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CSRF 2024 Editors

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CSRF 2024

Forward

The First International Conference on Sustainable and Regenerative Farming (CSRF 2024), held between November 17th, 2024, and November 21st, 2024, in Valencia, Spain, was a premier event dedicated to exploring and promoting groundbreaking advancements in agricultural technology. This conference served as a catalyst for collaboration among industry stakeholders, researchers, policymakers, and entrepreneurs, aiming to showcase the latest innovations in Sustainable and Generative Farming highlighting the transformative potential of technologies such as Artificial Intelligence (AI), Internet of Things (IoT), blockchain, and robotics in revolutionizing agriculture and ensuring sustainable food production for future generations.

We take here the opportunity to warmly thank all the members of the CSRF 2024 technical program committee, as well as all the reviewers. The creation of such a high-quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and effort to contribute to CSRF 2024. We truly believe that, thanks to all these efforts, the final conference program consisted of top-quality contributions. We also thank the members of the CSRF 2024 organizing committee for their help in handling the logistics of this event.

We hope that CSRF 2024 was a successful international forum for the exchange of ideas and results between academia and industry for the promotion of progress in the field of sustainable and regenerative farming.

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Smart Collars for Sheep: Leveraging Machine Learning for Improved Pasture Management

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***Abstract*— Effective control of animal feed and pasture management are increasingly important factors for animal health and farm sustainability. Recent technological advances in animal monitoring devices offer a significant potential for enhancing these practices. This paper presents the development of an innovative animal monitoring system for sheep, designed to capture images of pastures while minimizing redundant data collection. By integrating Machine Learning (ML)-based animal posture detection, the system autonomously triggers image acquisition only during relevant feeding activities. Additionally, the system automatically uploads the captured images for processing, reducing the need for manual intervention. Preliminary results demonstrate the system's feasibility and improved efficiency compared to state-of-the-art approaches.**

***Keywords-component; Ruminant monitoring; grazing behavior; floristic analysis*.**

I. INTRODUCTION

The control of animal feed and the management of pastures are essential for maintaining animal health and ensuring the economic sustainability of farms. Recent technological advances have made it possible to utilize animal monitoring devices, which can play a crucial role by collecting and processing data about animals' feeding behavior—data that was previously impossible to gather. These devices enable the collection of data for multiple purposes, including identifying feeding patterns, tracking areas of pasture, categorizing the plants consumed, and estimating the amount of nutrients consumed.

In recent years, there has been an increasing number of studies and technical solutions in the field of animal monitoring. These systems often incorporate various sensors, including video cameras, to support the monitoring process in diverse ways, *e.g.* observing behavior and activity, migration routes and location.

The approaches reported in the literature typically involve collars equipped with cameras configured to take photos at regular intervals during specific periods. Some collars also feature localization devices, such as Global Navigation Satellite System (GNSS) receivers, to identify feeding patterns. Despite providing valuable information, state-of-the-art approaches have inherent limitations that hinder their widespread adoption. For instance, image recordings are either pre-programmed or manually activated. Pre-programming often results in a significant amount of redundant or useless data (e.g., multiple photos of the same pasture, or photos taken when the animal is not eating) (see e.g. [1]). These unnecessary images consume a significant amount of memory and energy, limiting the autonomy of the devices and requiring substantial post-processing effort, often dependent on manual intervention. Manual activation, however, requires systematic human supervision, which is usually unfeasible. Moreover, these devices typically require manual intervention to collect and upload images to processing platforms, making the process cumbersome, inefficient, and costly. Another significant limitation is the use of Commercial Off-The-Shelf (COTS) cameras with low battery capacity, necessitating additional batteries that significantly increase the collar's total weight and size.

This work addresses the aforementioned issues and limitations of state-of-the-art approaches, with the primary objective of developing an animal monitoring device for sheep that captures images of the pastures and location while the animals are feeding. The device integrates Machine Learning (ML)-based animal posture detection functionalities, triggering image acquisition only at relevant moments, such as when animals begin eating after moving to a new location. Furthermore, the system automatically uploads images to a processing platform. These features result in a system that operates autonomously, with extended battery life, and minimizes redundant data, significantly improving cost, efficiency, and usability compared to state-of-the-art approaches.

This paper presents the initial steps toward developing this system, including its architecture and collar implementation. Preliminary results are also included, demonstrating the feasibility of the approach.

The remainder of this paper is organized as follows: Section II briefly reviews the state-of-the-art. Section III presents the system architecture. Section IV includes functional and performance results. Finally, Section V concludes the paper.

II. STATE OF THE ART

In recent years, there has been a growing number of studies and solutions in the field of animal monitoring. These studies often incorporate various sensors, including video cameras, to support the monitoring process in diverse ways, such as observing behavior [2], activity [3], feeding habits [1], births [4], habitat choices [5], migration routes [6], and location [7].

For example, a study presented in [5] monitors the feeding sites and habitats of pregnant migratory females of the Rangifer tarandus species during the summer. Sixteen females were fitted with Vertex Plus [8] collars that integrate a GNSS receiver and a camera. The collars were set to record ten-second video clips every 20 minutes, resulting in a total of 200,000 videos. These videos were then individually analyzed to identify those containing useful information for the study, which were around 25,869 videos. Another study focuses on analyzing the grazing behavior of sheep using collars with Point Of View (POV) cameras [1]. The study had a twofold objective: analyzing the feeding habits of sheep during the spring and determining if the behavior of a subset of sheep fitted with cameras could represent the behavior of the entire flock. The cameras were affixed to the sheep collars, along with a GNSS receiver and a set of batteries that extended the recording time. The cameras recorded video clips at fixed intervals throughout the day, resulting in a recording period of six to eight hours per day per sheep. This study provided valuable information about the animals' diet and revealed a relationship between the activity of the flock and the activity of the sheep with POV cameras.

Despite their value, these approaches face scalability and mass adoption challenges due to the significant amount of irrelevant information collected, resulting in inefficiency and autonomy limitations, and the dependence on human intervention at several stages.

III. SYSTEM ARCHITECTURE

The architecture of the system proposed in this paper is shown in Figure 1. It includes a collar with inertial sensors and a camera that captures images when a suitable software trigger is issued. The collar has a Bluetooth Low Energy (BLE) interface that connects to a data aggregation gateway located in the animal's shelter. When a collar and a gateway are within communication range, the images and accelerometer data stored in the collar's internal memory during the grazing period are uploaded to the gateway. The gateway, in addition to aggregate data from the various collars, contains a Tensor Processing Unit (TPU) [9] that identifies the species photographed through a previously trained learning model. The system also comprises a cloud-based application that centralizes information sent from one or more shelters and/or farms. Among other functionalities and uses, the collected data is used to train, in real-time, the image identification model. The updated model parameters are then sent back to the gateways' TPUs, to improve the performance of the species identification mechanism.

Image capture is based on the animal's behavior. The collar continuously monitors the animal's behavior via inertial sensors (accelerometers, in the case) and classifies them according to a previously defined ethogram [10]. Whenever it detects that the animal is eating in a new place, it triggers an image acquisition, to ensure that representative data is collected, while reducing redundancy. Images are saved in an internal memory of the collar, and they include a time stamp that allows the moment of collection to be identified.

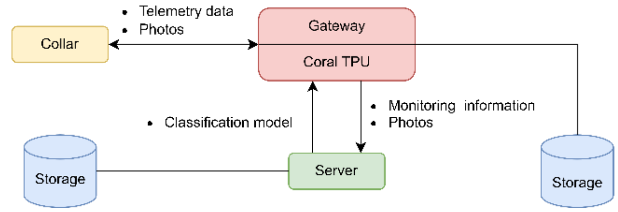

Figure 1. System architecture.

The data transfer between collars and the gateway is done through an opportunistic communication mechanism. To this end, collars periodically emit a BLE beacon [11], which, when detected by the gateway, triggers the information transfer process, which is illustrated in Figure 2. The gateway can connect to up to five collars simultaneously, allowing five data transfers to take place at the same time. As soon as the gateway connects to a collar, it sends the Get Info command, to which the collar responds with information about the device. The information packet sent by the collar to the gateway includes fields such as device ID, timestamp, animal type, battery status, number of files, and number of photos.

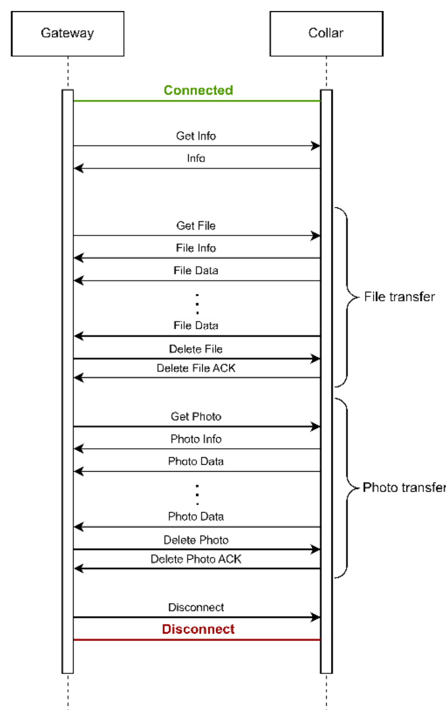

Figure 2. Information transferred between collar and the gateway.

If there is data or photos to transfer, the gateway sends one of the following commands: "Get File" for transferring data files or "Get Photo" for transferring photos. The collar replies with a "File Info" frame containing information about the name and size of the file, followed by eventually multiple packets to the gateway ("File Data"). After the data transfer is complete, the gateway sends the "Delete File" command to delete the transferred file, followed by a delete operation, when successful. The data file contains fields about the sensor data, as well as relevant device information such as the battery and timestamp value. The sequence of commands for sending photos follows a similar process, *mutatis mutandis*. The gateway transmits the "Get Photo" command to initiate the transfer of an image. Subsequently, the collar transmits a "Photo Info" frame to the gateway, which contains the name and size of the photo to be sent. After sending this information, several "Photo Data" frames are sent with the photo data. Once the transfer of the photo data has been completed, the gateway transmits a command to the device to delete the photo, which is acknowledged in case of success.

IV. SYSTEM EVALUATION

In the prototype implementation collar is based on an nRF52833 System on Chip from Nordic Semiconductor featuring an ARM Cortex-M4 at 64 MHz and a Bluetooth 5.4 module. The collar also has a 3-axis accelerometer that is used to monitor the animal's behavior. The camera is a Arducam Mega 5MP with a Serial Peripheral Interface, 5 MP maximum resolution, auto-focus, and power supply of 3.3 V or 5V. The images are stored in compressed JPG format and with UXGA resolution (1280x720 pixels). Based on the prototype, a few tests were carried out to show the feasibility of the approach and obtain preliminary performance data.

A. Storage tests

Table I presents the total time taken to capture a set of images in different conditions, including illumination and vegetable species. The acquisition time varies with the image contents, from 408 kB to 742 kB. This is expected as the image format used to store data uses compression to reduce the size and compression algorithms depend on spatial redundancy which, in turn, depend on the image and on the illumination. In the case of this test, it was observed that photos with poor lighting and blur have a shorter capture time and size compared to photos with good lighting and good detail, since they contain a higher spatial redundancy.

TABLE I. TIMES AND SIZES OBTAINED FOR DIFFERENT PHOTO SIZES

Photo Number	Total Time (s)	Photo Size (kB)
1	7.9	408
2	8.2	423
3	8.6	413
4	9.9	516
5	10.6	554
6	11.4	596
7	12.3	644
8	13.3	704
9	13.5	706
10	13.9	721
11	14.2	736
12	14.8	742

B. Communications test restults

Table II presents the transfer times of the images to the gateway, with the collar positioned at three distinct distances from the gateway. For the same set of images, the collar was positioned at distances of 5 meters, 15 meters and 25 meters. The images employed in this experiment exhibited a range of file sizes, from 107.6 kB to 761.9 kB. Table III reveals that the time required to transmit images increases in direct proportion to the distance between the collar and the gateway. The most notable alteration was observed between distances of 15 and 25 meters. This is attributed to the placement of the collar in an alternative room, which contained metallic objects, potentially influencing the connectivity between the two devices.

TABLE II. TIME TO TRANSFER AT DIFFERENT DISTANCES

Photo Size (kB)	Distance between collar and gateway		
	5 meters	*15 meters*	*25 meters*
107.6	10s	25s	2m3s
244.8	23s	59s	4m1s
280.6	26s	1m2s	4m42s
392.2	37s	1m34s	6m47s
432.2	40s	1m35s	6m29s
534.6	49s	1m59s	6m47s
638	1m	2m33s	7m51s
761.9	1m13s	2m58s	8m44s

Table III presents the results of an experiment conducted to determine the influence of an increased number of collars on the photo transfer time. The objective was to assess whether connecting five collars, which is the maximum number that can be connected and transferred to the gateway, would affect the transfer time. The four additional collars that were connected to the gateway only contained data files. The four collars were distributed throughout the test environment, with the test collar maintained in position at distance two (15 meters).

