Review

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Review

MOUNTAIN Precision AgriculturE Index. A REVIEW

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ABSTRACT: The paper develops the Mountain Precision Agriculture Index realized in 2020 at Oradea University – Doctoral School, Agronomy Specialization (Covaci-Sterpu, 2020). The article points the importance of entrepreneurship development, focusing on precision agriculture index in the mountain area. The reviewed papers show that *the implementation of precision farming within an IoT framework in highland regions* (ζ9) must be developed with attention to various essential aspects, precisely *the elevation of the mountain* (ζ1), *the gradient of the terrain* (ζ2), *the mean local altitude* (ζ3), *signal degradation due to the mountainous topography* (ζ4), *access to internet connectivity* (ζ6), *the level of smart technology utilization* (ζ7), and *the concentration of active ICT businesses in the region* (ζ8). The current paper show that ζ9 is dependent of other indices too, respectively *the interaction with the intensity of geomagnetic storms or weather shortcomings* (ζ5). The paper presents a specific map of the mountain peaks from the European area, highlighting the importance of the altitude in applying the precision agriculture index. The paper is a review of the articles *Covaci, B., & Covaci, M. (2023). Mountain Index Business Model Nexus Internet of Things Development and Sustainability. J. Mountain Res. Vol. 18(2), 191-205 (https://doi.org/10.51220/jmr.v18i2.21) and Covaci, B., & Covaci, M. (2023). Systemic Practice in the Business Mountain Models nexus Internet of Things, Research Square (https://doi.org/10.21203/rs.3.rs-2682687/v1).*

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INTRODUCTION

Mountain Precision Agriculture Index (MPAI) represent a precision agriculture index developed for mountain area, using entrepreneurship coordinates. Various researchers show the importance of precision agriculture for modern rural development.

Due to the numerous problems in the mountainous area, with unforeseen situations being much more numerous than in the plain area, the mountain index of precision agriculture is essential in the maintenance and sustainability of highland zones.

Certain researchers consider that digital agriculture represents the application of advanced technologies, including sensors, robotics, and data analytics, to transform traditional agricultural practices into highly automated and efficient systems. The effective management of information and systematic data collection have played a pivotal role in driving technological advancements and digitalization, facilitating a shift in the workforce from unskilled to skilled sectors. Agriculture, as a critical industry for meeting human needs, has greatly benefited from the integration of robotic technologies, which have significantly reduced operating costs and delivery times while enhancing the accuracy and precision of agricultural practices. Contemporary robotic systems are being designed to streamline and improve autonomous processes such as weed control, field analysis, and the harvesting of crops. This scientific paper explores key engineering innovations and examines the

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evolving trends in the adoption of new technologies, emphasizing their potential to modernize and advance precision agriculture. (Petre et al., 2022)

Other researchers believe that analyzing the feasibility of implementing precision agriculture reveals that it is not a rigid or static system but rather a framework composed of multiple interrelated concepts, including:

- Designing precision agriculture strategies tailored to diverse soil types and varying climatic conditions.
- Adopting different management and marketing approaches to suit specific agricultural contexts.
- Employing varied solutions to mechanize agricultural operations effectively.

From an agronomic perspective, the foundational elements critical to the realization of precision agriculture include comprehensive databases encompassing soil structure and composition, climatic data, crop diseases and pests, weed species, and other relevant parameters.

From a technical standpoint, precision agriculture relies heavily on advanced soil mapping systems, which can be achieved through:

1. Mapping agricultural plots using location-detection technologies, such as GPS or non-satellite systems, in conjunction with specialized software tools.
2. Performing precision agricultural operations based on real-time terrain mapping to ensure optimal resource utilization.
3. Soil mapping based on soil properties, aimed at determining the precise quantities of fertilizer required for specific units of land, ensuring efficient and sustainable use of inputs.
4. Soil mapping focused on weed infestation levels and species, facilitating the design of precision agricultural interventions tailored to controlling specific weed populations.
5. Weed infestation assessment systems, which utilize image transmission and automated processing via specialized software to detect and map infested areas. These systems rely on attributes such as crop size and color to distinguish infested zones and identify weed species.

