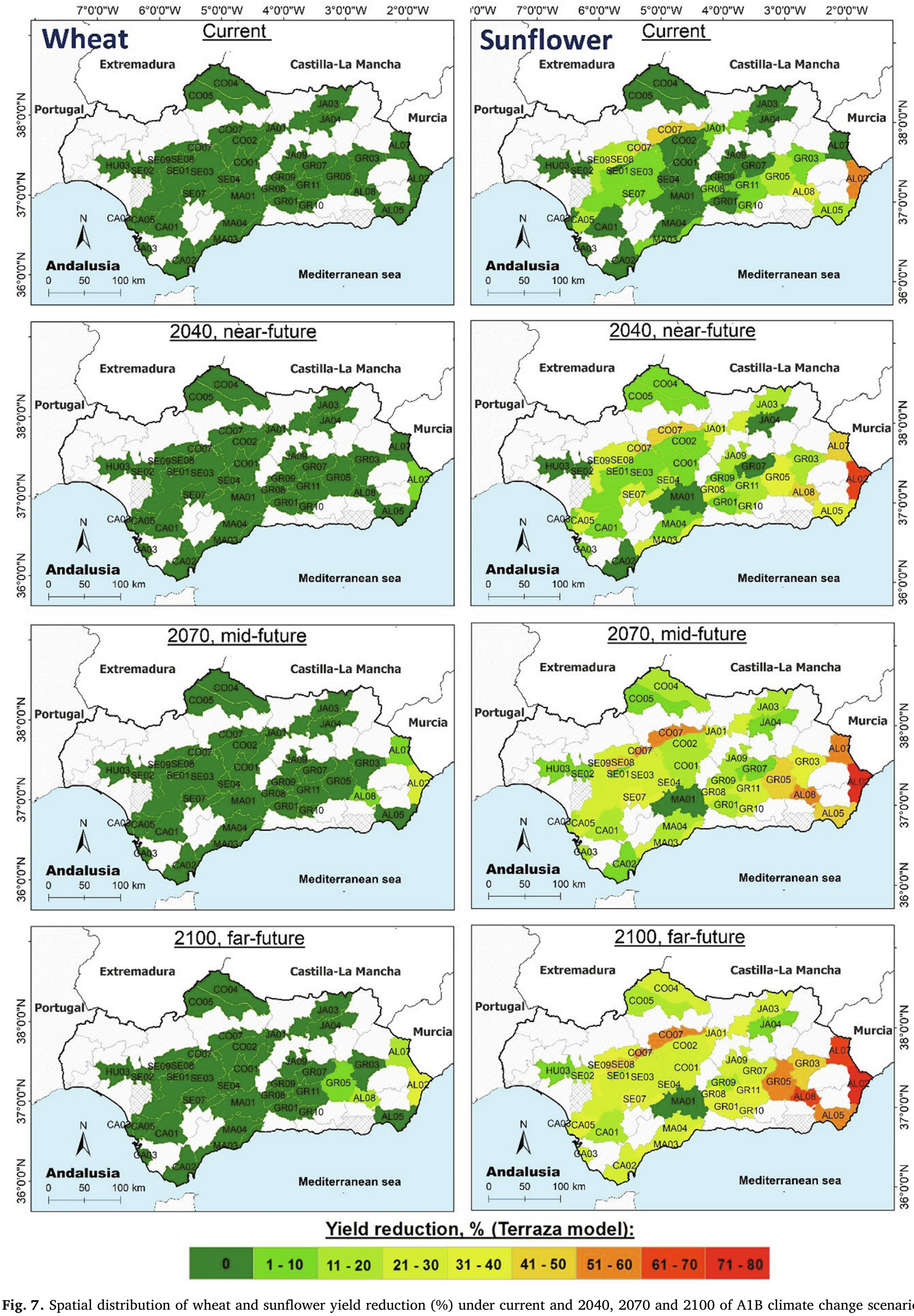

Fig. 7. Spatial distribution of wheat and sunflower yield reduction (%) under current and 2040, 2070 and 2100 of A1B climate change scenario.

impacted by the expected climate change in the future. Supporting these findings, Shahbazi and Jafarzadeh (2010) applied the Terraza model for studying the effect of climate change on yield reduction of wheat, alfalfa, sugar beet, potato, and maize; under the A1F1 scenario. In general, the studied crops will be under severe water stress leading to yield reduction for the future climate change scenario. Whereas, Blanco et al. (2017) used the WOFOST model to simulate the effects of climate change on different crop yields involving wheat and sunflower within the period from 2000 to 2050. They found that under rainfed conditions significant negative effects could be observed for sunflower cultivation. Also, sunflower could be more vulnerable to the direct effect of temperature rise and precipitation reduction, with both factors resulting in severe yield reduction, decreasing oil content, and alterations in fatty acids (Debaeke et al., 2017). The expected yield reductions for sunflower imply that the sunflower-cropped areas are projected to decrease dramatically in 2040, 2070 and 2100. These results are supported by Moriondo et al. (2011) who stated that in the southern regions of the European Mediterranean countries the cultivated sunflower was more prone to the direct effect of heat stress and drought during its growing cycle, leading to severe yield reduction.