TABLE III. TIME TO TRANSFER TO DIFFERENT COLLARS CONNECTED TO THE GATEWAY

Photo Size (kB)	Collars connected to the gateway	
	1 Collar	*5 Collars*
107.6	25s	1m12s
244.8	59s	2m55s
280.6	1m2s	3m45s
392.2	1m34s	4m25s
432.2	1m35s	4m58s
534.6	1m59s	5m27s
638	2m33s	7m20s
761.9	2m58s	7m52s

Analyzing Table III, it becomes evident that the time required to transmit images increases when the gateway is connected to five collars. For example, for a size of 432.2 kB the time elapsed increase from 1 minute and 35 seconds to 4 minutes and 58 seconds, which corresponds to an increase of 3m23s. This is due to the gateway having to divide its bandwidth and processing capacity between 5 devices, slowing down the transfer time for each one. As the gateway is only capable of connecting to a maximum of five collars at any given time, the presence of either ten or five collars does not affect the data transfer times. These times can be used to estimate the number of photos that can be transferred per hour. Assuming that the photos are approximately 535 kB in size, and that there are five or more collars on the sheepfold with five of them connected to the gateway, 11 photos can be transferred per hour. In the most unfavorable scenario, if the photos have an average size of 762 kB, only seven photos can be transferred per hour.

C. Photo results

Figure 3. presents the collar designed to integrate the camera and the rest of the system.

Figure 3. Collar detail.

Figure 4. Photo captured by the camera attached to the collar.

Figure 4. presents a picture taken with the camera while the sheep were feeding. The image shows that the photos have been taken with sufficient quality to allow the floral species in the photos to be identified. Depending on the lighting in the scene, the camera tends to focus on the best lit areas, sometimes leaving other areas darker or lighter.

V. Conclusions

In this paper, we have addressed the limitations of current animal monitoring systems by developing an innovative device that integrates machine learning-based posture detection to autonomously capture images of pastures during sheep feeding activities. Our approach minimizes redundant data collection and reduces the dependency on manual intervention, thus improving efficiency and extending the operational autonomy of the monitoring system. The implementation of the image transfer protocol between the collar and the gateway ensures efficient and reliable data transmission. By sending only relevant data and photos, and automating the deletion process post-transfer, the system significantly conserves memory and energy resources. The preliminary results show our approach's feasibility, highlighting its potential to enhance pasture management and animal health monitoring on a broader scale.

Future work will focus on implementing the full system and refining the ML algorithms for improving accuracy, expanding the system's applicability to other animal species, and further automating the data analysis process to provide real-time insights for farmers.

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Point Cloud Fusion Algorithm for High-Quality Digital Surface Model Generation from Multi-Date Stereo Images

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***Abstract*—This paper presents a novel methodology for generating high-quality Digital Surface Models (DSMs) through the fusion of point clouds obtained from multi-date stereo images. By applying a custom fusion algorithm to the point clouds generated by the Context-Aware Reconstruction of Scenes (CARS) software, the proposed approach enhances DSM quality in terms of completeness and error metrics compared to the original DSM. The fusion process effectively integrates multiple DSMs, resulting in a more comprehensive and accurate terrain representation. This method addresses challenges such as shadow occlusions and temporal variations, demonstrating significant improvements. The technique shows potential for applications in precision agriculture and other fields requiring detailed terrain models. Validation using the Intelligence Advanced Research Projects Activity (IARPA) challenge dataset highlights the method's robustness in mixed terrains, offering a notable increase in completeness and solving issues related to data gaps in shadowed areas.**

Keywords-Point Cloud Fusion; Digital Surface Model (DSM); Multi-Date Stereo Images; Terrain Representation.

I. INTRODUCTION

The world population has exceeded the 8 billion barrier according to a United Nations press release of November 2022. Moreover, the world population is expected to reach 8.5 billion by 2030, and 10.4 billion by 2100. This rapid growth is expected to place increasing pressure on land and other natural resources, presenting significant challenges to food security [1]. The growing need to produce more and higher-quality food with unsustainable agricultural practices, as well as climate change and urban growth, are accelerating the loss of available arable land, threatening sustainability in terms of productivity and environmental impact [2]. It is important to note that climate change will lead to extreme environmental events that will require a rapid and efficient response from the agricultural sector. The agricultural sector must adapt effectively to mitigate the adverse effects of such events and ensure global food security [3].

Several studies have already indicated that modernisation processes are crucial to overcome the difficulties caused by agricultural land change [4]. Among these processes is where Precision Agriculture (PA) can be mentioned and highlighted as one of the solutions to ensure food security for the whole world. The PA, also known as Smart Farming or Agriculture 4.0, is an agricultural management strategy focused on improving the efficiency in the use of resources, productivity, quality, profitability, and sustainability of agricultural production [5]. This discipline implements technologies and resources of all kinds, including, among others, Digital Surface Models (DSM). A DSM is a type of elevation model that not only represents the height of the terrain in areas devoid of objects but also considers all features present on the terrain, including buildings, tree canopies, and other elements on the earth's surface [6]. DSM can have a wide range of applications in the field of PA, notably in evaluating the suitability of terrain for agricultural use, crop yield monitoring, and biomass estimation [7]. DSMs are a fundamental starting point for the development of other models, among which the Digital Elevation Model (DEM) stands out. The latter represents the earth's surface once the elements that are not part of it have been removed, providing crucial information in various disciplines within the environmental field [6]; these models stand as pivotal spatial information tools in geomorphological applications, enabling the extraction of essential attributes like slope, aspect, profile curvature, and flow direction [8].

The extraction of elevation models can be derived from a variety of techniques; however, historically, aerial photogrammetry and LiDAR have been the most widely used methods for their generation. Nowadays, techniques derived from optical satellite imagery are also used. Among these, interferometric techniques based on radar images have been extensively investigated. Nevertheless, their application requires more complex processing involving the use of specialised algorithms and software, compared to techniques based on optical satellite imagery. In addition, optical imagery offers better interpretability and is more widely accessible and available [9].

One of the most commonly used techniques for DSM generation from optical satellite imagery is the stereo method. DSMs are generated using dense point clouds acquired from stereoscopic satellite imagery [10]. Point clouds are detailed sets of three-dimensional points that capture terrain features (buildings, vegetation, etc) using advanced image-matching algorithms [11]. Some research already mentions the importance that point cloud fusion brings to the quality and accuracy of DSM [12]. By integrating information from multiple viewpoints, point cloud fusion overcomes the occlusions and inaccuracies inherent in individual stereo pairs, resulting in more complete and detailed terrain representations. This approach not only improves spatial resolution and accuracy, but also facilitates the extraction of finer details [10].

This paper presents a methodology to generate high-quality

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DSMs by fusing point clouds obtained from stereo images captured at different dates. This approach uses point clouds generated by the Context-Aware Reconstruction of Scenes (CARS) software [13]. The main objective is to study the improvement produced by the fusion of DSMs and compare the results with other similar works like [10], where different software (S2P: Satellite Stereo Pipeline [14]) were used to generate the point clouds. As CARS appear to generate better results in the used stereo images dataset than S2P [13], it is significant to analyse the improvement made by the fusion of the results from CARS.

The rest of the paper is structured as follows. The Methodology section is divided into three parts. First, we present the Align and Fusion methodology. Then, the considered real context for validation purposes is detailed. The Methodology section is closed with a description of the obtained results. Finally, the Conclusion section summarizes the main contributions of the presented work and future perspectives.

II. METHODOLOGY

A. Align and Fusion methodology

The present subsection describes the iterative procedure to fusion P point clouds generated by CARS from different multi-date image pairs in order to create a unique fused DSM for a given Region of Interest (ROI). Each point cloud $p \in 1, ..., P$ is aligned with a reference point cloud selected by the user, and the P aligned point clouds are fused along with the reference one. The final fused point cloud is rasterised into an image for display. The proposed procedure includes the following steps:

1) Preparation: Pre-alignment processing of the point clouds composed from each image pair.

- CARS generates multiple point clouds for each DSM, as it separates the processing into tiles. Subsequently, the point cloud files generated for each tile are merged to generate a single point cloud for each DSM to be fused. The common set of pixels in both point clouds is projected for each DSM onto a grid with a specified node spacing, ideally equal to or greater than the image resolution. This forms a two-dimensional matrix in which the value of each cell represents the estimated height z in the coordinates (x, y).
- Applying a grayscale-closing interpolation, single pixel holes are filled averaging the values of elements in a surrounding 3x3 area, while the larger holes are kept as non-data. These larger holes are usually consequence of being located in shadow areas. This creates the new DSMs, that will be the reference DSM and the DSM p to be fused: E_{ref} and E_p respectively, which will be the inputs to the fusion step (Section II-A3).
- Another pair of DSMs D_{ref}, D_p is generated from the previous E_{ref}, E_p by completely filling all holes using the lowest hole edge values (using the 5th percentile), so that the occluded parts where no data has been generated are assumed to be at ground level. These DSMs will be used for alignment purposes (Section II-A2).

2) Alignment: Due to the pointing errors of RPCs (*Rational Polynomial Coefficients*) models [15], 3D point clouds obtained from different images are usually not aligned. The usual method for adjusting the parameters of all cameras uses correspondences between images (e.g., by Scale-invariant Feature Transform algorithm [16] matching). However, this method is sensitive to noise and radiometric changes, which are common in a multidate analysis [10]. The error induced in the point clouds by the pointing error is mainly a 3D translation, so following the strategy proposed by Facciolo et al. [10] the translation of D_p that maximizes the Normalized Cross-Correlation (NCC) over D_{ref} is calculated as follows:

$$NCC(\mathbf{u}, \mathbf{v}) \equiv \frac{1}{|\hat{\Omega}|} \sum_{j \in \hat{\Omega}} \frac{(\mathbf{u_j} - \mu_{\mathbf{u}}(\hat{\Omega}))(\mathbf{v}_j - \mu_{\mathbf{v}}(\hat{\Omega}))}{\sigma_{\mathbf{u}}(\hat{\Omega})\sigma_{\mathbf{v}}(\hat{\Omega})} \tag{1}$$

where $\mathbf{u}, \mathbf{v}$ are each one of the DSMs to align (in this case D_{ref}, D_p respectively), $\hat{\Omega} \equiv \Omega_{\mathbf{u}} \cap \Omega_{\mathbf{v}}$ is the intersection of the sets of known pixels in both DSMs, j represents an index that iterates over the pixels within the intersection set $\hat{\Omega}$, $\mathbf{u}_j$ refer to the pixel values of DSM $\mathbf{u}$ at position j. $\mu_{\mathbf{u}}$ and $\sigma_{\mathbf{u}}$ represents the simple mean and the standard deviation of $\mathbf{u}$, respectively. The same notation applies to $\mathbf{v}$.
We then look for the pair (dx^*, dy^*) under which the offset dx, dy maximizes NCC:

$$(dx^*, dy^*) = \arg\max_{dx,dy} NCC(\mathbf{u}, \mathbf{v}_{dx,dy}) \tag{2}$$

where $\mathbf{v}_{dx,dy}$ represents the DSM $\mathbf{v}$ shifted dx and dy. A search for (dx^*, dy^*) is applied following a coarse-to-fine method:

- 1) Shift v in coarse steps (e.g:25 cells) and calculate the NCC at each shift.
- 2) The offset that gives the largest NCC value in the initial search is selected.
- 3) New consecutively smaller steps (e.g: 5 and 1 cells) are added to the coarse shift (shifting in total always less than the value of the previous coarse shift) until (dx^*, dy^*) that maximizes NCC is found.

Shift in z (dz^*) is calculated as the difference between the height means of D_{ref} and D_p.
Finally, the translation (dx^*, dy^*, dz^*) is applied to E_p to obtain $E_{p,aligned}$, which is saved as a point cloud file.

3) Fusion: In this step all point cloud files aligned in the previous step are combined into a single matrix:

$$M(x, y, k) = \begin{cases} E_{ref}(x, y) & \text{if } k = 0 \\ E_{p,aligned}(x, y) & \text{for } k = 1, 2, \ldots, P \end{cases} \tag{3}$$

A three-dimensional matrix is generated, where x, y represent the pixel location and every value of k is a layer which represents one of the point cloud in the fusion. The dimension k has a maximum value equal to the number of fused point clouds. The value of each cell in the matrix, $M(x, y, k)$, represents a height z. For each pixel x, y we perform a k-medians clustering analysis of the values of the heights along k with a similar approach than [10], increasing the number of clustering from a single one to a maximum number n_{max}, with the difference that in [10] n_{max} is always 8, and in our approach $n_{max} = min(8, length(k) - 1)$, such that n_{max} is equal to the number of existing heights minus 1 if there are equal or less than 8 heights or 8 if there are more. By this way, we are able to perform better with small numbers of fused DSMs, where using 8 clusters with less than 8 heights values has no sense. The number of clusters is increased until every cluster has a span between the minor and maximum height of each cluster less than a predefined value (arbitrary value used in this analysis: grid resolution + 1m). If one or two clusters are detected, the lowest level is saved, and if more are detected, it is saved as non-data, since the results are not considered coherent. Once the cluster is saved, the value of its median is taken as the height in that pixel, forming the DSM merged in a two-dimensional matrix.

