Review

The role of precision farming in crop production's adaptation to climate change – Review

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Abstract: As a result of climate change, agricultural production is facing ever-greater challenges, including rising temperatures, changes in the distribution and quantity of precipitation, and an increase in the frequency of extreme weather events. The aim of this study is to outline the role of precision farming in adapting to climate change, with a particular focus on remote sensing, drone-based data collection, water and soil management, and the application of vegetation indices. The methodological basis of the research is a comprehensive review of relevant domestic and international literature. The study carries out a comparative assessment of the climate adaptation technologies and practical applications of precision farming, drawing on scientific publications, book chapters, doctoral theses, as well as statistical and specialist data sources. Following a review of the literature, it can be concluded that precision technologies contribute to the continuous monitoring of cropland, the implementation of site-specific interventions and the more efficient use of resources. Vegetation indices – in particular the NDVI, GNDVI, NDRE, NGRDI (VI-Green) and the leaf area index (LAI) – have proved to be particularly important in practical application, as they provide objective information on the current condition of the crop and support evidence-based decision-making regarding cultivation techniques. When combined with an appropriate agronomic approach and state-of-the-art digital technologies, precision farming can significantly increase the adaptability of agriculture, thereby contributing to the realisation of sustainable crop production. From a practical perspective, the findings of this review can facilitate the more targeted selection and application of precision technologies and vegetation indices, thereby directly supporting farmers' data-driven decision-making, increasing resource efficiency, and mitigating production risks arising from climate change.

Keywords: climate change, precision farming, remote sensing, UAV, vegetation indices, sustainable crop production

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1. Introduction

The relationship between agriculture and global warming is two-way: greenhouse gas emissions are significant in the agricultural sector, whilst the agricultural sector itself is highly vulnerable to the negative effects of climate change. Extreme weather events – primarily the increasing frequency of droughts, rising temperatures and changes in precipitation patterns – pose serious challenges to crop production. Temperature extremes cause significant yield losses during the reproductive stages of plant development. [1] A study by Lesk et al. (2016) analysed cereal yields globally and concluded that drought and variable weather conditions caused significant yield reductions during the period under review. [2] This further supports the view that, within agricultural production, the adaptation of crop production to climate change is of increasing importance in ensuring crop security and the sustainability of food supply.

The success of crop production is influenced by factors other than weather conditions. Even within a single growing area, there is considerable heterogeneity in the physical and chemical properties of the soil, its water availability and its nutrient-supplying capacity, all of which have a significant impact on crop yield. Studies by Miao et al. (2006) on maize support the importance of site-specific cultivation, as they also observed significant spatial heterogeneity in soil properties and, consequently, in the quantitative and qualitative parameters of the crop. [3] Lobell and Azzari (2017) also used satellite data to demonstrate the spatial heterogeneity of maize and soya bean yields in the Midwestern growing regions of the United States. The significance of site-specific differences is further accentuated under extreme weather conditions; consequently, a comprehensive, integrated assessment of soil, topographical, meteorological and crop stand data becomes crucial for the timely identification of production risks. [4]

Precision farming offers a partial solution to this complex problem; it supports agricultural production by utilising state-of-the-art digital technologies whilst taking into account the spatial and temporal heterogeneity of the growing area. Precision farming, which is based on the integration of sensors, information systems, GPS technology and state-of-the-art machinery, centres on the site-specific, resource-efficient application of production inputs. [5] Through continuous data collection and real-time monitoring, farmers can respond much more quickly and precisely to changes in environmental and site-specific conditions. This adaptability is becoming crucial in the face of increasingly unpredictable growing conditions caused by climate change. Remote sensing technologies, satellite and UAV-based data collection, and various vegetation indices are playing an increasingly significant role in the development of precision crop production at an international level. Remote sensing enables the repeatable collection of data across large areas on spatial and temporal changes in crop stands. Vegetation indices are suitable, amongst other things, for assessing the vitality and developmental dynamics of vegetation, and their application has expanded further with the development of UAV technology, in addition to satellite and aerial platforms. [6] Modern approaches increasingly combine remote sensing information with meteorological, pedological and agronomic data. Research by Bhattarai et al. (2025), for example, demonstrated that integrating soil moisture and weather data into machine learning models can improve maize yield forecasting and contribute to data-driven decision-making adapted to varying environmental conditions. [7] Xia et al. (2026) investigated the spatial heterogeneity of maize yields under extreme precipitation conditions by integrating Sentinel-2 data, environmental variables and machine learning methods; their results also highlight the importance of combining data from multiple sources [8].