This framework underscores the integration of agronomic knowledge and technological advancements as essential for achieving the objectives of precision agriculture. (Ioan et al., 2006)

A group of professors show that compared to conventional agricultural machinery, agricultural robots in precision agriculture offer significant advantages, including enhanced flexibility, adaptability, and environmental sustainability. These benefits are attributed to advanced technologies such as spectral sensors and cameras, which enable the detection of weeds, pests, diseases, and nutrient deficiencies in soil or plants. Additionally, agricultural robots exhibit interoperability with other robotic systems or individuals, integrate soil analysis subsystems, and utilize sophisticated algorithms and navigation systems. Precision agriculture, as a relatively novel paradigm, has transformed traditional agricultural practices by incorporating processes of observation, measurement, analysis, and response. This evolution is further augmented by the integration of advanced intelligent systems, including innovative materials and products, state-of-the-art equipment and machinery, dynamic process control strategies, and tailored management approaches, all designed to achieve superior agricultural performance and sustainability. (Pandelea et al., 2018)

A complex study regarding precision agriculture, develop a structured research which present advanced technologies and equipment utilized in agricultural measurements that should include: artificial vision, spectroscopy, X-ray technology, magnetic resonance, chemical detection methods, wireless sensor networks and RFID sensors. The application of multispectral detection methods is essential for assessing crop nutritional levels by analyzing reflectance across multiple spectral bands. For effective monitoring, hyper- or multispectral equipment is preferred, as it enables the observation of large areas with high precision. To detect, identify, quantify, and monitor crop diseases, optical sensors are employed, with thermography, chlorophyll fluorescence, and multi- and hyperspectral sensors delivering particularly effective results. Challenges associated with mobile terrestrial systems

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in monitoring crop vegetation status can be mitigated through the adoption of aerial solutions. Some key limitations of land-based systems include:

- Potential damage to crops in areas traversed by the mobile system.
- Shocks and vibrations caused by uneven terrain.
- Misalignment of sensors with the intended measurement direction.
- Challenges in synchronizing data acquisition speed with the velocity of agricultural machinery.
- Limited scanning speed, reducing operational efficiency.

Aerial solutions address these obstacles by enabling more efficient, accurate, and less invasive monitoring of agricultural landscapes. (Afanas, 2022)

MATERIAL AND METHOD

In accordance with literature review from the introduction and others research, authors consider that *the implementation of precision agriculture within an IoT framework in highland regions* (ζ9) must be developed with attention to various essential aspects: *the elevation of the mountain* (ζ1), *the gradient of the terrain* (ζ2), *the mean local altitude* (ζ3), *signal degradation due to the mountainous topography* (ζ4), *the interaction with the intensity of geomagnetic storms or weather problems* (ζ5), *access to internet connectivity in the mountain area* (ζ6), *the level of smart technology utilization in the mountain area* (ζ7), and *the concentration of active ICT businesses in the region in the mountain area* (ζ8).

The precision agriculture mountain index focus on the deployment of precision agriculture within an IoT infrastructure in mountainous areas (ζ9), as showed in the published papers reviewed through this article, and the resulted equation is given below (Covaci, B., & Covaci, M. 2023a; Covaci, B., & Covaci, M. 2023b):

$$\zeta 9 = 1/\zeta 1 + 1/\zeta 2 + 1/\zeta 3 + 1/\zeta 4 + 1/\zeta 5 + \zeta 6/100 + \zeta 6/100 + \zeta 8/100 \quad (1)$$

ζ1, ζ2, ζ3, ζ4, ζ5 are sub unitary indices, while ζ5, ζ6, ζ7 are expressed percentual.

The indices have been composed by the authors. The figure has been realized using drawings software in accordance with the data presented in the original papers.

This paper has been academic language revised using artificial intelligence.

RESULTS AND DISCUSSION

ζ1 develop the most significant part of the precision agriculture in the mountain area, and it has provided values (Figure 1).