Wheat is cultivated during winter (November–March), when Andalusia receives excess precipitation. Consequently, there is little response of wheat to climate change. Based on the results presented here, wheat cultivation would not be affected by expected future climate change as most of the area would theoretically experience no wheat yield reduction till 2100 under the SRES A1B emissions scenario (balanced). This observation is consistent with findings of Tao et al. (2014) who observed that although the climate during the wheat-growing period changed significantly between 1981 and 2009 in China, this had produced only slight impacts on wheat yield, with reductions ranging between 1.2 and 10.2%.

Additionally, Asseng et al. (2015) and Hernandez-Ochoa et al. (2018) tested different wheat crop models to estimate the change in wheat production with expected rising in the global mean temperature. Asseng et al. (2015) concluded that there will be a reduction in global wheat production of about 6% for each °C increase in global mean temperature, where in our result the mean annual temperature will increase 5 °C by 2100 compared with the current temperature, and will cause a considerable reduction in wheat yield by 36%, particularly in Al02 soil unit. Asseng et al. (2015) noticed wheat yield declines of between 1% and 28% across 30 global locations with an increase of 2 °C in temperature and between 6% and 55% within those sites with an increase of 4 °C between 1981 and 2010. Furthermore, Valizadeh et al. (2014) simulated effects of climate change on wheat production using two general circulation models; United Kingdom Met Office Hadley Center (HadCM3) and Institute Pierre Simon Laplace (IPCM4), under three climate change scenarios of SRES- A1B, -B1 and -A2 in three time periods 2020, 2050 and 2080 in an arid and semi-arid region of Iran. Their results indicated that the reduction rate of wheat yield as winter crop was variable between 1% and 37% and the maximum reduction was observed in the time of 2020, under the HadCM3 model and the A1B scenario. Finally, the assessment models showed a change in crop suitability, but did not take into account the potential of farmers to modify their agricultural practices and therefore to adapt to those threats. The future cultivation of sunflower in Europe is undoubtedly related to its potential adaptation to climate change (Debaeke et al., 2017).

For example, many moderate and marginal lands may become more suitable for agriculture if irrigation is applied. Corbeels et al. (2018) showed the importance of climate-crop modeling for identifying suitable crop management methods as an adaptation plan towards climate change.

In addition, some researchers (Atlin et al., 2017; Abd-Elmabod et al., 2019b; Wiebe et al., 2019) illustrated recommendations to adapt agriculture and soil systems to climate change. As the breeding of new varieties that would be a long-term strategy to adapt cropping systems to convalesce the future biotic stress and water deficit that will caused by future climate change (Chapman et al., 2012; Reynolds et al., 2016; Atlin et al., 2017). Also, improving the of manageable soil characteristics as improving the soil drainage, reducing salinity, and declining alkalinity and sodicity would be a rapid adaptation strategy to climate change (Abd-Elmabod et al., 2017, 2019a,b). Likewise, soil organic carbon is a key mechanism to mitigate and adapt soil systems to climate change (Lal et al., 2011; Flint et al., 2018; Wiebe et al., 2019). Thus, adapting with climate change for sustainable agriculture, it is necessary to safeguard land resources and consequently increasing the agriculture production.

As many modeling approaches and climate change impact assessments, this study has some limitations. For example, the models used here, i.e. Terraza and Cervatana, do not account for the potential effects of atmospheric CO_2 in contrast with other models such as the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003; Amouzou et al., 2019; Cammarano et al., 2019; Guarin et al., 2019). Nevertheless, although currents developments in predicting climate effects on yield responses include CO_2 concentrations as a variable, i.e. using free-air CO2 enrichment (FACE), large uncertainties remain in the prediction of the CO_2 fertilization effect. This is particularly relevant in a long-term period, because CO_2 levels can reach saturation, and other factors such as water deficit, or addition of nitrogen could have a significant role (Manderscheid et al., 2018).

This research is a first step in developing more advanced methodologies and multiple climate projections, e.g. multi-model ensembles, and crop models should be compared in future work. Nevertheless, one of the strengths this study is that we harnessed 18 regional climate models specifically developed for the study area (Muñoz-Rojas et al., 2013) in order to reduce part of the projection uncertainties associated to climate models at different scales/regions (Xiong et al., 2020). The spatialization of the model outputs as presented in this study is a great advantage for potential implementation of targeted land management strategies for climate change adaptation (Abd-Elmabod et al., 2019b).