The objective of this method is to obtain the best estimation of the height, by saving a height level which is similar between some of the DSM to be fused. The intention is to prevent objects above ground level, such as variable vegetation, from distorting the result by preserving the value that should represent the ground level, using the lowest height cluster. The heights corresponding to the object that perturbs the height value at that point would be stored in another cluster, obtaining the one cluster corresponding to the ground and that of the upper object. If more than two clusters are obtained, the value of the height at that point is considered invalid because it does not fit any of the cases, assumed to be a spurious result and stored as non-data.

4) Rasterization: Once the fused DSM has been obtained as a matrix, the objective is to generate a georeferenced raster image. This goal is achieved creating a 2D matrix for the DSM with dimensions defined by the resolution and the boundaries of the region of interest:

$$\text{width} = \left[\frac{x_{\text{max}} - x_{\text{min}}}{r}\right] + 1 \tag{4}$$

$$\text{height} = \left[\frac{y_{\text{max}} - y_{\text{min}}}{r}\right] + 1 \tag{5}$$

Where x_{min}, x_{max} is the maximum and minimum co-ordinate respectively in the chosen Coordinate Reference System (CRS), and the same for y_{min}, y_{max}. r represents the resolution of the DSM grid.

The matrix is initialized with NaN (Not a Number) values to indicate the absence of data. Each point in the point cloud is inserted into the DSM matrix. For each point (x, y), the corresponding position in the matrix is calculated and the value of z is assigned to that position.

To smooth the DSM and reduce noise, a weighted Gaussian filter is applied. This filter considers the proximity of the points and their height values to generate a more accurate DSM. The motivation for this method, not applied in [10], is to use one equivalent to the one used in the CARS rasterization [13], in order to make a fairer comparison between an original CARS DSM and the DSM resulting from the fusion.

Figure 1: Panchromatic band image (PAN) from the IARPA database

Finally, a raster image is created. The image is georeferenced using the geographic coordinates of one of the corners (typically the upper left corner) and the defined resolution. The geographic projection is established using a CRS corresponding to the worked portion of the surface. The final raster image, representing the DSM, is saved in GeoTIFF format. Each pixel of the image corresponds to a cell in the DSM matrix and its brightness value represents the height.

B. Real context validation

1) Dataset: The algorithm is used for fusing DSMs generated from the IARPA challenge dataset [17], which covers the city of Buenos Aires, Argentina. This dataset contains, among other files, 30 cm resolution NITF images from World-View 3 satellite, which can be converted specifying ROI to TIF images as in Figure 1 and GEOM files with the RPCs corresponding to each image. The specific site analyzed contains high- and low-density urban areas corresponding to city areas. They do not represent agricultural fields but contain some tree zones and a flat highway area, thus allowing the study of the algorithm's behavior in different types of terrain.

Based on the fusion method presented in Section II-A, different DSMs obtained from pairs of manually selected images have been fused under two of the criteria selected by [10]:

- The angle between the views of the image pair must be within 5º and 45º.
- Temporal proximity

For the generation of the DSMs and the visualization of the subtended angle between the views, a graphical interface of our own creation was used, which uses CARS for the generation of the point clouds for each pair of images.

2) Metrics: We compared the fused DSM with the original DSM generated by CARS using a very high quality LiDAR-generated DSM as ground truth. The following DSM quality metrics are used:

- Completeness: Percentage of pixels with valid values (not NaN).
- Root Mean Square Error (RMSE).
- Standard Deviation (STD).

C. Results

Following the procedure described in Section II, we obtain point clouds and their corresponding raster images as shown in Figures 2 and 3, respectively. Most of the occluded and vegetated areas visible in Figure 2 indicate that ground data has been obtained after the fusion (examples in red circles, where tree crowns, represented as groups of points higher than the ground with reddish colours, have been removed and ground points have been obtained).

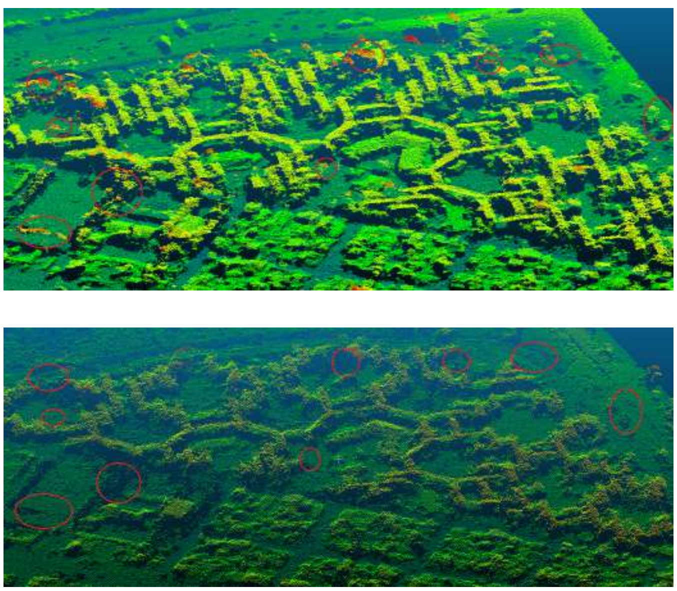

Figure 2: Original and fused point clouds. Top: Original DSM generated by CARS. Bottom: Fusion of 8 DSMs by applying the procedure described in section II-A.

This increase in completeness for number of DSMs within 3-12 is shown in Figure 4, where sections of the DSMs are shown: in Figures 4(a-I) and 4(a-II) we observe shadowed areas with no data (white color), whereas in the fused DSM of Figures 4(b-I) and 4(b-II) those areas are complete. It must be mentioned that in Figure 4 it is easy to see how some part of the trees have been removed in the fusion, and the more percentage of ground is shown, thanks to obtaining data on their height from the different views and dates of the DSMs.

The quality metrics of the fused DSM are plotted in Figure 5. In this case, we observe that there is a general trend of RMSE and STD reduction in Figure 5(a), and a quick increase in completeness, followed by a reduction from 12 fused DSMs.

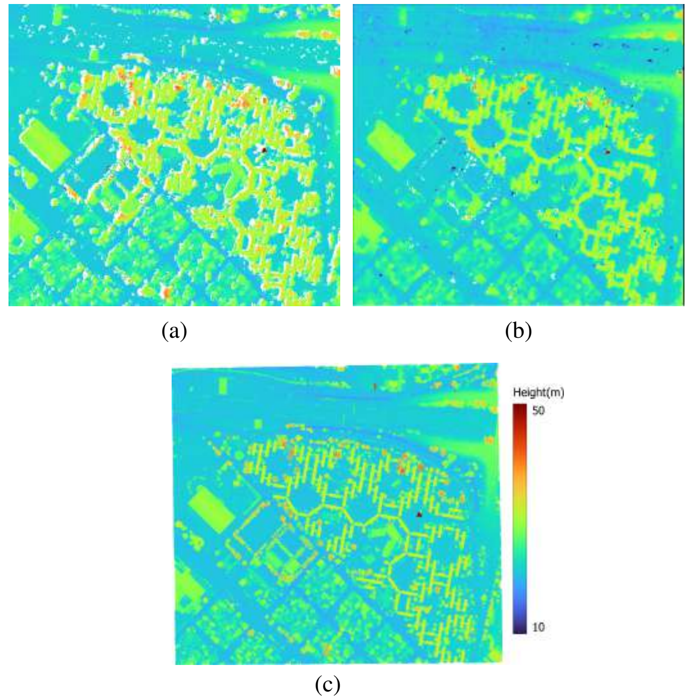

Figure 3: DSM comparison: a) Best individual DSM (from one pair only) among the ones used in the fusion. b) Fused DSM obtained from 8 DSMs from individual pairs. c) DSM obtained by LiDAR, used as ground truth.

Figure 6 shows the difference between the fused DSM and the ground truth taken by the LiDAR.

It must be mentioned that the improvement in results occurs with a lesser number of fused DSMs compared to [10], where the best results were obtained at around 50 fused DSMs. On the other hand, by adding a significant amount of DSM to fuse the completeness drop, as more pixel heights are considered as non-data. It is not clear whether this different behavior from [10] is due to differences in the algorithm used in the present work, or differences in the characteristics of the point clouds generated by CARS and S2P.

One of the advantages provided by this method is the possibility of removing a large part of the trees from the fused DSM by simply adding DSMs generated from images taken in the leafless trees season or by fusing DSMs generated from different views, so that data can be obtained for the occluded area. In Figure 6, we observe that the error of the merged DSM is significantly concentrated in the tree areas, as in the merged DSM the latter were eliminated, while being present in the image taken by the LiDAR. The k-clustering algorithm takes the cluster with the lowest value, which should correspond to the ground, and stores it as the height at that point. We can observe this phenomenon in Figure 4, where many trees have been removed. This has a negative impact on the error metrics, as this removal of trees, although not detrimental to the terrain representation, increases the error with respect to a LiDAR image with trees, so the overall STD and RMSE values do not accurately represent the improvement of the fused DSM with respect to the surface and are not reduced as much as possible due to the increasing of the error in the

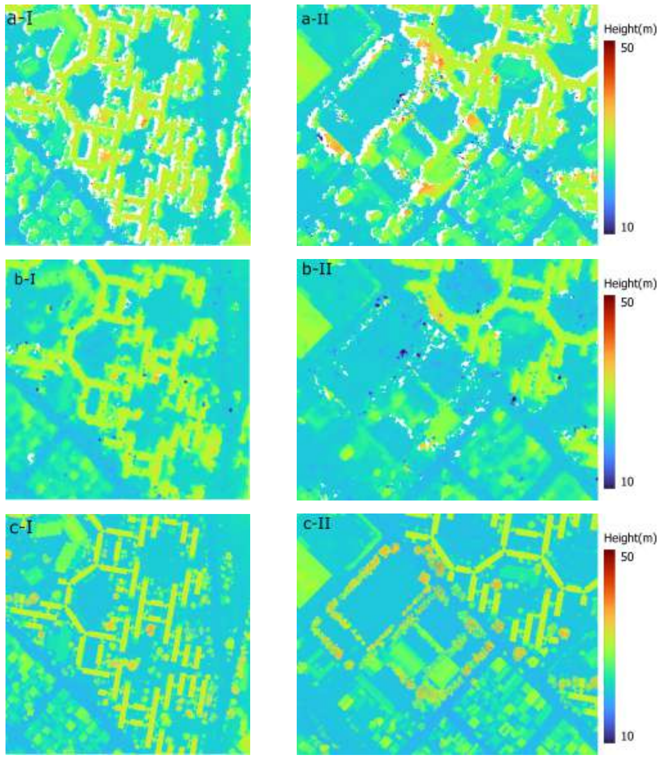

Figure 4: Sections of the DSM where different types of surfaces are shown. Horizontally: I) area with buildings and trees, II) area with trees on a flat sports field. Vertically: a) Best individual DSM (lowest RMSE value) b) Fused DSM. c) DSM obtained by LiDAR, used as ground truth.

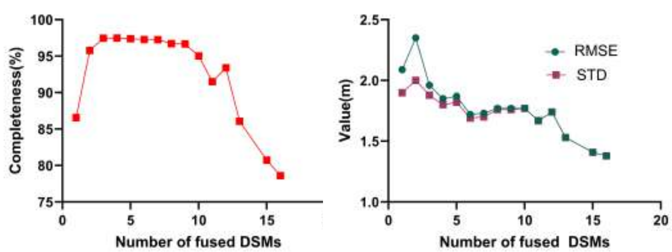

Figure 5: Metrics of the results obtained. Left: Completeness of the resulting DSM. Right: STD and RMSE values.

areas with trees. It should also be mentioned that while the improvement in RMSE and STD is around 15%-20% and 7%-12% respectively for the fused DSM with best results (with a completeness higher than the original DSM, using between 6-12 DSMs), the improvement in completeness is remarkable, offering a fused DSM with values greater than 97%, so that the problem of shadow areas without data in the original DSM is practically solved by this method.