Precision farming therefore does not, in itself, eliminate the adverse effects of climate change on crop production, but rather provides a set of tools that can facilitate their earlier detection, a more accurate identification of site-specific differences, and more targeted interventions in cultivation techniques. The aim of this review is to examine the role of precision farming in adapting to climate change, with a particular focus on remote sensing, UAV-based data collection, water and soil management solutions, and the application of vegetation indices. The study also aims to summarise the potential and limitations of precision technologies, and to demonstrate how these tools can support the enhancement of crop production's adaptability and yield security under changing climatic conditions.

2. Materials and Methods

This study examines the role of precision farming in adapting to climate change through a review of the literature. The literature search was conducted between March and August 2026. Relevant domestic and international literature was identified primarily via the ScienceDirect, ResearchGate and MDPI online platforms, using the Google search engine, as well as university library resources.

The main English and Hungarian search terms used during the literature search included *'precision agriculture'*, *'climate change'*, *'remote sensing'*, *'UAV'*, *'NDVI'*, *'vegetation index'* and 'maize/corn'. I used the search terms both individually and in combinations appropriate to the subject areas under investigation. I did not apply any restrictions based on year of publication. Both Hungarian and English-language literature were included in the review.

The selection of sources took place in several stages. Firstly, I examined the abstracts and research objectives of the publications. Those publications whose content was related to precision farming, climate change and its effects on crop production, remote sensing, UAV-based data collection, vegetation indices, and precision water and soil management were further evaluated on the basis of their full text. I excluded from the review any sources unrelated to the topic, those whose full text was not accessible, and online sources without a scientific or institutional background. In addition to the scientific literature, I also utilised data sources and reports published by official national and international institutions to present statistical and background data relevant to the topic.

The final literature review includes those publications which, based on an evaluation of their full text, directly contributed to the presentation of a specific topic area examined in the study.

3. Results

3.1. The impact of climate change on crop production

Approximately 85 per cent of Hungary's territory is suitable for agricultural cultivation; however, as a result of global warming, the environmental conditions for production are undergoing significant changes. [9] The rise in average temperature intensifies evapotranspiration, increases the risk of water shortages and makes periods of drought more frequent. [10] Climate change is leading to greater crop yield fluctuations, a deterioration in soil condition, and changes in the spread of pests and diseases. [11]

According to the 2022 report by the Intergovernmental Panel on Climate Change (IPCC), agriculture is responsible for approximately 20–24 per cent of global greenhouse gas emissions. This significant share of emissions is primarily attributable to the use of nitrogen fertilisers, livestock farming and land-use change. [12] In summary, this sector is both a victim of and a driver of climate change.

The adverse effects of climate change on crop production can be particularly significant in the case of arable crops that are sensitive to environmental factors; maize, in particular, serves as a good example of the consequences of heat and water stress on crop yields.

Maize production is significantly affected by climate change. Rising temperatures accelerate the plant's growth cycle and shorten the growing season, which often leads to reduced yields. [1] The flowering period is particularly critical, as temperatures above 35 °C impair pollen formation and fruit set, thereby reducing yield. Extreme weather events – such as hailstorms or gale-force winds – can also cause direct physical damage to the crop. [2]

To mitigate the effects of climate change, the use of drought-tolerant hybrids, the selection of the optimal sowing time, and modern agronomic solutions designed to conserve soil moisture play a key role.