5. Conclusions

Climate change in Andalusia (Southern Spain) is predicted to affect directly and negatively on agricultural crop production, especially on summer-grown rainfed crops such as sunflower, as a result of decreasing precipitation and increasing temperature. Variations in land capability occur as consequence of the high variability of soil characteristics and climate condition in Andalusia. In the studied area the highest land capability class (S1) rarely occurs because there is always at least one soil characteristic or climate parameter as a limiting factor. This high variability of the evaluation results demonstrates the importance of using soil factors, climate and crop information in conjunction in decision-making regarding the formulation of site-specific soil use and management strategies.

Future climate change impacts on land capability and yield reduction need to be sufficiently considered. Our assessment of climate change impacts on the studied crops suggests an improvement of the soil characteristics, crop systems and cultivar traits in order to adapt to climate change and improve future sustainability. Likewise, further work should also focus on the potential for agricultural practices to moderate some of these effects, or for alternative crops to replace sunflower, to improve future planning for agricultural sustainability. Future studies should also consider indirect effects of climate change, e.g. the influence of atmospheric CO_2 or extreme climatic events on crop production.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geoderma.2020.114453.

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(Review Article)

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AI in precision agriculture: A review of technologies for sustainable farming practices

Adebunmi Okechukwu Adewusi [1], Onyeka Franca Asuzu [2], Temidayo Olorunsogo [3], Chinwe Iwuanyanwu [4], Ejuma Adaga [5] and Donald Obinna Daraojimba [6, *]

[1] *University of Ilorin, Nigeria*
[2] *Dangote Sugar Refinery Plc, Lagos, Nigeria.*
[3] *Independent Researcher, Colorado, USA.*
[4] *PhD Independent Researcher, Illinois, USA.*
[5] *Independent Researcher, Illinois, USA.*
[6] *Department of Information Management, Ahmadu Bello University, Zaria, Nigeria.*

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Abstract

Precision agriculture, facilitated by advancements in Artificial Intelligence (AI), has emerged as a transformative paradigm in modern farming. This review comprehensively examines the integration of AI technologies in precision agriculture to enhance sustainability and optimize farming practices. The paper synthesizes recent research and developments in AI applications, covering key areas such as crop monitoring, resource management, decision support systems, and automation. The adoption of AI-driven techniques, including machine learning, computer vision, and sensor technologies, is reshaping traditional farming methods by providing farmers with real-time data and actionable insights. Crop monitoring applications utilize satellite imagery, drones, and ground-based sensors to assess plant health, detect diseases, and optimize irrigation strategies. AI-driven decision support systems empower farmers to make informed choices based on data-driven predictions, weather forecasts, and historical patterns, contributing to resource-efficient practices and minimizing environmental impact. Resource management is a critical aspect of sustainable farming, and AI plays a pivotal role in optimizing the use of water, fertilizers, and pesticides. Smart irrigation systems, enabled by AI algorithms, ensure precise and efficient water distribution, reducing water wastage and promoting water conservation. AI-driven analysis of soil conditions helps farmers tailor fertilization practices, enhancing nutrient utilization and minimizing environmental runoff. The review also explores the role of AI in automating farming operations through robotics and autonomous vehicles. These technologies not only alleviate labor shortages but also improve efficiency in planting, harvesting, and crop maintenance. Additionally, the integration of AI fosters connectivity in agriculture, enabling seamless communication between devices, sensors, and farming equipment. As precision agriculture continues to evolve, the review highlights challenges and future prospects. Ethical considerations, data security, and the digital divide in rural areas are among the challenges that need attention. Moreover, the paper discusses potential avenues for further research, emphasizing the need for interdisciplinary collaboration to address the complex issues associated with the sustainable implementation of AI in precision agriculture. This review provides a comprehensive overview of the transformative impact of AI in precision agriculture, offering insights into current technologies, challenges, and future directions. The integration of AI not only enhances productivity and efficiency but also contributes to the long-term sustainability of farming practices, ensuring food security in the face of a growing global population.

Keywords: Precision agriculture; Artificial Intelligence (AI); Sustainable farming; Technology review; Crop monitoring