III. Conclusions

A methodology to generate high-quality DSMs through the fusion of point clouds obtained from stereo images taken at different dates has been presented. This approach leverages the CARS software to generate point clouds, offering an improvement over previous software such as S2P. The study demonstrates that the fusion process significantly enhances the

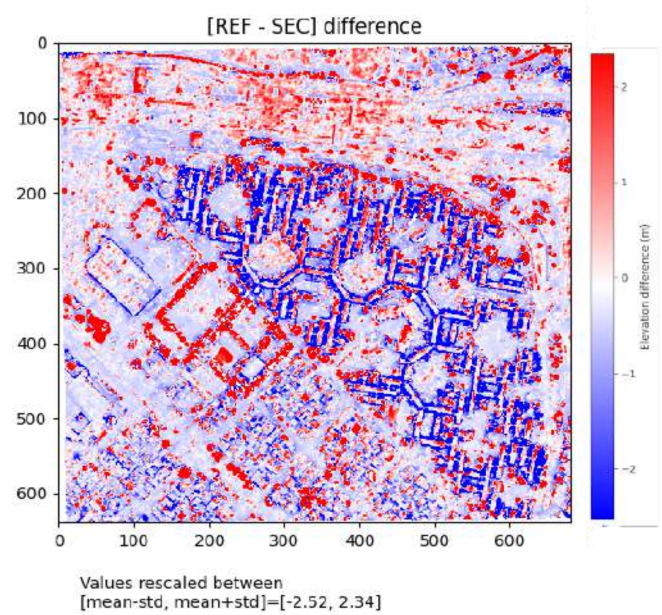

Figure 6: Difference between the fused DSM from 8 point clouds and the actual LiDAR value.

quality of the DSMs, particularly in terms of completeness and error metrics. The results validate the effectiveness of the proposed method in a mixed terrain, showcasing its potential for applications in precision agriculture and other fields requiring detailed terrain models. The successful integration of multiple DSMs results in a more comprehensive and accurate representation of the terrain, addressing challenges like shadow occlusions and temporal variations in the data.

These results confirm that the DSM fusion procedure improves the quality of the results, having improved them using a similar procedure from point clouds generated with different software.

Considering future continuation of this work, the quality metrics of our DSMs could potentially be improved by employing a more sophisticated procedure. This would involve generating all possible DSMs from pairs of images, organizing these DSMs based on their parameters, and selecting the most suitable ones. Additionally, incorporating enough different dates for covering the maximum surface area while considering changes in vegetation and luminosity would ensure a more comprehensive analysis. This approach, aimed at enhancing the accuracy and completeness of the DSMs, remains a subject for future work.

Finally, it should be mentioned that sustainable farming practices can be improved through the use of static DSMs, as they provide valuable insights for efficient irrigation, soil erosion prevention, optimized fertilizer application, and other key activities.

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Securing Digital Identities with Blockchain and Smart Contracts

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***Abstract*—The identity management model based on Self-Sovereign Identities, unlike classic models such as the centralized or federated model, allows users to have full control of their identity, without depending on external entities. A key element in a Self-Sovereign Identities-based system is the Verifiable Data Registry, where proofs and signatures of user credentials are securely recorded. This paper will present a Verifiable Data Registry that has been developed based on blockchain technology and implemented in an identity manager for a Data Space in the agri-food sector. In addition, the Smart Contracts developed to implement the necessary functionalities within the Self-Sovereign Identities context will be explained.**

Keywords-Self-Sovereign Identities; Blockchain; Verifiable Data Registry; Smart Contracts.

I. INTRODUCTION

Self-Sovereign Identities (SSI) systems are revolutionizing digital identity management by giving individuals direct control over their credentials, enhancing privacy and security [1]. The agri-food sector, a vital part of the European economy, faces significant challenges in managing sensitive data. In response to these challenges, within the European project DIVINE [2], an SSI-based identity management system is being developed [3] for a Data Space tailored to the agri-food sector, enabling stakeholders to benefit from shared data.

This paper presents an SSI-based system for the agri-food sector, focusing on the Verifiable Data Registry (VDR) [4]. The VDR, developed on a private Ethereum blockchain, enhances trust and transparency by immutably recording all transactions and credential issuance [5]. The use of Smart Contracts (SCs) further automates and enforces credential and permission management rules, reducing human error and increasing operational efficiency.

The structure of this paper is as follows: Section II covers the components and functionalities of the SSI system. Section III examines the VDR configuration and SC customization. Section IV summarizes key insights and suggests future improvements.

II. BACKGROUND

SSI represents a modern approach for managing digital identities, granting individuals complete control over their personal information [1]. Unlike traditional systems reliant on centralized authorities, SSI allows users to own and manage their digital credentials directly. This model enhances privacy by storing data in personal digital wallets (digital applications for managing, storing, and presenting Verifiable Credentials (VCs) securely), rather than on vulnerable central servers, thereby reducing the risk of breaches and unauthorized access. SSI also simplifies identity verification through cryptographic proofs, enabling secure presentation and validation of credentials.

Interactions within the SSI ecosystem rely on secure protocols and standards for trustless exchanges. VCs [4], which include metadata, claims, and cryptographic proofs, serve as digital equivalents to physical credentials. Metadata provides details about the credential, claims represent specific attributes, and cryptographic proofs ensure integrity and authenticity. Issued by trusted entities, VCs are securely stored and can be validated digitally.

The SSI ecosystem comprises three main actors and a VDR:

- **Holder**: The individual or entity that owns and controls their VCs, stored in a digital wallet.
- **Issuer**: The trusted entity that signs credentials, such as organizations or companies.
- **Verifier**: The party responsible for verifying the presented VCs. The verifier ensures that the VCs are properly signed by a trusted issuer and not revoked.
- **VDR**: A public or private ledger, functioning as a system or database, that stores public keys about issuers and other relevant data. The purpose of this ledger is to verify the authenticity of the VCs, holding the necessary information for verifiers to reliably assess their validity, without having to establish direct communication with the issuer, as illustrated in Figure 1. Often, blockchain technology is used as the VDR to ensure immutability and transparency.

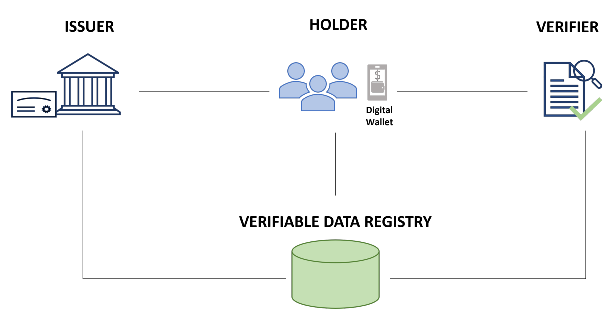

Figure 1. SSI Ecosystem.

This paper covers the development of a VDR based on blockchain technology for an SSI-based identity management system. Using a private Ethereum network with a Proof of Work (PoW) consensus, the VDR features distinct SCs for different SSI actors to meet the DIVINE project's needs. Key features of this solution will be outlined below.

III. Functional Analysis

This section explores the **VDR** and its associated **SCs** designed to improve secure and efficient identity management. The VDR, based on the SSI framework, gives users control over their identity data, using blockchain technology for secure and immutable record-keeping.

The VDR operates on a private Ethereum blockchain consisting of three nodes. It utilizes PoW as its consensus mechanism, ensuring secure and immutable management of identity records. Ethereum was chosen for its robust SC capabilities and decentralized nature, while PoW provides network security and resistance to censorship [6].

SCs tailored to each participant in the SSI ecosystem - holders, issuers, and verifiers - have been created in Solidity [7] and implemented within the VDR to automate the management and validation of VCs. These self-executing programs enforce agreements based on predefined conditions, improving efficiency and security by eliminating intermediaries [8]. Developed as part of the DIVINE project, these SCs follow Ethereum's ERC-735 and ERC-725 standards, enhancing SSI system functionality and security. ERC-735 [9] manages VCs on the blockchain and ERC-725 [10] governs key and permission management associated with these digital identities.

For the **holder's** SC, based on ERC-735, the development includes:

- **Status Field Addition**: A status field in the Claim structure indicates if a claim is signed, pending, denied, or revoked, improving claim management.
- **Claim Editing Functions**: Functions allow holders to edit claim data and URI. Modifying data revokes the claim, requiring re-submission to the issuer for re-signing if valid.
- **Verifier Management Functions**: A verifier field in the Claim enables holders to manage who can access their claims and control verifier access.
- **Claim Overview Functions**: Functions for viewing all claims and retrieving claim IDs have been added.

The SC for the holder includes the following functions: *getClaimId, getClaim, getClaimIdsByType, addClaim, editData, editScheme, editUri, removeClaim, addVerifier, removeVerifier, generateClaimToSign, getClaims, and editStatusHolder*. The Claim structure for the holder's SC contains the following fields: *topic, scheme, issuer, signature, data, uri, verifiers* and *status*.

For the **issuer's** SC, based on ERC-734, the design includes:

- **Key Struct Revision**: The Key structure has been simplified to include keyType (e.g., Elliptic Curve Digital Signature Algorithm (ECDSA) or Rivest–Shamir–Adleman (RSA)) and key fields.
- **Claim Struct Introduction**: A new Claim structure with fields for claimId, holder, signature, data, timestamp, and status enhances claim management and tracking.
- **Function Enhancements**: New functions for managing and handling claims and keys have been added, including features for authenticating and verifying claims, retrieving specific claims, and updating claim statuses.

This SC includes the following functions: *getKey, signClaimToHolder, getClaim, getClaimSignature, addrToKey, addHolderClaim, getClaimList, unsignClaimToHolder, editClaimStatus, getClaimIssuer, and removeClaimIssuer*. The issuer uses the *getClaim* function to view the holder's claim. If the data provided in the topic field is valid, the issuer will sign the claim. This will modify the *signature* field in the claim, adding a cryptographic proof that contains information of the holder, the data and the topic of the claim.

A specialized SC fulfills the role of **verifier**, including the following features and functionalities:

- **Validate Claims**: Functions to verify if a claim's topic aligns with the holder's context.
- **Issuer Managements**: Functions for allowing issuers to sign claims on specific topics, enhancing verification and topic integrity.

For the verifier's SC, the design includes the following functionalities: *checkClaimPurposes, checkClaimByPurpose, claimToSign, addTopicToIssuer, removeTopicFromIssuer, getSignatureAddress, and checkPurposesByIssuer*. Once the holder's claim has been signed, the verifier will check the *signature* field in the claim, which contains a cryptographic proof of the *issuer* who signed it. The verifier will then verify that the *status* field in the claim is set to "approved" and that one of the entries in the *verifiers* field corresponds to the verifier performing the check. These enhancements collectively strengthen the system for managing digital identities and claims.

IV. Conclusion and Future Work

In this work, a VDR for an SSI-based identity management system based on blockchain technology has been developed, which improves security and immutability. As part of the DIVINE project, participants in the identity management system - known as holders - obtain digital identities through VC. These participants register their applications, designed for the agri-food sector, on the platform, with the applications functioning as issuers. The credentials will represent roles within specific applications, and the issuer will sign this credentials. An identity provider will act as the verifier, ensuring the validity of the VCs in each request.

Future improvements will include migrating the credential format to align with the European Blockchain Services Infrastructure (EBSI) [11] for regulatory compliance and better interoperability. Additionally, transitioning from PoW to Proof of Stake (PoS) will be explored to enhance system efficiency and sustainability.

Acknowledgment

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The Contribution of Benchmarking Tools to Increasing Transparency in Agricultural Data Sharing in Value Chains and Farmer's Trust

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***Abstract*— The digitalization of agriculture through the proliferation of Information Technology (IT) capabilities has generated exponential growth in data. In this context, agriculture generates a large amount of data, but its potential often remains unexplored. The reasons are identified in technical interoperability, commercial relationships between stakeholders and social acceptability issues related to data ownership and market transparency. However, a lack of experience in managing data or adopting data-driven services can limit the opportunities arising from digital transformation. This study shows how the development of benchmarking tools serves as a support to promote greater trust in sharing data by farmers who should be informed about the purpose of the survey they are invited to participate in, and to ensure the success of the surveys.**

Keywords-agricultural data sharing; interoperability; farmer's trust.

I. Introduction

This study investigates the use of benchmarking tools to help increase farmers' confidence in sharing agricultural data. The digitalization of agriculture has generated exponential growth in agricultural data. Although data sources in agriculture and software for their analysis and valorization are growing, there still seems to be a lack of true interoperability between systems that allows for adequate exploration. In the institutional context, the European Commission has stressed in several documents the need to facilitate and strengthen the agricultural data sharing and optimise their use for better policies design [1][2][3]. The increase in connected devices during daily operations has led farmers to become more digitalized and more aware of the potential benefits of digital technologies for their business and related data sharing scenarios.