One of the biggest problems facing our country is the occurrence of droughts. On 23 April 2025, the National Chamber of Agriculture published a study on the country's rainfall levels and their distribution over the past two decades. The study was compiled using data from 67 HungaroMet monitoring stations between 2002 and 2024. Whilst there was no significant difference in the national average, a very large discrepancy becomes apparent when the data is broken down by season and region. The greatest disparity can be observed during the summer months; however, although the amount of rainfall in autumn and winter has increased, this is not sufficient to compensate for the shortfall during the summer months. [13]

At the same time, we cannot ignore the fact that our groundwater resources are being overused, whilst our surface water resources are showing a downward trend. [14]

According to data from the Hungarian Central Statistical Office (KSH), there were seven occasions between 2000 and 2020 when at least 70 per cent of the country was affected by drought damage. It is interesting to note that this occurred on a total of three occasions between 2021 and 2024. During these periods of drought, the demand for irrigation also increased significantly, as the risk of crop failure rose considerably in the cultivation of climate-sensitive crops. This also demonstrates that climate change is very much a part of our everyday lives, and that we can only mitigate it to some extent through sustainable agricultural practices.

3.2. The role of precision farming in adapting to climate change

Precision farming is based on the close integration of information technology and agronomy. Its key tools include GPS-based positioning, satellite and drone-based remote sensing, various sensors, automated machinery systems, decision-support software and artificial intelligence. Site-specific farming enables the application of inputs and cultivation practices tailored to the heterogeneity of cropland, thereby increasing the efficiency and sustainability of production. [15]

One of the most important climate adaptation benefits of precision technologies is the support they provide for data-driven decision-making. The analysis of weather data, satellite imagery and sensor readings enables rapid, data-driven decision-making, thereby enabling farmers to prevent major damage – such as the risk of drought, the outbreak of plant diseases and nutrient deficiencies – and thus minimise the risk of crop yield losses. Precision technologies can reduce yield variability; through site-specific farming, more stable yields can be achieved even under adverse weather conditions. Digital agriculture enables continuous monitoring and immediate intervention, which is particularly important in the event of extreme weather conditions.

One of the most significant tools for data-driven monitoring is remote sensing. Remote sensing is a truly key element of precision farming, enabling the continuous and site-specific monitoring of cropland. The method is based on sensors recording electromagnetic radiation reflected or emitted from the surface; by processing this spectral information, conclusions can be drawn about the physical and biological condition of the crop and the growing site. [16]

Unmanned aerial vehicles (UAVs) are one of the increasingly widely used tools for remote sensing data collection.

The use of UAVs has now become one of the key tools in precision crop production. Drones enable fast, high-resolution and repeatable data collection, whilst they can also be equipped with RGB, multispectral, hyperspectral and thermal camera sensors. [17] The data obtained in this way are suitable, amongst other things, for assessing biomass, nutrient deficiencies, plant stress, diseases, weed infestation and expected crop yield. [18] Vegetation indices calculated from RGB images taken in the visible spectrum often show a close correlation with NDVI values derived from multispectral data, which enables cost-effective monitoring. [19] However, the application of UAV technology may be limited by weather conditions, the management of large data volumes and complex data processing.

Climate change is one of the most serious threats to agriculture. Precision irrigation systems, which regulate water application based on data from various sensors and meteorological data, can provide an effective solution to increasing water scarcity, thereby significantly improving the efficiency of irrigation water use. [20] The use of soil moisture sensors not only prevents over-irrigation and direct water wastage, but the technology also offers significant economic benefits, as the energy consumption of irrigation systems can be substantially reduced through more precise water application. [20]

The use of precision farming can also make a substantial contribution to improving soil condition; site-specific cultivation within the field can minimise soil compaction, as well as damage caused by erosion and deflation. The combination of soil-conserving tillage systems and precision technologies can help increase the soil's organic matter content, thereby enhancing its long-term carbon sequestration capacity. [21]

Appropriate soil management is key to mitigating the negative effects of climate change by improving water retention capacity and increasing yield stability. [21]

In this century, the primary task for farmers is to address the effects of global warming and then to mitigate them by selecting appropriate methods.