* Corresponding author: Donald Obinna Daraojimba

1. Introduction

Precision agriculture, fueled by the integration of cutting-edge Artificial Intelligence (AI) technologies, stands at the forefront of a transformative era in modern farming (Sharma, et al., 2023). As the global population burgeons and environmental concerns intensify, the need for sustainable farming practices has become increasingly paramount. The convergence of AI with precision agriculture represents a promising avenue to address these challenges by optimizing resource utilization, enhancing crop management, and ultimately fostering a more sustainable and efficient agricultural ecosystem (Karunathilake, et al., 2023). The application of AI in precision agriculture revolves around leveraging advanced computational techniques, machine learning algorithms, computer vision, and sensor technologies to facilitate data-driven decision-making processes. This review aims to provide a comprehensive exploration of the multifaceted role that AI plays in reshaping conventional agricultural practices, emphasizing the pivotal technologies and their collective impact on achieving sustainability objectives. Central to the integration of AI in precision agriculture is the paradigm shift from traditional, uniform farming methods to a more personalized and adaptive approach (Misra and Ghosh, 2024). This transition is enabled by the real-time data acquisition capabilities of AI-driven technologies, such as drones, satellites, and ground-based sensors, which empower farmers with detailed insights into crop health, soil conditions, and environmental factors. By harnessing this wealth of information, farmers can make informed decisions regarding irrigation, fertilization, and pest control, thereby minimizing waste, optimizing resource allocation, and reducing the environmental footprint of agriculture (Patel, et al., 2023). The multifaceted applications of AI in precision agriculture extend beyond data analysis to encompass autonomous systems and robotics. Smart machines equipped with AI algorithms are revolutionizing farming operations, from planting and harvesting to crop maintenance (Mishra and Mishra, 2023). These autonomous technologies not only enhance operational efficiency but also address challenges associated with labor shortages, paving the way for a more sustainable and economically viable future for agriculture. As precision agriculture becomes increasingly data-centric, ethical considerations, data security, and equitable access to technology emerge as critical concerns (Wilgenbusch, et al., 2022). This review delves into the ethical implications of AI in agriculture, emphasizing the importance of responsible data management and addressing potential disparities in technology adoption. Furthermore, it explores the challenges associated with the digital divide in rural areas, underscoring the need for inclusive strategies that ensure all farmers can benefit from the advancements in precision agriculture (Robinson, et al., 2020). this review aims to provide a holistic examination of AI in precision agriculture, offering insights into the technologies shaping sustainable farming practices. By elucidating the current state of AI integration, challenges faced, and future prospects, this exploration contributes to the ongoing discourse on leveraging advanced technologies to meet the growing demands of global food production while ensuring environmental stewardship and long-term agricultural sustainability.

2. Technologies in Crop Monitoring

Crop monitoring is a pivotal aspect of precision agriculture, and the integration of advanced technologies has revolutionized the way farmers assess and manage their crops (Sishodia, et al., 2020). The utilization of cutting-edge tools enables real-time data acquisition, analysis, and decision-making, contributing to improved crop health, disease detection, and resource optimization. In this section, we explore the key technologies shaping crop monitoring in the era of AI-driven precision agriculture. Satellite technology provides a bird's-eye view of agricultural landscapes, offering invaluable insights into crop conditions, growth patterns, and overall health (Khan and Shahriyar, 2023). High-resolution satellite imagery enables farmers to monitor large expanses of land efficiently, identifying areas that may require specific attention, such as pest infestations or nutrient deficiencies. The continuous advancements in satellite technology have enhanced the temporal and spatial resolution, making it an integral tool for precision agriculture (Fotso Kamga, et al., 2021). Unmanned aerial vehicles, commonly known as drones, have emerged as versatile tools for precision agriculture. Equipped with cameras and sensors, drones can capture high-resolution images and collect data with exceptional precision (Ballesteros, e). Drones enable farmers to monitor crops at a finer spatial scale, offering detailed information on plant health, growth variations, and potential issues. The agility and accessibility of drones make them particularly useful for timely and targeted interventions (Rejeb, et al., 2021). Deploying ground-based sensors directly in the field provides real-time, localized data on various crop parameters. These sensors can measure soil moisture levels, nutrient content, temperature, and other critical factors influencing crop health. The data collected from these sensors facilitate precise decision-making, allowing farmers to tailor irrigation and fertilization strategies to the specific needs of different areas within the same field (Mutyalamma, et al., 2020). The integration of AI enables real-time data acquisition from various sources, including satellites, drones, and ground-based sensors. This continuous stream of data allows for dynamic monitoring of crop conditions, enabling farmers to respond promptly to emerging issues (Leitão, et al., 2019). Real-time data acquisition forms the foundation for adaptive and responsive farming practices, contributing to increased efficiency and sustainability.

AI algorithms analyze data from different monitoring sources to assess the overall health of crops (Pimenov, et al., 2023). By identifying patterns associated with healthy and stressed plants, these algorithms can detect early signs of diseases, nutrient deficiencies, or pest infestations. This proactive approach empowers farmers to implement timely interventions, minimizing the impact of potential threats and optimizing crop yields (Liang and Shah, 2023). AI plays a crucial role in automating the detection of diseases in crops. By analyzing images and data collected from various monitoring technologies, machine learning algorithms can identify subtle signs of diseases before they become visually apparent. Early detection allows for targeted responses, reducing the need for broad-spectrum treatments and minimizing the environmental impact of pest control measures (Dinarello, et al., 2012). The integration of satellite imagery, drones, ground-based sensors, real-time data acquisition, crop health assessment, and disease detection technologies exemplifies the multifaceted approach to crop monitoring in precision agriculture (Kirsch, et al., 2018). These technologies collectively empower farmers with unprecedented insights, facilitating informed decision-making and contributing to the sustainable and efficient management of agricultural resources.