Although datasets are useful for analysis at individual stages of the supply chain, they also have significant potential for widespread use if they are made interoperable. The valorisation and use of agricultural data implies that the owners of the data also agree with their sharing. However, the willingness to share by data owners is low and it is precisely this lack of sharing and its acceptance that is the biggest obstacle. Therefore, despite a rigorous set of rules, cultural barriers and security concerns remain, which slow down the exploitation and sharing of data. This reduces the actual value that data can play for the for the European Union (EU)'s agricultural competitiveness. The nature of agricultural data is highly specific, but very diverse, and the economic value it generates both for farmers and the entire value chain requires that the necessary safeguards be established. Due to these features, it is difficult to monitor who is authorized to share data and which data is shared. Furthermore, it is known that transparency is necessary to consolidate farmers' trust regarding data sharing. The lack of transparency and clarity on issues such as data ownership, portability, privacy, trust and accountability in the business relationships that govern smart agriculture are contributing to farmers' reluctance to engage in widespread sharing of agricultural data. At the heart of the concerns is a lack of trust among farmers as data providers and third parties, regarding unauthorized access, collection and sharing of their data with third parties by agricultural technology providers. Additionally, ambiguity in agreements and legal frameworks on data collection, processing and sharing can lead to practical uncertainties regarding data privacy. A major concern is transparency and distributional concerns about who in the value chain will benefit from accessing and using "*farmer data*." These concerns create skepticism about their potential use among stakeholders and particularly farmers [4]. This paper is structured as follows. The first Section shows the introduction; in Section II, we present the methodology of our approach. Section III discusses our results and we conclude the discussion in Section IV.

II. Methodology

Our study presents a benchmarking model implemented with data provided by farmers. We intend to contribute to increasing farmers' trust by demonstrating that sharing agricultural data can provide them with valid support for farm management. The tool was developed within the DIVINE project (DemonstratIng Value of agri data sharIng for boostiNg data Economy in agriculture) [6] that aims at building an Agricultural Data Space Ecosystem or sharing and analyzing agricultural data, funded by the European Union through the Horizone Europe program. To proceed with the construction of a benchmarking system, we identified the useful indicators, based on several studies available in the literature about the topic of Key Performace Indicators (KPIs). According to Bodini et al. [5], important sources of data which are currently of potential use for benchmarking in agriculture include: i) accountancy data (e.g. Farm Accountancy Data Network (FADN) or other accountancy data); ii) official statistics data (e.g. Farm Structure Surveys, Economic accounts for agriculture); iii) specific administrative registers (e.g. animal traceability databases, land use and ownership databases, producer and subsidies registers, animal veterinary drug use registers); iv) industry supply/processor databases; v) technical data inputted by primary producers directly or collected by specialist bodies; vi) machine/sensor-derived data.

Following this approach, our benchmarking tool has been developed by the implementation of a set of DIVINE compliant components that can be demonstrated in the pilot activities, based on available data.

III. Results

As a result of the analysis of pilot requirements, three types of benchmarking were selected to be applied to the specific components:

– Generic Farm Comparison: a generic tool usable by all farms with a minimum set of requested inputs, that allows each farm to know its performance over the years. The component will provide, to each farm, a set of basic indicators to be used to get a general benchmark of the farm activities. The system should be connected to the FADN or other farm-level data sources and will be able to provide each farm with an estimated reference of the farm performance indicators. From the farm's general structure, a set of general indicators (European regions, dimension, surface by crops, composition of livestock) will be defined.

– Farm Group Benchmarking: a tool usable by a single farm to compare its results with those of a group of similar farms in terms of type of farming, location area, economic size, etc.

– Top Farms Benchmarking: a tool helping farmers evaluate their performance in comparison with a group of farms that realized the best performance in the considered. The benchmarking tool use the Agricultural Interoperability Spaces (AIS) [7] to access the farm data in a standard format. When a user accesses the benchmarking tool, the general interface of the benchmarking system will clearly explain the required data and each farmer will have control of their data. It will be possible to define which data to send to the benchmarking component and if the user agrees that the resulting indicators will be available. The indicator can be used anonymously, to calculate a set of reference values to be used for benchmarking. Our results, i.e. the development of our benchmarking tool, aim to fill the lack of concrete examples of how data sharing in the agri-food sector can be useful for the analysis of economic performances. Although some attempts have been made to encourage interoperability, there are still important challenges to address. The sharing of this data between supply chain actors and interested parties therefore requires greater depth if we want to introduce greater efficiencies and further added value to the agricultural data economy.

IV. Conclusions

Our research study intends to offer a contribute to show the cost and benefit and added value of sharing agri-data to support policy makers, technology providers, farm representatives and other agri-data stakeholder.

Acknowledgment

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Forecasting Agricultural Time Series Sensor Data Using Long-Short Term Memory Autoencoders

Towards Regenerative Farming

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***Abstract*—Conventional Agriculture is evolutionizing towards Regenerative Farming, which involves a range of techniques supported by innovative technologies to address climate change. Among them is the IoT (Internet of Things) technology in agriculture, which has seen continuous streams of data in real-time. From the use of drones to deployment of Wireless Sensors in the field, data is collected and transmitted via a communication channel to an Internet of Things platform. In this paper, we analyze the use of digital tools in regenerative farming, specifically soil sensors, and demonstrate this with the use of Long-Short Term Memory (LSTM) autoencoders to forecast future sensor readings based on historical data which can help a farmer make better farming decisions. LSTM networks are a type of Recurrent Neural Networks (RNNs) and have the ability to capture long-term dependencies, handle complex patterns in sequential data, and learn from past errors. This is evident through their use in predicting household power consumption, network traffic speed prediction, and predicting the crop yields. The proposed model is applied to the Cook Agronomy Farm (CAF) dataset, which contains field-scale sensor dataset for soil moisture and soil temperature at various levels. Using the Root Mean Square Error (RMSE) to evaluate the performance, the proposed model takes in multiple features as input and forecasts multiple steps and multiple parallel features. Traditional models such as Autoregressive Integrated Moving Average (ARIMA) have been used to forecast multivariate time series data. However, the proposed LSTM autoencoders perform with high accuracy and robustness in forecasting agricultural sensor data.**

Keywords-time series forecasting; LSTM autoencoders; precision farming; wireless sensors.

I. INTRODUCTION

Traditionally, farmers have been relying on the natural resources like rain [21] and sunshine for plant growth, as well as farmers instincts based on routine practices with emphasis on manual labor and simple tools like hoes. This generally leads to low yields and losses due to uncertainty caused by climate change. Over time, farming has evolved with farmers adopting modern farming practices, organizations and governments investing in advanced technology, and mechanization. Wireless sensors are deployed in the garden to measure soil moisture, temperature, Nitrogen, Phosphorus, and Potassium (NPK) and soil nutrients. The data collected can be analyzed to help improve farming practices.

Current prediction methods for agriculture sensor data focus on the real-time data to make recommendations. For example, in 2020, an IoT-based software system was proposed [1] for monitoring soil nutrients such as Nitrogen, Phosphorus, Potassium, soil pH, and temperature in real-time and can make recommendations regarding the quantity of water and fertilizers. Reashma and Pillai [3] discussed the use of machine learning techniques like Random Forest, Support Vector Machine (SVM) in three soil factors which are soil properties, soil moisture, and selection of crops. This is quite important when incorporated with domain knowledge to determine the course of action. This approach, however, seems hectic and would require much attention to the predictions. Time series data is a sequence of data collected over time intervals, allowing for tracking changes of a certain magnitude over time [5]. Sensor data collected over a period of time exhibits patterns such as trends, seasonal fluctuations, irregular cycles and occasional shifts in level or variability. Analyzing such series data helps us to extrapolate the dynamic patterns in the data to forecast future observations, estimate the effect of known exogenous interventions, and to detect unsuspected interventions. This has helped address real-world problems, like health monitoring, Web-Visitor traffic, and Network-wide traffic speed prediction [7].

Time series data can be univariate, i.e., data containing only one feature variable, or it can be multivariate i.e., data with multiple feature variables. Traditionally, time series forecasting includes methods such as K-Nearest Neighbor (KNN) [8] and Autoregressive Integrated Moving Average (ARIMA) [9], which can handle time-dependent data and achieve high forecasting accuracy on multiple frequencies (e.g., hourly, daily, weekly, monthly). However, the recent advancement of deep learning, neural network architectures, and compute capacity has seen breakthroughs in robustness and performance for a variety of problems including sequence-to-sequence-learning tasks [10][11] surpassing traditional forecasting models with data generated from retail, stock markets, traffics, to mention but a few, and are yet to gain momentum in the field of agriculture. Thus, in

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this paper, we aim to demonstrate the significance of deep learning in the shift towards regenerative learning particularly, building a model for multistep time series forecasting of agriculture sensor data. We use publicly available sensor data collected from different fields over a certain period of time and analyze it using the LSTM autoencoder.

The major contributions of this paper are:

- A detailed explanation on the significance of deep learning to achieve regenerative farming.
- An approach for multistep output forecasting using LSTM autoencoders.
- A demonstration of the proposed work using the publicly available sensor data [4] for validation.

The rest of this document is structured as follows: Section 2 explains regenerative farming in detail and briefly surveys the literature on LSTM and time series forecasting using LSTM autoencoders. Section 3 briefly formulates the challenge that we address in this study. Section 4 formally defines the proposed approach and provides the details of the implemented model. Section 5 describes the experimental evaluations and provides an interpretation of the results. Finally, Section 6 concludes the paper and discusses the next steps of this work.

II. REGENERATIVE FARMING

Regenerative farming is an evolution of conventional agriculture, where farmers rotate different types of crops over time reducing the use of water and other inputs and preventing land degradation and limiting pest infestations. It protects and improves soil biodiversity, climate resilience, and water resources while making farming more productive and profitable. From Africa to Asia, all the way to Europe and America, we have witnessed the impacts of climate change where some areas have had devastating impacts and others are yet to. This makes it hard for conventional farming to be profitable with high productivity. Hence, the need for more sustainable practices aimed at restoring soils and biodiversity, as seen in Figure 1. These practices, though they vary from place to place, include:

- Minimizing soil disturbances by adopting no-till or reduced till techniques.
- Planting cover crops between cash crops to prevent soil erosion and increase carbon inputs.
- Integrating livestock when possible.
- Diversifying crops in time and space by adopting intercropping.
- Precision application of biological and inputs.

Data-driven is a key part of regenerative agriculture, which involves the use of digital tools like wireless sensors connected to other IoT systems which collect the data, process and analyze it to provide a farmer with clear insight with what is happening on the ground. This, in turn, leads to the use of the optimal amount and the right type of product needed for a productive crop. Regenerative agriculture mitigates climate change through carbon dioxide removal, that is, it draws carbon from the atmosphere and sequesters it [12]. Deep learning has been widely adopted for time series data analysis [13] as models learn better with huge amounts of data, with the ability to extract both temporal and spatial features effectively. It offers significant potential to enhance regenerative agriculture practices through precise soil data analysis and forecasting. By analyzing soil sensor data, deep learning models can provide real-time updates on soil moisture, temperature, nutrient levels, and other critical parameters. We can forecast crop yields based on soil conditions [22] and determine the optimal timing and amount of fertilizer based on soil nutrient needs [6], reducing waste and environmental impact.

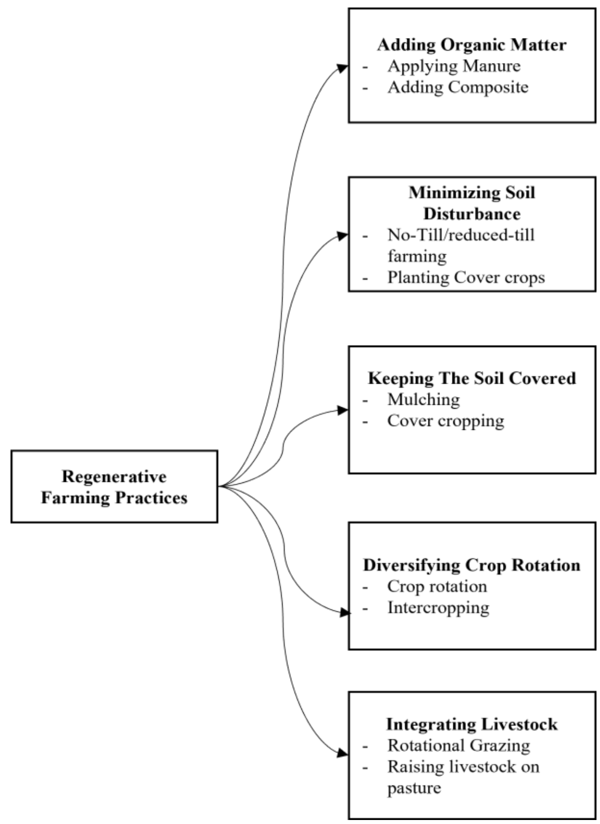

Figure 1. Core Principles of Regenerative Farming.

A. *Time Series Forecasting*

Time Series Forecasting plays an important role in weather prediction, stock market forecasting, etc., it is the use of a computer model to predict future values based on previously observed values, i.e., fitting a model to historical, time-stamped data in order to predict the future values. Traditional approaches include moving average, exponential smoothing, and ARIMA but recently, due to massive data generated by IoT devices, deep learning models like Recurrent Neural Networks (RNNs), Transformers, XGBoost, etc., have proven effective in extracting features from the data for forecasting. One of the most advanced models for forecasting time series is the Long-Short Term Memory (LSTM) Neural Network.