Strictly for this indicator, precision agriculture mountain it is increasingly easier to apply gradually, from class 1 to class 7. For this indicator IoT comport different types of precision agriculture in the mountain area. In the European mountain zone, class 1 is marked on the figure with red, class 2 – orange, class 3 – yellow, class 4 – blue, class 5 – purple, and class 6 – blue.

Specific for the European area, from the figure can be understood that, according to FAO, precision agriculture is hardly to apply in some mountain areas from France and Italy (classes 1, 2, 3, 4), Austria (classes 2, 3, 4), Poland (classes 3, 4), Romania (classes 3, 4), Slovakia (classes 3, 4), Czech Republic (class 4), Croatia (class 4), Portugal (class 4).

From the 5^{th} to 7^{th} classes precision agriculture mountain become simpler to apply for all the European analyzed countries, respectively Austria, Czech Republic, Croatia, France, Italy, Poland, Portugal, Romania, Slovakia.

ζ2 is a percentual calculated value – a distance with maximum and minimum slopes, while ζ3 take into consideration maximum and minimum local altitudes.

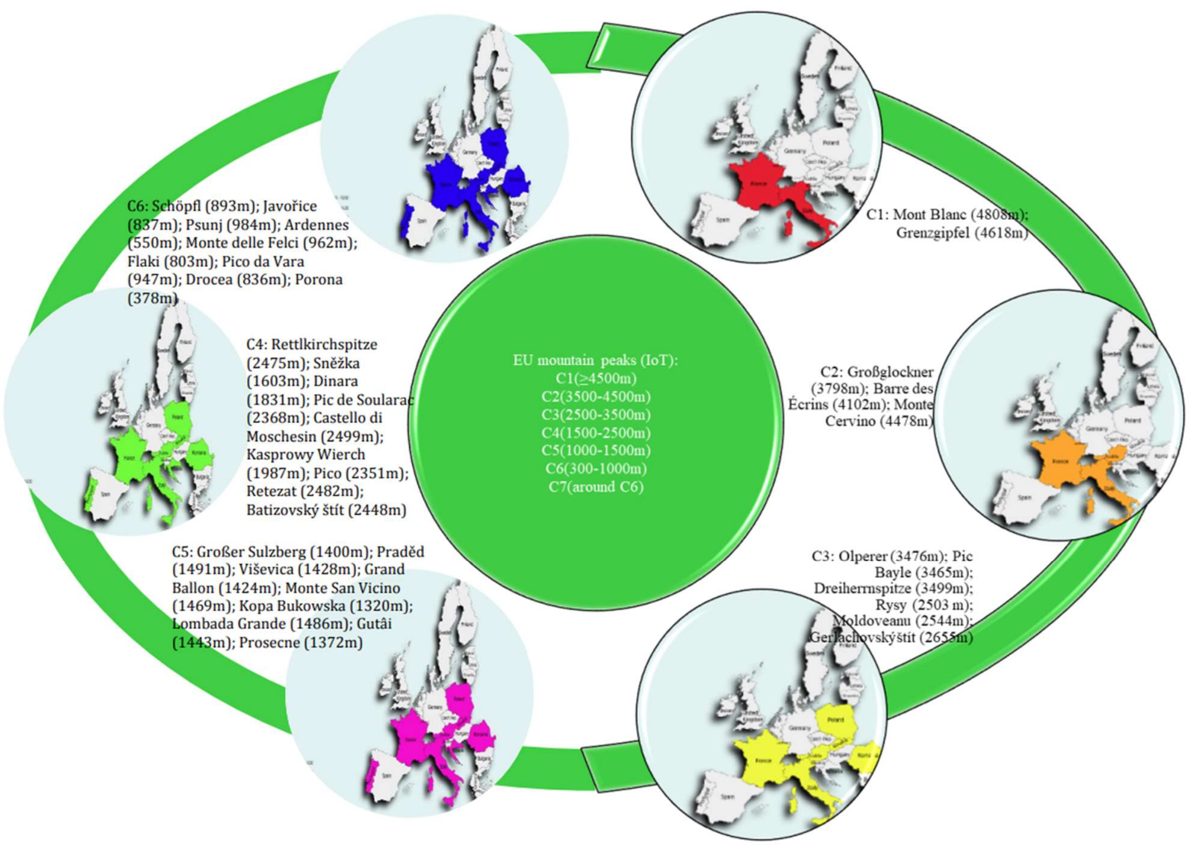
The most important factor in the precision agriculture mountain index is ζ4, due to signal degradation, considering μ, D, I_c (Covaci, B., & Covaci, M. 2023a; Covaci, B., & Covaci, M. 2023b).