3. Machine Learning in Decision Support Systems

In the realm of precision agriculture, the fusion of Machine Learning (ML) with Decision Support Systems (DSS) has emerged as a powerful force, empowering farmers with data-driven insights and predictive analytics. This synergy facilitates informed decision-making, enhances resource management, and contributes to the overall sustainability of farming practices (Liu, et al., 2008). This comprehensive exploration delves into the various facets of how machine learning integrates with decision support systems in precision agriculture. Machine Learning algorithms are adept at processing vast amounts of data, extracting meaningful patterns, and generating predictions. In decision support systems, this capability enables farmers to make data-driven decisions based on historical data, current conditions, and predictive analytics (Beriya and Saroja, 2019). By leveraging ML, decision support systems move beyond traditional rule-based approaches, providing more nuanced and adaptable recommendations for farmers. One of the key strengths of ML in decision support systems is its ability to forecast future trends and outcomes (Sutton, et al., 2020). Through the analysis of historical data, weather patterns, and crop-specific parameters, machine learning models can predict crop yields, identify optimal planting times, and anticipate potential challenges such as disease outbreaks. Predictive analytics empower farmers to proactively plan and implement strategies for maximizing productivity (Liang and Shah, 2023). Machine Learning plays a pivotal role in improving the accuracy of weather forecasting within decision support systems. ML algorithms analyze historical weather data, satellite imagery, and real-time meteorological information to provide more precise and localized weather predictions (Salcedo-Sanz, et al., 2020). Accurate weather forecasts enable farmers to optimize irrigation schedules, plan for adverse weather events, and mitigate the impact of climatic variations on crop yields. By examining historical data, machine learning algorithms can uncover patterns and trends that may not be apparent through traditional methods (Sarker, 2021). In decision support systems, this capability allows for a deeper understanding of how different factors, such as soil conditions, crop rotations, and pest prevalence, influence agricultural outcomes. Farmers can then adjust their practices based on these insights to enhance long-term sustainability. ML-driven decision support systems contribute significantly to the optimization of agricultural resources (Karthikeyan, et al., 2021). These systems can analyze data related to soil health, nutrient levels, and water usage to recommend precise irrigation and fertilization strategies. By tailoring resource application to the specific needs of each part of a field, farmers can achieve higher efficiency, reduce waste, and minimize environmental impact.

The integration of Machine Learning in Decision Support Systems for precision agriculture is not without its challenges (Lindblom, et al., 2017). Ensuring the reliability of predictive models, addressing data quality issues, and providing user-friendly interfaces are among the considerations. Additionally, the ethical implications of relying on algorithmic decision-making in agriculture warrant careful examination.

The marriage of Machine Learning and Decision Support Systems marks a significant advancement in precision agriculture (Shorten, et al., 2021). The ability to harness the power of data for predictive analytics, optimize resource management, and facilitate informed decision-making holds immense promise for fostering sustainability and efficiency in modern farming practices. As technology continues to evolve, the synergy between ML and decision support systems will likely play a central role in shaping the future of agriculture.

4. Resource Management through AI

Effective resource management is at the core of sustainable and efficient agriculture. The integration of Artificial Intelligence (AI) technologies in precision agriculture has revolutionized how farmers optimize the use of resources such as water, fertilizers, and pesticides (Shaikh, et al., 2022, Adebukola et al., 2022). This comprehensive exploration delves into how AI contributes to resource management, ensuring a judicious and environmentally conscious approach to farming practices. AI-driven smart irrigation systems represent a paradigm shift in water management for agriculture (Sinwar, et al., 2020). These systems leverage real-time data from various sources, including soil moisture sensors, weather forecasts, and crop requirements, to precisely control the timing and amount of irrigation. By dynamically adjusting water delivery based on actual needs, smart irrigation minimizes water wastage, promotes water conservation, and ensures optimal crop hydration (Abioye, et al., 2020). AI algorithms play a crucial role in the conservation of water resources by analyzing data related to soil moisture, weather patterns, and crop types (Ukoba and Jen, 2023). Through machine learning, these systems can learn and adapt to specific conditions, allowing farmers to implement efficient irrigation practices (Cravero and Sepúlveda, 2021). The result is not only reduced water consumption but also increased resilience to water scarcity, a critical consideration in the face of changing climate patterns. AI contributes to precision agriculture by optimizing the application of fertilizers. Machine learning models analyze soil composition, nutrient levels, and historical yield data to recommend personalized fertilization plans for different sections of a field (Ewim et al., 2021). This targeted approach enhances nutrient utilization efficiency, minimizes overuse of fertilizers, and mitigates the environmental impact of nutrient runoff into water systems (Hirel, et al., 2011). AI-driven systems assist in precisely managing nutrient levels in the soil. By continuously monitoring and analyzing data related to soil health, crop requirements, and nutrient content, these systems provide real-time insights into the nutritional needs of plants. This granular approach ensures that crops receive the appropriate nutrients at the right time and in the right quantities, promoting optimal growth and minimizing waste (Singh, et al., 2018). The implementation of AI in resource management contributes to a more environmentally sustainable agriculture sector (Mouchou et al., 2021, Owebor et al., 2022). By reducing water and fertilizer usage through targeted applications, AI helps minimize environmental pollution, soil degradation, and the eutrophication of water bodies. The ability to tailor resource management practices to the specific needs of each crop and field contributes to the overall reduction of the ecological footprint of farming. As AI continues to advance, the integration of robotics and autonomous vehicles in resource management further enhances efficiency. Automated equipment equipped with AI algorithms can precisely apply resources based on real-time data, reducing the reliance on manual labor and optimizing the use of resources. The incorporation of AI in resource management represents a transformative shift towards precision agriculture (Chowdhury, et al., 2023). By harnessing the power of data-driven insights, AI enables farmers to optimize water usage, fertilization practices, and overall resource allocation. The result is not only increased agricultural efficiency but also a significant step towards environmentally sustainable and resilient farming practices.