B. *Precision Farming*

Precision Farming is the use of technology to make farming more accurate, controlled, and optimized. It involves observing, measuring, and responding to inter- and intra-field variability. Precision Farming can help implement and maintain Regenerative Agriculture practices like precisely applying chemicals and monitoring soil health by leveraging technology to optimize resource use and maximize yield, while minimizing environmental impact.

1) *Long Short Term Memory Networks*

The Long Short-Term Memory (LSTM), illustrated in Figure 2, is a type of Recurrent Neural Network (RNN) designed to overcome the exploding and vanishing gradient descent with the ability to effectively capture temporal dependencies and to make accurate predictions. Through the standard recurrent layer, self-loops, and the internal unique gate structure, the LSTM network effectively improves the exploding and gradient vanishing problem existing in the traditional RNN. It has the form of a chain of repeated modules of neural networks, where each module includes three control gates, i.e., the forget gate, the input gate, and the output gate. As seen in Figure 2, each gate is composed of a sigmoid neural net layer and a pointwise multiplication operation. The sigmoid layers output numbers in the interval [0, 1], representing a portion of input information that should be let through. As the use of a RNN for time series data, the LSTM reads a sequence of input vectors $X = \{x_1, x_2, \ldots, x_t, \ldots\}$, where $x_t \in R_m$ represents an m-dimensional vector of readings form variables at time-instance t.

Given the new information x t in state t, the LSTM module works as follows. Firstly, it decides what old information should be forgotten by outputting a number within [0, 1], say f_t with

$$f_t = \sigma_1(\mathbf{W}_f .[h_{t-1}, x_t] + \mathbf{b}_f), \quad (1)$$

where h_{t-1} is the output in state $t-1$, W_f and b_f is the weight matrices and the bias of the forget gate. Then, x_t is processed before storing in cell state. The value i_t is determined in the input gate along with a vector of candidate values $\tilde{C}_t$ generated by a tanh layer at the same time to updated in the new cell state C_t, in which

$$i_t = \sigma_2(\mathbf{W}_i .[h_{t-1}, x_t] + \mathbf{b}_i), \quad (2)$$

$$\tilde{C}_t = tanh(\mathbf{W}_c [h_{t-1}, x_t] + \mathbf{b}_c) \quad (3)$$

and

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t, \quad (4)$$

where $(\mathbf{W}_i, \mathbf{b}_i)$ and $(\mathbf{W}_c, \mathbf{b}_c)$ are the weight matrices and the biases of input gate and memory cell state, respectively.

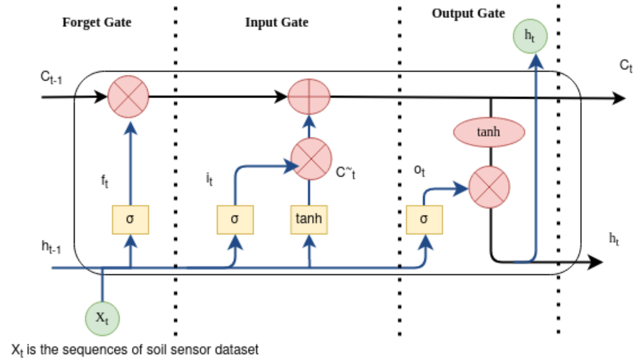

Figure 2. LSTM Network.

Finally, the output gate, which is defined by

$$o_t = \sigma_3(\mathbf{W}_o .[h_{t-1}, x_t] + \mathbf{b}_o), \quad (5)$$

$$h_t = o_t * tanh(C_t). \quad (6)$$

where $\mathbf{W}_o$ and $\mathbf{b}_o$ are the weight matrix and the bias of output gate, determines a part of the cell state being outputted. Figure 2 presents an illustration of the structure and the operational principle of a typical vanilla LTSM module. In this figure, the cell state runs straight down the entire chain, maintaining the sequential information in an inner state and allowing the LSTM to persist the knowledge accrued from subsequent time steps. Note that there are no weights and biases that can modify the cell state (Long Term memory). This allows it to flow through a series of unrolled units without causing the gradient to **explode** or **vanish**. Short-Term memories are directly connected to weights that can modify them. The first stage in the Long Short-term Memory unit determines what percentage of the Long-term memory is remembered. It is usually called the **Forget Gate**. The other part of the LSTM is usually called the **Input Gate**. The final stage of the LSTM updates the Short-term memory. The new long-term memory is used as input to the Tanh activation function. The previous three cases to determine the percentage of long-term memory to remember we use a sigmoid activation function. Because the new short-term memory is the output from this entire LSTM unit, this stage is called the **output gate**.

Besides forecasting, LSTMs have been used to solve other sequence learning problems like language modeling and translation, audio and video data analysis, handwriting recognition and generation among others.

2) *Autoencoders*

An autoencoder is a special type of feed forward neural network trained to efficiently compress (encode) input data down to its lower dimensional representation containing essential features or latent variables only (bottleneck), then reconstruct (decode) the original input from this compressed representation. Most autoencoders are used to solve AI related tasks like feature extraction [15], data compression

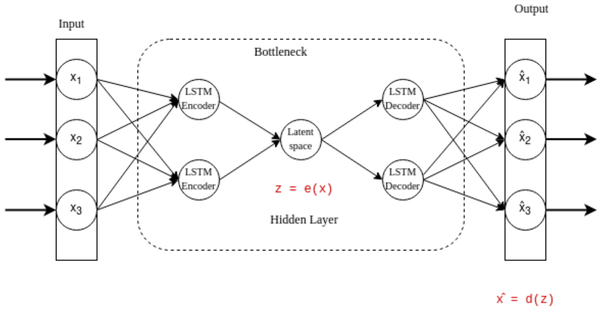

Figure 3. Illustration of LSTM Autoencoders.

[16][17], image denoising [18], anomaly detection [19], and facial recognition [20]. We use LSTM autoencoders, as illustrated in Figure 3, for multistep output forecasting of time series data.

LSTM autoencoders (Figure 3) utilize the capabilities of both the LSTM neural network and autoencoder which builds the LSTM network on the encoder and decoder schemes of Autoencoder. To forecast, we provide each one-dimensional time series to the model as a separate input sequence. The network then creates an internal representation of each input sequence that will together be interpreted by the decoder.

III. DATASET DESCRIPTION

The Cook Agronomy Farm (CAF) sensors folder [4] consists of a field-scale sensor network dataset for monitoring and modeling the special and temporal variation of soil moisture in dryland agricultural field. It includes hourly and daily measurements of Volumetric Water content (VW) sensor and soil Temperature (T) sensor readings, collected at 42 monitoring locations, and 5 depths (30, 60, 90, 120, and 150 cm) across Cook Agronomy Farm, collected from 2007 to 2016. As described below:

- VW_30cm: Volumetric Water readings at 30 cm depth (m^3/m^3)
- VW_60cm: Volumetric Water readings at 60 cm depth (m^3/m^3)
- VW_90cm: Volumetric Water readings at 90 cm depth (m^3/m^3)
- VW_1200cm: Volumetric Water readings at 120 cm depth (m^3/m^3)
- VW_150cm: Volumetric Water readings at 150 cm depth (m^3/m^3)
- T_30cm: temperature readings at 30 cm depth (C)
- T_60cm: temperature readings at 60 cm depth (C)
- T_90cm: temperature readings at 90 cm depth (C)
- T_120cm: temperature readings at 120 cm depth (C)
- T_150cm: temperature readings at 150 cm depth (C)

Note that not all these features will be used. For demonstration purposes, only a few features will be selected. Figure 4 is a plot for the sensor data between 2009 to 2012 and helps us to see the trends and seasonality.

A. Problem Statement

The CAF sensors data above is multivariate time series data describing the soil moisture and temperature sensor readings at different ground levels. Before planting any crop, it is important to have an idea of the crop requirements aforehand. We will use the data to address the question:

"We know the optimal soil water content and soil temperature for a certain crop at various stages of growth so, given the recent soil sensor readings, what is the expected soil sensor readings for the week ahead?"

This calls for the building of a predictive model to forecast the soil sensor readings over the next seven days. Technically, this is a multi-step time series problem, given the multiple forecast steps. Since we are dealing with multiple input variables, and predicting multiple steps ahead, this is called multi-step multivariate time series forecasting.

Note that, before we extract any useful insights from the data, we must clean the raw data by performing data wrangling and reshaping it into formats acceptable by the model for training. Good enough, the CAF data set is already separated into daily and hourly so in this paper, we are working with the daily sensor readings, not the hourly. We see from Table 1 that the data contains a lot of missing values. Table 2 shows how the dataset looks like after removing the missing values, converting the data type to numeric, and setting the date column as index.

The dataset has been split into training and test dataset. Furthermore, the train and test dataset has been organized into sequences of 7 days. The training dataset has 203 sequences, while the test dataset has 46 sequences. Remember it is a multivariate time series data, so we are dealing with 4 features.

Deep learning makes it easy for the farmer to analyze the soil and other parameters for better course of action such as knowing when to apply fertilizers, irrigating or performing drainage. In this paper, we are using LSTM Autoencoders on historical soil sensor readings to predict the possible future readings. The data in Table 2. Is not ready to be ingested into the LSTM model yet. We first normalize it using either the standard scaler or the minmax scaler to improve the model performance before splitting it into train and test dataset.

TABLE 1. RAW DATA CONTAINING MISSING VALUES.

Date	VW_30cm	VW_60cm	VW_90cm	T_30cm
04/20/2007	nan	nan	nan	nan
04/21/2007	nan	nan	nan	nan
04/22/2007	nan	nan	nan	nan
04/23/2007	nan	nan	nan	nan
04/24/2007	nan	nan	nan	nan

TABLE 2. SAMPLE DATA AFTER CLEANING.

Date	VW_30cm	VW_60cm	VW_90cm	T_30cm
05/21/2009	0.244	0.273	0.303	14.49
05/22/2009	0.243	0.276	0.308	13.61
05/23/2009	0.244	0.277	0.311	14.42
05/24/2009	0.244	0.279	0.313	15.15
05/25/2009	0.244	0.28	0.315	15.35

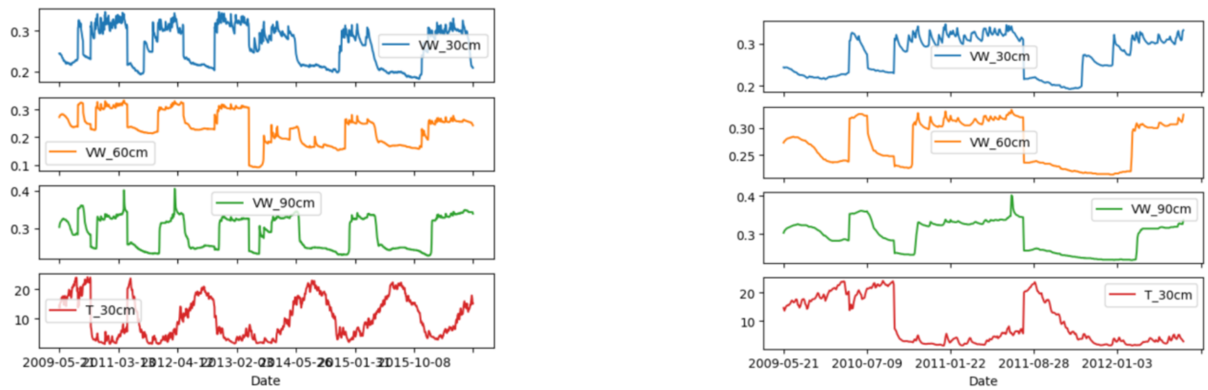

Figure 4. Soil Sensor Readings from 2009 to 2012.

B. Evaluation Metrics

Our model is going to forecast seven values, each representing the reading for a day in the week ahead. We will evaluate each forecasted timestep separately, doing so helps us to:

- Comment on the skill at a specific lead time (for example, +3 days versus +6 days) thereby helping us select an accurate forecast horizon.
- Contrast models based on their skills at different lead times

We will use the Root Mean Square Error (RMSE) as our performance metric. Evaluating the performance for each lead time from day 1 to day 7.

IV. MODEL ARCHITECTURE

We built the Encoder Decoder LSTM model to forecast Multiple Parallel Input and Multi-step multivariate time series sensor data using Tensorflow. Figure 5 shows the summary of the model architecture.

The Encoder-decoder architecture is good for sequence-to-sequence learning and as seen above, each is configured with 200 LSTM units. The first layer of the LSTM is the encoder, and the second one is the decoder. The latent vector is a 1-D array which is converted to the original number of features in the decoder level. The encoder is responsible for reading and interpreting the input, it compresses the input into the small representation of the original input (latent vector), which is then given to the decoder part as input for interpretation and forecasting. A RepeatVector layer is used to repeat the context vector obtained from the encoder. It is repeated for the number of future time steps (7 in our case) and fed to the decoder. The output received from the decoder in terms of each mixed. A fully connected Dense layer is applied to each time step via TimeDistributed wrapper, which separates the output for each time step.