3.3. Vegetation indices and the practical application of precision technologies

The Normalised Difference Vegetation Index (NDVI) is the most widely used vegetation index. Its scientific foundations were laid by Rouse and colleagues in 1974 [22] based on the red and near-infrared bands of the MSS sensor on the ERTS–1 (later Landsat–1) satellite. The introduction of the NDVI is regarded as a milestone in remote sensing, as it enabled the objective, quantitative assessment of vegetation condition. Since then, numerous studies have confirmed its applicability in estimating biomass, chlorophyll content and plant stress [6, 23, 24]

Vegetation indices include LAI, NGRDI (VIGreen) and NDVI. According to a study by Á. Törőcsik (2023), vegetation indices enable the indirect, non-destructive estimation of biomass: although they do not measure plant mass directly, their values accurately reflect the relative amount of biomass. [25]

NDVI (Normalised Difference Vegetation Index). This is a dimensionless number determined using specialised digital cameras. Whilst the NGRID (VIGreen) is based on the visible light (400–700 nm) wavelength range, the NDVI uses the normalised difference between near-infrared (NIR) and visible (VIS) wavelengths to characterise the condition of vegetation. One of the physiological characteristics of vegetation is that it absorbs visible light in the 400–700 nm range, whilst significantly reflecting wavelengths above 700 nm. A high NDVI value is based on this principle, thus indicating intense photosynthetic activity and high chlorophyll content in the vegetation. [25] However, the NDVI tends to saturate when biomass is high ( ), and its sensitivity therefore decreases in dense vegetation. For this reason, the GNDVI and NDRE indices are increasingly being used, as they provide a more accurate indication of the physiological state of vegetation under certain conditions.

$$NDVI = \frac{NIR - R}{NIR + R}$$

GNDVI (Green Normalised Difference Vegetation Index). It is calculated in a similar way to the NDVI and its applications are also similar. There is one very important difference between the two measurement methods: whilst the NDVI measures in the red wavelength range, the GNDVI collects data exclusively from the green range. This is significant because this value provides information on the photosynthetic activity of plants and, consequently, on nitrogen availability. GNDVI is particularly suitable for assessing nitrogen availability and photosynthetic activity, which is why it is frequently used to support nutrient management decisions. [6, 29]

$$GNDVI = \frac{NIR - Green}{NIR + Green}$$

LAI (Leaf Area Index). It is closely correlated with the NDVI value, which represents the vertical extent of vegetation, i.e. it indicates the total leaf area per unit of soil surface. This dimensionless number, ranging from 0 to 18, is a key indicator for determining stand density. [26, 27]

$$LAI = \frac{T}{t}$$

The methods for calculating LAI also include determining its value from the light intensity measured beneath the canopy and the light intensity falling on the vegetation. [26, 27]

$$LAI = \frac{-1}{k} * (LN \frac{I}{10})$$

Where T is the total leaf area, t is the soil surface area per unit, k is the extinction coefficient, I is the light intensity measured beneath the canopy, whilst I_0 is the light intensity measured above the stand. [26, 27]

The light transmittance of the vegetation is determined by the extinction coefficient (k), which characterises the spatial arrangement and orientation of the leaves (Beer–Lambert's law); for grasslands, this value is typically 0.8. As stand density increases, both biomass and LAI values will rise; this is also supported by the spectral data of the NDVI. However, whilst the relationship between LAI and biomass is linear (the measurement does not lose its sensitivity even at higher biomass masses), the NDVI has limitations due to its exponential nature; consequently, it reaches a saturation point at higher values. This means that in dense, closed stands, the NDVI is no longer able to track the increase in biomass. [26, 27]

Using VIGreen (Visible Atmospherically Resistant Index Green), i.e. the green vegetation index (NGRDI = Normalised Green Red Difference Index), we can determine these values from photographs taken with digital cameras. The technology is based on the separation of colours into three colour components: red (R), green (G) and blue (B). This vegetation index is a dimensionless number expressing, as a percentage, the normalised ratio of the green (G) and red (R) wavelength ranges reflected by the vegetation. [28] The advantage of the NGRDI is that it can be calculated using a conventional RGB camera; however, due to the absence of the near-infrared range, its sensitivity is generally inferior to NDVI-based approaches.