5. Automation and Robotics in Farming Operations

Automation and robotics have become integral components of modern agriculture, revolutionizing traditional farming practices and contributing to increased efficiency, productivity, and sustainability. In this comprehensive exploration, we delve into the diverse applications and transformative impact of automation and robotics in various farming operations. Autonomous vehicles equipped with precision technology navigate fields with unprecedented accuracy, optimizing planting and harvesting processes (Luettel, et al., 2012, Enebe, Ukoba, and Jen, 2019). These vehicles leverage AI algorithms to plant seeds at optimal depths and spaces, contributing to uniform crop growth. During harvesting, advanced sensors and robotic arms allow for selective and timely picking, reducing waste and increasing overall yield efficiency (Rajendran, et al., 2023).

Autonomous vehicles equipped with robotic systems and AI-driven algorithms identify and target weeds or pests with precision. This targeted approach minimizes the use of herbicides and pesticides, reducing environmental impact while ensuring the health of crops. Robotics, guided by computer vision and machine learning, perform automated weeding by distinguishing between crops and weeds. This not only reduces the need for herbicides but also addresses labor shortages, making weed management more sustainable and cost-effective (Norsworthy, et al., 2012). Robotic arms equipped with cameras and sensors perform precise pruning and thinning of crops. This level of automation ensures consistent and optimal spacing between plants, promoting healthier growth and facilitating efficient harvesting.

Automation and robotics address the challenges associated with labour shortages in agriculture. The use of autonomous machines for repetitive tasks allows human labour to be directed towards more skilled and complex aspects of farming, increasing overall operational efficiency. While the initial investment in automation technologies can be substantial, the long-term economic viability becomes evident through reduced labor costs, increased productivity, and improved yield quality. The overall cost-effectiveness contributes to the sustainability of modern farming practices. The integration of IoT technologies allows for seamless connectivity between various robotic systems and agricultural equipment (Vermesan, et al., 2020, Ukoba and Jen, 2019). This interconnected network enables real-time data exchange, facilitating adaptive decision-making and enhancing the overall efficiency of farming operations. Farmers can remotely monitor and control robotic systems, making adjustments based on real-time data and changing conditions. This level of control ensures that farming operations can be fine-tuned for optimal outcomes, even from a distance (Dong, et al., 2021). Automation and robotics have ushered in a new era of precision and efficiency in farming operations. The integration of AI, robotics, and connectivity technologies not only addresses traditional challenges but also contributes to the sustainability and economic viability of agriculture. As technology continues to advance, the role of automation in reshaping the future of farming is poised to become increasingly central to global agricultural practices.