The RepeatVector increases the dimension of the output shape by 1. TimeDistributed is kind of a wrapper and expects another layer as an argument. It applies this layer to every temporal slice of input and therefore allows to build models that have one-to-many, many-to-many architectures and expects inputs of at least 3 dimensions.

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 200)	164,000
repeat_vector (RepeatVector)	(None, 7, 200)	0
lstm_1 (LSTM)	(None, 7, 200)	320,800
time_distributed (TimeDistributed)	(None, 7, 100)	20,100
time_distributed_1 (TimeDistributed)	(None, 7, 1)	101

Figure 5. Summary of the LSTM Model

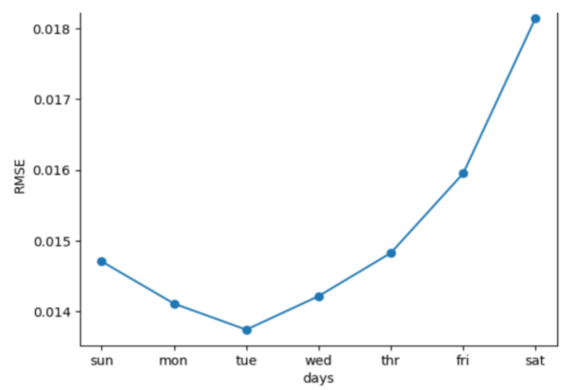

Figure 6. Plot of the RMSE for the 7 days.

A. Model Performance

We ran several experiments tuning the batch size, number of epochs, number of LSTM units and the time steps and obtained different results. However, when we set the batch size to 4 and ran 100 epochs, looking back 14 days to predict the next 7 days of the soil sensor readings (since we used the Root Mean Square Error as the evaluation metric), the model performed well with the overall RMSE of 0.015 (Figure 6).

V. Conclusion and Future Work

The agricultural sector is undergoing a significant transformation, driven by the urgent need for sustainable and regenerative practices. Among the latest innovations making waves are the technology-driven solutions which include use of advanced sensors and data analytics to assess soil quality, organic matter, and nutrient levels, guiding tailored interventions. Adopting precision farming by leveraging drones, satellite imagery, and Artificial Intelligence can help to optimize the use of resources, monitor crop health, increase yields and attaining regenerative farming in the process. The challenge, however, is that many farmlands are located in rural areas with poor network connectivity but with time, infrastructures are being put in place to improve connectivity. The LSTM autoencoders are state of the art networks and have been used in predicting indoor air quality, power load forecasting, among others. We just demonstrated its use in forecasting agriculture sensor data which is crucial in regenerative farming as it saves farming costs through effective use of resources. The experiments carried out to test the proposed model show that the performed well with high accuracy. This means farmers can confidently make better decisions depending on the forecast.

As future work, we will develop a Farm Management Information System (FMIS) using Fiware Technology and embed the proposed model to forecast. The FMIS will automate the farm activities thereby saving the farmer time and money.

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Identity Provider based on Self-Sovereign Identities and Blockchain Technology

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***Abstract*—The paper presents a work in progress on the improvements made to CredSSI, an identity management system based on Self-Sovereign Identities (SSI), developed as part of a European initiative for a data space in the agri-food sector. Enhancements include the development of a digital wallet for secure and efficient user credential management, the incorporation of a Police Enforcement Point Proxy to streamline user request handling by service providers, and the implementation of a traceability module that uses blockchain technology to log and secure system events. These improvements enhance security, privacy, and operational efficiency in digital identity management through the Self-Sovereign Identities approach.**

Keywords-SSI; blockchain; identity wallet; verifiable credential.

I. Introduction

Protecting personal data is essential for cybersecurity in the digital age. Users need to trust that their data stays secure and private online, making identity management crucial for safe and efficient service access.

Traditional identity management methods, like centralized or federated systems, focus on the organizations managing user identities. This can lead to potential privacy vulnerabilities and data protection law breaches. As an alternative, a new model of identity management is emerging, with the user at the center. This is called Self-Sovereign Identity (SSI) [1][2], providing the user with full control over their information. This reduces reliance on centralized authorities and enhances privacy and security using cryptographic and blockchain techniques. This technology provides an extra layer of protection and trust, which means that recorded transactions cannot be altered or erased. In addition, its transparency facilitates tracking of all transactions. Because of these advantages, SSI is increasingly becoming a solution for identity management across various sectors, including the agri-food industry [3]. This industry is transitioning digitally to enhance efficiency, traceability, and sustainability through data and identity management processes with secure, reliable, and user-centric solutions to ensure secure access and facilitate interactions within complex data systems.

As part of the European DIVINE project [4], an advanced identity management system based on SSI is being developed for a Data Space related to the agri-food sector. This project addresses critical needs in agriculture, where secure, efficient data sharing supports both sustainability and digital transformation goals. Each of the DIVINE pilots demonstrates unique use cases that benefit from the SSI system by enabling safe data exchange and reliable user interaction across various agricultural services. This work builds upon previous studies [5], by implementing enhanced features such as a traceability module, which provides a robust, immutable record of system events, and a digital wallet for secure credential management. Additionally, a Police Enforcement Point Proxy (PEP-Proxy) has been activated to streamline requests, improving both security and user experience.

This paper will study the design, implementation, and benefits, showing how it addresses challenges related to data security, access control, identity management and its traceability, thereby supporting the sector's digital transformation.

The rest of the paper is organized as follows: Section 2 outlines the key background concepts essential for understanding digital identities, with a particular focus on SSI. Section 3 presents an analysis of the related work on SSI and applications already being implemented. Section 4 presents the use case architecture, detailing the main components involved in the SSI model. Section 5 focuses on an explanation of the process used to verify the system's functionality. Section 6 focuses on the results obtained, and comparisons with other models, in addition to the initial version. Finally, Section 7 presents the conclusions drawn from the work and future lines of improvement.

II. Preliminaries

The landscape of identity management has undergone significant transformation over the years. Initially, centralized systems were prevalent, wherein a single entity had full control over user information for authentication purposes. One notable drawback of this model was the inconvenience for users of having to remember passwords for each identity manager, as well as the need to have databases where user information was stored, with the danger that this could be stolen by hackers.

To resolve this issue, the federated system was introduced, enabling the sharing and reuse of credentials across different organizations [6], thus reducing the number of accounts for the user. Nevertheless, both centralized and federated models harbored serious security concerns due to potential vulnerabilities leading to user information exposure.

In response to these challenges, the SSI model has emerged as a solution, seeking to decentralize user information management and empower individuals as the rightful owners of their own information. The SSI system is structured around a standard, Verifiable Credentials (VCs), and four principal actors: Holder, Issuer, Verifier, and a Verifiable Data Registry (VDR). VCs serve as digital counterparts to traditional physical credentials, comprising metadata for subject and issuing authority identification, claims encompassing specific individual traits, and cryptographic proofs for credential verification by the issuing authority. In addition, the main actors participating in the SSI model are:

- **Holder**: The individuals or entities that own and control their VCs. The Holder stores, manages and shares its VCs.
- **Issuer**: Trusted entities, e.g., universities, governments, etc., that validate and sign the VCs of holders.
- **Verifier**: The service provider or entity with whom the holder shares their credentials. This entity verifies the authenticity of the credential presented.
- **VDR** [7]: Acts as a secure database for managing and verifying digital identities. The VDR does not store credential information. Instead, it stores the issuers' public keys, credential schemas and other crucial data for verifiers to assess their authenticity, often using blockchain technology for immutability and security. This system allows verifiers to trust the information without needing direct issuer-verifier communication, since the issuer registers the validity of the credential in it by signing it and the verifier can consult in the VDR that the credential is valid.

III. Related work

SSI represents an innovative solution to the constraints associated with traditional identity management systems. As digitalization advances, there is an escalating demand for identity systems that empower users with enhanced, secure control over their data. In recent years, new European initiatives have emerged to advance the SSI methodology, such as the European Blockchain Services Infrastructure (EBSI) [8]. This initiative uses blockchain to create reliable cross-border services for public administrations, businesses, and citizens, with a decentralized, tamper-proof structure.

With all this, significant work is being done in the field of SSI, as well as with the use of blockchain technology to create decentralized and secure structures. In this aspect, Cocco et al. [9] preset a solution with an SSI system that seeks to guarantee the quality of the products marketed and compliance with standards and regulations through the use of food certifications. In [10], Stockburger et al. propose a theoretical design of an SSI-based identity manager with blockchain for a transportation system in Europe, allowing students to obtain discounts using VCs from their universities. It ensures secure and decentralised verification.

Due to the great advantages seen in studies on the SSI model, it has started to be implemented in different commercial solutions. For example, Shobanadevi et al. [11] have developed ShoCard, a digital authentication platform that uses the Bitcoin blockchain to allow secure identification for both users and businesses. This technology enables quick and reliable identity verification and transactions, as identities are stored on the Bitcoin blockchain, and users manage their private keys on their mobile devices. However, it is worth noting that this solution does not adhere to Web3 standards and is not open source. Another commercial solution is proposed by Lundkvist et al. [12], called uPort, which is a mobile application allowing users to transfer their information using Decentralised Identifiers (DIDs) and VCs on the Ethereum blockchain.

This paper utilizes a model based on SSI in the agri-food sector as part of the DIVINE project on Data Spaces. This model uses a system of roles and permissions, represented by VCs, to enable users to access resources from various services within the agri-food sector. It represents an advance over [5], as it introduces new features such as event traceability registration and the implementation of a digital wallet for users, where they can securely and compactly store all their VCs. Furthermore, to the best of our knowledge, it is the first solution that uses SSI for this use case.

IV. Architecture

The SSI method has been used to manage identities, in order to give users greater control over their information and ensure its integrity. Once registered in the system, users (Holders) will obtain a digital identity based on VC. These credentials will represent roles within specific applications or services. The service provider will act as the "Issuer", signing the credentials that assign roles to users. An identity provider will perform the role of Verifier, validating the authenticity of the VCs in each request made.

The system presented in this paper builds on the development from [5] to create a fully functional SSI-based Identity Management (IdM) system.

- **Identity Provider (IdP)**: Keyrock [13], FIWARE's identity management component that supports protocols such as OAuth 2.0 and OpenID Connect, and facilitates role-based access control. This component acts as a Verifier within our SSI system.
- **PEP-Proxy**: Derived from FIWARE's Wilma [14], which manages access to resources and services by acting as an intermediary with the user. This component collects calls made to the service and queries the IdP to determine if the user has the appropriate permissions.
- **Blockchain tool**: A private network with three nodes has been deployed, based on Ethereum's ERC735 [15] and ERC734 [16] standards, implementing Smart Contracts (SCs) for SSI. In this network, each component of the ecosystem (holder, issuer and verifier) has its own contract. The network uses a Proof of Work (PoW) consensus mechanism to develop the VDR for the SSI environment. Modifications have been made to the original standards to create SCs suitable for use within CredSSI, including a new contract specifically designed to oversee the functions of the verifier.

Using the existing blockchain, the system now includes a new contract that adds the Traceability module. This module allows for a detailed logging of user interactions with the IdP and Identity Wallet, securely and immutably storing each action on the blockchain. With a specific SC on the Ethereum platform, it ensures an unalterable record of all events, facilitating thorough investigations.

Finally, an additional element to the system is being developed, which is the Identity Wallet. The Identity Wallet is a digital tool accessible via mobile applications and web services, designed for users to securely manage their digital identities and credentials. It supports operations such as adding, modifying, deleting, and presenting credentials. This component has been included to make it easier for users to interact with their credentials, providing greater accessibility to their various VCs. Another interesting aspect of the wallet is that fingerprint access through the FIDO2 protocol is enabled for logging in.

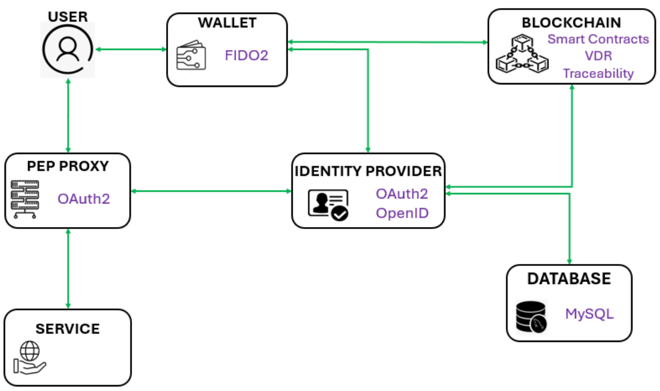

Figure 1. Model Architecture.

In Figure 1, the communication between the different elements that make up our SSI system are shown, where the blockchain includes the three mentioned elements.

The system's structure is demonstrated in four main DIVINE pilot projects, which showcase the agri-food services supported by our SSI-based model.