The mountainous region has numerous factors that contribute to signal attenuation, frequency and wavelength being the most significant.

As shown in the reviewed papers, the general attenuation index takes into consideration the signal degradation, as follow (Covaci, B., & Covaci, M. 2023a; Covaci, B., & Covaci, M. 2023b):

$$\mu_v = -\frac{1}{\phi e,v}\frac{d\phi e,v}{dz} = -\frac{1}{\frac{\delta\phi e}{\delta v}}\frac{d\left(\frac{\delta\phi e}{\delta v}\right)}{dz} = -\frac{1}{\frac{\delta\left(\frac{\delta Qe}{\delta t}\right)}{\delta v}}\frac{d\left(\frac{\delta\left(\frac{\delta Qe}{\delta t}\right)}{\delta v}\right)}{dz} \tag{2}$$

$$\mu_\lambda = -\frac{1}{\phi e,\lambda}\frac{d\phi e,\lambda}{dz} = -\frac{1}{\frac{\delta\phi e}{\delta\lambda}}\frac{d\left(\frac{\delta\phi e}{\delta\lambda}\right)}{dz} = -\frac{1}{\frac{\delta\left(\frac{\delta Qe}{\delta t}\right)}{\delta\lambda}}\frac{d\left(\frac{\delta\left(\frac{\delta Qe}{\delta t}\right)}{\delta\lambda}\right)}{dz} \tag{3}$$



The explanations can be found in the original papers (Covaci, B., & Covaci, M. 2023a; Covaci, B., & Covaci, M. 2023b).

This review addresses dz (which was not properly explained in the previous papers).

For μv, dz represents the distance of the spectral frequency flux from beginning to end, while for μλ, dz refers to the distance of the spectral wavelength flux from start to finish.

While D represent the distance from the signal emission source to the signal reception source, I_c (I_d in the original papers) is the concentration index of a forest.

Regarding ζ5, associated with the influence of geomagnetic storms (K-index) or with simple weather problems, it should be noted that this have fixed values. This indicator can be used or substituted for all types of storms. K-index is used to determine the magnitude of geomagnetic storms. Some researchers consider that weather index is associated with temperature, wind,

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precipitation, UV index, and fire danger (”Farmonaut’s weather intelligence for Ellerslie, Tasmania”) (Farmonaut, 2024).

The other indices outlined in the original papers remain unchanged, namely access to internet connectivity in the mountain region (ζ6), the level of smart technology adoption in the mountain region (ζ7), and the concentration of active ICT businesses in the mountain region (ζ8).

CONCLUSION

This paper presents a comprehensive review of the original Mountain Precision Agriculture Index based on articles published in 2023.

It underscores the critical role of spectral frequency flux and spectral wavelength flux in the development of the Mountain Precision Agriculture Index.

The study emphasizes the necessity of establishing a specialized precision agriculture index tailored to mountain regions, which are characterized by numerous challenges, notably high altitude.

Additionally, the paper identifies geomagnetic disturbances and meteorological conditions as significant constraints impacting agricultural precision in these areas.

Focusing on the European mountain regions, the paper highlights the strategic importance of fostering entrepreneurial activities through precision agriculture.

Specific emphasis is placed on efforts undertaken in Austria, the Czech Republic, Croatia, France, Italy, Poland, Portugal, Romania, and Slovakia, illustrating the regional commitment to advancing precision agriculture practices in mountainous terrains.

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