6. Connectivity in Agriculture

Connectivity in agriculture refers to the seamless integration of technologies and data exchange systems, creating a networked ecosystem that transforms traditional farming practices. This interconnected approach, fueled by advancements in communication and sensor technologies, plays a pivotal role in precision agriculture (Habibzadeh, et al., 2018). In this exploration, we delve into the significance of connectivity and its multifaceted applications in modern agriculture. The deployment of smart sensors in the field, coupled with the Internet of Things (IoT) technology, enables the real-time collection of data on various parameters such as soil moisture, temperature, and crop health (Vermesan and Friess, 2013, Uddin et al., 2022). These interconnected devices provide a continuous stream of valuable information, forming the foundation for data-driven decision-making in precision agriculture. Connectivity allows farmers to remotely monitor their fields through sensor-equipped devices. This real-time surveillance ensures that any anomalies, such as changes in weather conditions or signs of disease, are promptly detected, empowering farmers to take timely and informed actions. Connectivity extends to aerial technologies, including drones and satellites, which capture high-resolution images and data. These technologies provide a comprehensive view of the entire farm, aiding in crop monitoring, disease detection, and assessment of overall field health (Lytos, et al., 2020). The data collected is transmitted for analysis, contributing to the generation of actionable insights. Ground-based sensors form an integral part of the connectivity network. Placed strategically across the field, these sensors measure soil conditions, nutrient levels, and other critical factors. The collected data is relayed to a centralized system for analysis, enabling precise decision-making regarding irrigation, fertilization, and pest control. Connectivity facilitates the integration of data from diverse sources onto centralized platforms or cloud-based systems. This aggregated data provides a holistic view of the farm, enabling comprehensive analysis and decision-making (Žuraulis and Pečeliūnas, 2023, Okunade et al., 2023, Maduka et al., 2023). Cloud computing ensures accessibility to information from anywhere, fostering flexibility and convenience for farmers. Connected systems leverage machine learning algorithms to analyze integrated data. Predictive analytics based on historical patterns and real-time inputs enable farmers to anticipate future trends, such as crop yields, weather conditions, and pest outbreaks. This predictive capability forms a cornerstone for proactive and informed decision-making (Petropoulos, et al., 2020). Connectivity fosters collaboration among farmers, researchers, and agricultural experts through online platforms. Information sharing on best practices, emerging technologies, and local insights enhances the collective knowledge base of the agricultural community, contributing to the sustainable advancement of the industry. Connected farm management software allows farmers to streamline their operations by integrating data on crop rotation, resource usage, and yield history. This comprehensive approach enables efficient planning, resource optimization, and the implementation of sustainable farming practices (Ikwuagwu et al., 2020, Little, et al., 2013). Conclusion, connectivity in agriculture is a transformative force that underpins the evolution of precision agriculture. The integration of interconnected devices, sensor networks, data integration, and collaborative platforms empowers farmers with real-time information and analytical tools, facilitating precision, sustainability, and informed decision-making. As the connectivity landscape continues to evolve, agriculture stands at the forefront of a digital revolution that promises to reshape the future of global food production.

7. Ethical Considerations in AI-driven Agriculture

The integration of Artificial Intelligence (AI) in agriculture brings about unprecedented advancements, transforming traditional farming practices. However, as the agricultural landscape evolves with the infusion of technology, ethical considerations become paramount. This exploration delves into the ethical challenges associated with AI-driven agriculture, emphasizing the need for responsible implementation and addressing potential societal impacts. The vast amount of data generated by AI-driven agriculture, including crop information, weather patterns, and farm management practices, raises concerns about data privacy. Farmers and stakeholders must ensure that sensitive information is securely managed, and individuals have control over how their data is used. The ownership and sharing of agricultural data pose ethical dilemmas. Farmers, technology providers, and researchers must establish clear guidelines regarding data ownership rights, and mechanisms for fair data sharing must be established to foster collaboration without compromising individual interests. The use of advanced monitoring technologies, such as drones and satellite imagery, may inadvertently lead to farm surveillance. Striking a balance between monitoring for crop health and respecting farmers' privacy is crucial to avoid unwarranted intrusion. Ethical considerations extend to the impact of monitoring on individuals and local communities. The deployment of AI technologies should be sensitive to cultural norms, community consent, and the potential consequences of data collection on the social fabric of agricultural communities. The adoption of AI in agriculture should address concerns related to equitable access to technology.

Ensuring that small-scale farmers, in addition to large-scale operations, have access to and can benefit from AI-driven advancements is essential to prevent exacerbating existing disparities. The digital literacy divide among farmers may pose ethical challenges. Efforts should be made to provide training and support to ensure that farmers, regardless of their technological background, can effectively navigate and make informed decisions in the AI-driven agricultural landscape.

The automation of farming operations through AI-driven technologies raises ethical questions regarding the potential displacement of agricultural labor. Mitigating the impact on employment and ensuring a just transition for affected workers should be integral to the ethical considerations in AI-driven agriculture. The adoption of AI should respect and align with local cultural and ethical values. Agricultural technologies should be implemented in ways that resonate with the values of the communities they serve, fostering acceptance and minimizing cultural disruptions. The opacity of AI algorithms raises concerns about accountability. Establishing transparency in algorithms used in decision support systems ensures that farmers understand the basis for recommendations and can trust the technology. Governments and international bodies must establish robust regulatory frameworks to govern the ethical use of AI in agriculture. These frameworks should address issues of data privacy, algorithmic transparency, and the responsible deployment of AI technologies. While AI-driven agriculture holds immense promise for enhancing productivity and sustainability, it is crucial to navigate its implementation with ethical considerations at the forefront. Striking a balance between innovation and responsibility ensures that AI technologies contribute positively to agriculture while safeguarding the interests of farmers, communities, and the broader society. Ethical considerations should be an integral part of the ongoing dialogue surrounding the future of AI in agriculture to create a resilient and equitable agricultural ecosystem.