$$VIGreen = \frac{Green - Red}{Green + Red}$$

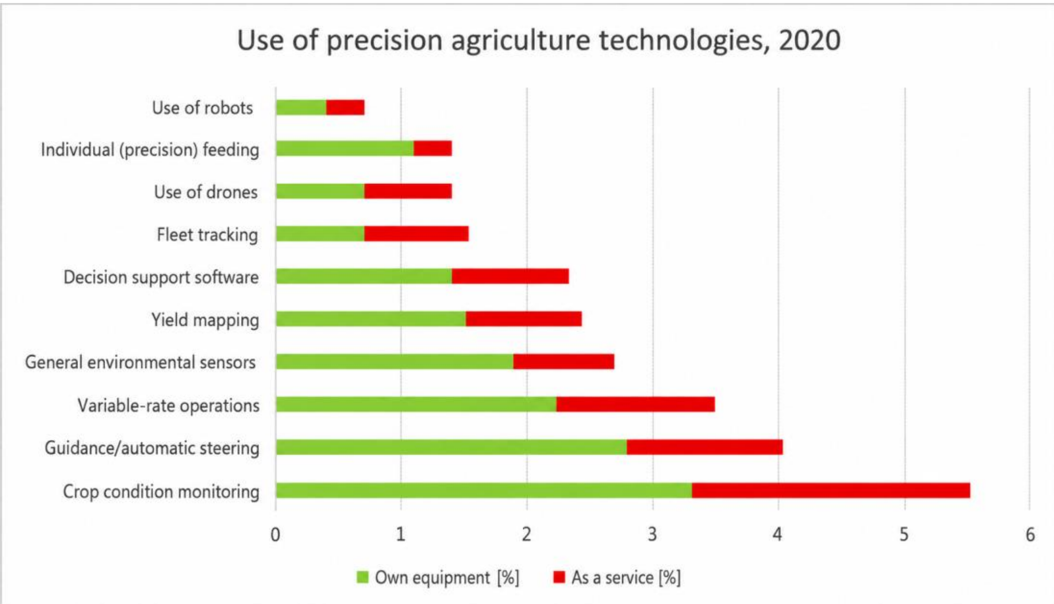
NDRE (Normalised Difference Red Edge Index). It is primarily suitable for crop health monitoring, as changes in chlorophyll composition can be detected most accurately in the red edge range; it is also suitable for monitoring nitrogen availability and stands at later stages of development. This index is most effective at mapping biotic stress factors (pathogens, pests); it is used to monitor conditions during critical epidemic periods and to facilitate prevention. [6, 29] The advantage of the NDRE is that, even with a high leaf area index, it does not saturate as quickly as the NDVI; consequently, it often provides more accurate results when monitoring more mature stands.

$$NDRE = \frac{NIR - Red\ \ Edge}{NIR + Red\ \ Edge}$$

In today's precision farming practices, vegetation indices are primarily determined using drone-based multispectral cameras. The maps produced in this way help to determine the heterogeneity of the crop stand, identify stress factors and plan site-specific interventions. [30]

Although vegetation indices provide a reliable picture in their own right, as they offer highly valuable information on the condition of the crop stand, they also play a key role in precision agriculture, as they serve as input data for machine learning models. When NDVI, GNDVI or NDRE data are combined with meteorological, pedological and agronomic data and information, this can provide opportunities for more accurate crop yield forecasting and the development of decision support systems. [31]

Based on the Hungarian Central Statistical Office's (KSH) 2020 Agricultural Digitalisation Survey, it can be stated that the higher a farm's production value, the greater the use of digitalisation tools. There is also a correlation between the age of farm managers and their willingness to invest in such tools, as younger managers show greater interest in these technologies. In Hungary, the uptake of precision farming tools is very low (only 12 per cent of farms use some form of precision farming tool). By contrast, this proportion is considerably higher in other European countries; a good example is Denmark, where, in 2018, 23 per cent of farms were already using precision technology on more than half (57 per cent) of their total cultivated area. [32] In Hungary, the tools most widely adopted are those used for crop condition assessment, which are used by 5.6 per cent of farms; farmers either carried out these assessments using their own equipment or commissioned them as a service. (Figure 1) (KSH)



1. Figure: Proportion of precision tools in use in 2020 *(compiled by the author, source: KSH)*

In 2023, the use of precision farming tools on farms increased by 4.2 per cent (to 9.8 per cent) compared with 2020. (KSH)

In summary, it can be concluded that precision farming is one of the most promising areas of innovation in modern agriculture, capable of playing a key role in combating climate change and adapting to it. The integration of digital technologies enables a more efficient use of resources, thereby significantly reducing the sector's environmental impact.