8. Challenges and Future Prospects

As Artificial Intelligence (AI) continues to transform precision agriculture, ushering in a new era of sustainable farming practices, several challenges and exciting future prospects emerge on the horizon. This review comprehensively explores both the hurdles faced by AI in precision agriculture and the potential avenues for future developments. The quality and integration of diverse data sources, including satellite imagery, sensor data, and historical records, present challenges in creating a unified and reliable dataset for AI algorithms. Addressing concerns related to data privacy and security remains critical, especially as the amount of sensitive agricultural data collected continues to grow. Ensuring equitable access to AI technologies poses challenges, particularly for small-scale farmers who may lack the resources or digital literacy required for effective adoption. Ensuring that AI algorithms are unbiased and interpretable is a complex challenge, as biases may inadvertently be introduced during model training, leading to unfair outcomes. In regions with limited technological infrastructure, challenges related to network connectivity and access to advanced hardware may hinder the widespread adoption of AI-driven precision agriculture.

The development of edge computing technologies can address infrastructure limitations by enabling data processing closer to the source, reducing the reliance on centralized computing resources.

The evolution of Explainable AI (XAI) techniques holds promise for addressing the challenge of algorithmic interpretability, ensuring that farmers can understand and trust the recommendations provided by AI systems. Integrating block chain technology can enhance data security and privacy by providing a decentralized and tamper-resistant system for managing agricultural data. Establishing collaborative platforms for research and knowledge sharing can help overcome challenges related to data quality, providing a collective understanding of best practices in AI-driven precision agriculture.

The development of comprehensive policy and regulatory frameworks can guide the ethical and responsible implementation of AI in agriculture, addressing concerns related to data privacy, security, and fairness. Fostering inclusive technology adoption programs that prioritize digital literacy and provide support for small-scale farmers can contribute to overcoming the digital divide. The integration of expertise from diverse fields, including agriculture, computer science, ethics, and policy-making, is crucial for developing holistic and sustainable solutions that address the multifaceted challenges of AI in precision agriculture. Involving farmers, technology developers, policymakers, and researchers in ongoing dialogues ensures that the development and implementation of AI technologies align with the needs and values of the agricultural community.

The challenges faced by AI in precision agriculture are opportunities for innovation and improvement. Future prospects lie in advancements in technology, the development of responsible frameworks, and fostering collaboration among stakeholders. As the agricultural landscape continues to evolve, addressing these challenges and embracing the potential of AI in precision agriculture will play a pivotal role in shaping a sustainable and technologically advanced future for global farming practices.

9. Conclusion

The integration of Artificial Intelligence (AI) in precision agriculture marks a transformative journey towards sustainable and efficient farming practices. The comprehensive review of technologies and their applications underscores the profound impact AI has on revolutionizing traditional approaches to crop monitoring, resource management, and decision support systems. The amalgamation of satellite imagery, drones, ground-based sensors, and machine learning algorithms has empowered farmers with real-time data, facilitating proactive and informed decision-making. The precision achieved in crop monitoring not only enhances productivity but also enables early detection of diseases and pests, minimizing the environmental impact of interventions. Machine learning, with its predictive analytics capabilities, has emerged as a cornerstone in decision support systems. The ability to analyze historical data, weather patterns, and crop-specific parameters equips farmers with invaluable insights, fostering resource optimization and contributing to long-term sustainability. Resource management, a critical aspect of sustainable agriculture, has been revolutionized through AI technologies. Smart irrigation systems, precise fertilization strategies, and the reduction of environmental impact demonstrate the potential of AI to address the challenges of resource scarcity and environmental degradation. The advent of automation and robotics in farming operations presents a paradigm shift, enhancing labor efficiency and economic viability. Autonomous vehicles, robotic systems, and connected machinery streamline tasks such as planting, harvesting, and crop maintenance, laying the foundation for a more technologically advanced and productive agricultural sector. Connectivity in agriculture, facilitated by interconnected devices and data integration, has paved the way for a holistic approach to farming. Real-time monitoring, collaborative platforms, and the exchange of knowledge among stakeholders contribute to an ecosystem where information flows seamlessly, fostering innovation and sustainable practices. However, amidst the promising advancements, ethical considerations loom large. Issues related to data privacy, the digital divide, and the impact of automation on employment demand careful attention. Striking a balance between innovation and responsibility is crucial to ensure that the benefits of AI in precision agriculture are equitably distributed and aligned with ethical principles. As we navigate the future of agriculture, challenges such as data quality, privacy concerns, and algorithmic biases must be met with proactive solutions. The prospects of advancements in edge computing, explainable AI, and inclusive technology adoption offer exciting avenues for overcoming these challenges and shaping a more resilient and equitable agricultural landscape. In essence, AI in precision agriculture is not just a technological evolution but a pathway to a more sustainable and productive future. The collaboration of stakeholders, interdisciplinary research, and responsible innovation will be key in harnessing the full potential of AI for the benefit of farmers, communities, and the global food system. The journey towards sustainable farming practices with AI at its core is an ongoing narrative, and with ethical considerations at the forefront, the agricultural sector is poised for a future that harmonizes technological progress with the principles of environmental stewardship and societal well-being

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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