As a result of global warming, systems that simultaneously ensure productivity, sustainability and the efficient use of resources will become increasingly valuable in the future. Precision farming could be one of the most promising tools for this. A genuine breakthrough within the sector can only be achieved if the technology becomes available on a wider scale and to the greatest possible number of people, particularly smaller farms.

Although precision farming has numerous advantages, we must not overlook the factors that are slowing its uptake. The most significant barriers are the high investment costs and the substantial machinery requirements. The lack of digital infrastructure, data management challenges and, last but not least, a lack of specialist knowledge present serious obstacles. The introduction of modern technologies causes financial problems, particularly for smaller farms. At the same time, it is very important to note that technology does not mean that the harmful, negative effects of climate change can be completely eliminated; rather, a genuine breakthrough can only be achieved in conjunction with appropriate agricultural and environmental policy measures. [11]

4. Conclusions

Climate change is one of the most significant challenges facing agriculture today, posing an ever-increasing risk to production through rising temperatures, changes in rainfall patterns and the increasing frequency of extreme weather events. To ensure sustainable crop production, it is necessary to apply state-of-the-art technological solutions that enable the continuous monitoring of cropland, the efficient use of resources and rapid, data-driven decision-making.

The research reviewed clearly shows that precision farming is one of the most promising tools for adapting to climate change. Site-specific cultivation technology, remote sensing, drone-based data collection and the use of various sensors provide the means to accurately monitor the condition of crops , detect stress factors at an early stage and optimise interventions. As a result, the risk of crop yield losses can be mitigated, the efficiency of input use can be improved, and the environmental impact of agricultural production can be reduced.

Vegetation indices – in particular the NDVI, the GNDVI, NDRE, NGRID (VIGreen) and the leaf area index (LAI)—play a key role in precision crop production, as they provide objective information on the physiological status of the crop, photosynthetic activity, biomass quantity and nutrient supply. The NDVI is widely applicable, but it becomes saturated at high biomass levels. The GNDVI is more sensitive to changes related to photosynthetic activity and nitrogen status. The NDRE is a more advanced index; in stands with a large leaf area, it is less prone to rapid saturation and may therefore be preferable under such conditions. RGB-based indices can enable more cost-effective monitoring, but they have limitations due to the absence of NIR data. Combining vegetation indices with meteorological, pedological and agronomic data can also aid yield estimation and decision-making. The varying sensitivity and applicability of individual indices allow farmers to select the method best suited to the purpose of the analysis, thereby enabling them to make more informed decisions regarding cultivation techniques.

Based on a comparison of the international research reviewed, the value of precision farming for climate adaptation lies not primarily in the standalone application of individual technologies, but in the integration of different data sources. Remote sensing and UAV data provide high-spatial-resolution information on crop stand heterogeneity; however, on their own, they are not always sufficient to identify the processes underlying yield variations. The integration of meteorological, pedological and agronomic data can therefore enhance the reliability of decision support and yield estimation. This is particularly important in the context of increasing environmental variability resulting from climate change, when the same technological solutions may yield different results across different growing locations and crop years.

Based on the research presented, it can be concluded that precision farming does not in itself provide a solution to the problems caused by climate change; however, when combined with an appropriate agronomic approach and state-of-the-art digital technologies, it can contribute significantly to increasing the adaptability of agriculture. One of the most important tasks for the future is the wider adoption of precision technologies, the development of farmers' digital skills, and the further development and integration of decision-support systems based on remote sensing, sensors and artificial intelligence into crop production practices.

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