- **ITC - Inovacijsko Tehnoloski Grozd Murska Sobota (Innovation and Technology Cluster of Murska Sobota)**. This pilot, in Slovenia, focuses on sustainable food production, enabling Slovenian farmers and advisors to access benchmarking data.
- **University College Dublin**. This pilot runs a crop yield prediction model in which farmers share anonymized yield metrics and data related to climate, soil, and disease.
- **Neuropublic Ae Pliroforikis and Epikoinonion (Neuropublic Information and Communications Incorporated)**. In this pilot, Greek farmers share weather data and agricultural calendars, enabling data-driven decisions to optimize production
- **Dynamic and Security Computations SL**. This pilot, in Spain, focuses on traditional olive and almond plantations, facilitating a secure exchange of environmental data and agricultural calendars, thus supporting sustainable farming practices.

These pilot projects demonstrate the system's ability to provide flexible and secure management of access to a variety of agri-food applications. Each pilot benefits from the credential-based role and permission structure provided by the SSI model, allowing users to access services while enabling service providers to control access.

V. Functional Analysis

To ensure the Identity Management System runs smoothly and securely, it is important to understand how each part works within the SSI framework. The process below outlines the steps to follow from account creation to resource access:

1) The user creates an account in Keyrock (Holder).
2) The service owner registers the service in Keyrock (Issuer).
3) The service owner defines the roles and permissions.
4) The user requests a role (VC).
5) The service owner approves this request (signs the VC).
6) The user accesses the service with his VC.
7) The user requests a resource.

Regarding what has been developed in [5], the first three steps correspond to the first two diagrams, which remain unchanged. On the other hand, steps 4 and 5 correspond to the third diagram, although with the new presence of the Identity Wallet, this sequence changes to the following (see Figure 2):

1) The user accesses his Wallet with his Keyrock credentials.
2) The user creates a credential with a role in a service.
3) The issuer receives the signing request for this credential.
4) The service owner signs the user's credential and registers the signature proof in the VDR.
5) The user receives the signed VC.

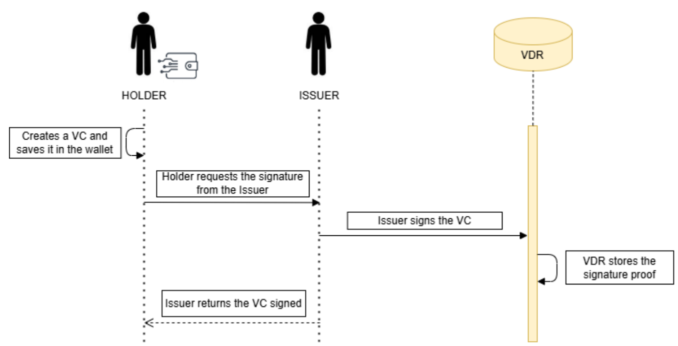

Figure 2. VC signature by the Issuer.

When the user has the signed VC, he can access the service (see Figure 3). He must first authenticate (which aligns with step 6), using the following sequence:

1) The user attempts to access the service.
2) The service redirects him to Keyrock, where he enters his username, password and Claim ID from his signed VC.
3) The IdP checks the credentials in the MYSQL database, while the validity of the claim is checked in the VDR, acting as a Verifier.
4) If the received information is correct, it allows the user to access the service by providing an access token.

After authentication, the user can request resources using his token, which contains information about the user, such as roles or permissions (see Figure 4). This token will be checked each time a request is made, resulting in an authorization process (which corresponds to step 7). The steps to request a resource are as follows:

1) The user requests a resource to the proxy with his token.
2) The proxy asks Keyrock to verify the validity of the token for that request.

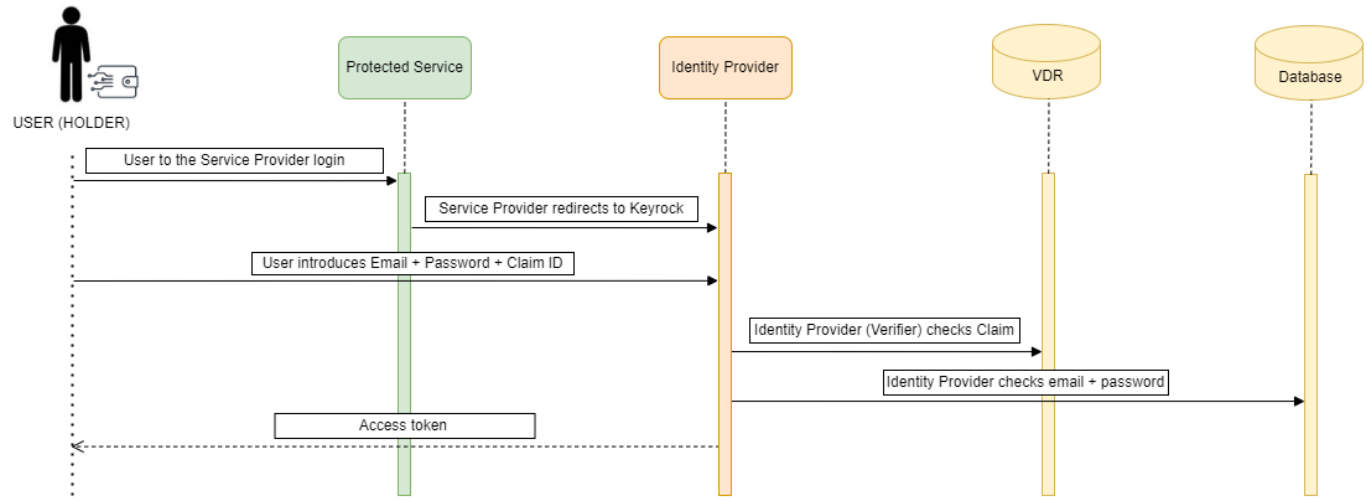

Figure 3. Authentication service.

3) Keyrock checks its database to determine if the user has the permissions to request that resource and confirm it to the proxy.
4) Once the validity is confirmed, the proxy requests the resource from the service.
5) The service provider returns the requested resource to the proxy, and the proxy delivers it to the user.

All events will be recorded in the blockchain by the Traceability module to ensure a correct forensic analysis and avoid malicious interactions by third parties. This module collects all the movements carried out by Issuer, Holder and Verifier, to record all the activities carried out in the ecosystem. The storage of this information is done by deploying a new SC that exclusively collects all the events carried out, the information collected being the following:

- Type of event produced.
- User that triggers the event
- Timestamp.
- Extra description of the event produced.

This information is collected every time a participant carries out an event both in the identity manager and in the Wallet of each of them, with the exception of read-only events.

VI. Discussion And Evaluation

After developing the implemented system, it becomes that an SSI system based on roles and permissions through VCs represents an advancement over traditional identity management systems, as it grants control of information to the users, allowing them to share their information with the entities they choose. Compared to its predecessor [5], it also constitutes an improvement by completing the process of resource acquisition through user authentication and authorization, as well as enhancing robustness by developing a traceability module that records events, providing greater transparency and improving the security of the developed system. Additionally, the introduction of the digital Wallet for users allows them greater control over their credentials, enabling them to manage these as they see fit, whether adding, reading, or deleting them from their Wallet.

This project is a work in progress, which means it is not fully completed, allowing for continuous improvement. Nonetheless, this tool is operational within the European project DIVINE, where project partners are starting to use this tool.

VII. Conclusion and Future Work

Developing an SSI identity management system in an agri-food environment such as the European project DIVINE represents a step forward in the methodologies used, as it allows users to have full control of their information, being able to manage their own VCs themselves through their digital Wallet thanks to blockchain technology, which provides greater robustness and trust. Likewise, the use of blockchain together with a system based on roles and permissions allows the owners of the services to have control over who can access their resources, as they are in charge of assigning these roles and permissions, through the signature of the users' VCs, making this model a decentralised system but also maintaining control by the providers. At the same time, thanks to the incorporation of a traceability module, it is possible to record the events that occur during the course of the resource request, making this system even more secure and robust and improving on its predecessor, CredSSI [5]. Even so, this project is still active, so that further improvements are possible, such as:

- Standardisation of VCs, as they do not explicitly follow W3C standards.
- Gathering feedback from users, as it is in a current state of deployment where few users are using it regularly, which makes it difficult to identify areas for improvement.
- Adding new functionalities to the system, such as the inclusion of new authorization servers for more elaborate permissions management; or the inclusion of new forms of authentication in the Wallet, such as voice biometrics.

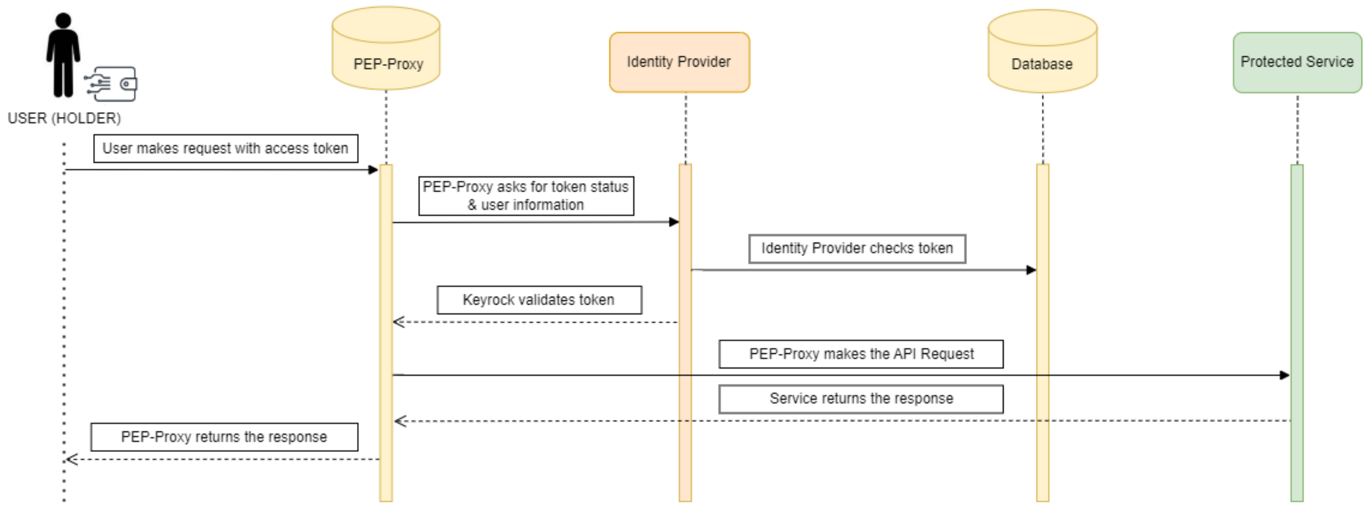

Figure 4. Authorization service.

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Regenerative Agriculture – Where Is the World Going?

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***Abstract*—The increasing impacts of climate change, such as more frequent heatwaves, natural disasters, and rising sea levels, are severely affecting regions around the glob. This paper examines the potential of Regenerative Agriculture (RA) to address these challenges through sustainable land management practices. Techniques like improved soil and crop management, farm diversification, low-carbon livestock integration, and agroforestry contribute to enhanced soil health, better water retention, increased carbon sequestration, and reduced dependency on synthetic inputs. RA offers innovative technologies, practices, and policy tools to transform agriculture into a more resilient, profitable, and competitive system in the face of climate change. Additionally, the under-explored potential of blue carbon is addressed. The study reviews successful global implementations, such as India's resource conservation technologies, China's water-use efficiency projects, and the African Union's emission reduction initiatives. Regenerative practices, including crop management, farm diversification, livestock integration, and agroforestry, demonstrate benefits like improved soil structure and reduced erosion in countries such as New Zealand, Australia, and the United States. Furthermore, the paper emphasizes the importance of incorporating Regenerative Agriculture into national agricultural policies, backed by financial incentives, technical support, and data science for accurate climate predictions and farm management. Adaptation strategies include adopting new crop varieties, adjusting cultivation schedules, and implementing soil conservation measures. Mitigation efforts focus on promoting renewable energy, agroforestry, and carbon markets to ensure fair participation and effective outcomes. The long-term co-benefits of regenerative practices highlight the need for risk management strategies that include social protection for smallholder farmers. Overall, Regenerative Agriculture is presented as a comprehensive solution for addressing climate challenges, building resilience, and promoting sustainable livelihoods through global collaboration and policy support.**

Keywords-Regenerative Agriculture; Climate Change; Agricultural Policies.

I. INTRODUCTION

Over the past 40-50 years, environmental degradation and poor soil health have been significant concerns, now worsened by climate change. This has led to more frequent and severe floods, landslides, and droughts. Global temperatures have risen since 2018, with 2023 marking the hottest year on record. The resulting climate impacts—intensified heatwaves, natural disasters, and rising sea levels—have severely affected human health, increasing the spread of diseases, causing heat stress, and worsening other health issues. Sub-Saharan Africa is widely recognized as the most climate-vulnerable region globally due to its exposure to rising temperatures, sea level rise, and unpredictable rainfall patterns. These shifts are increasing the frequency and intensity of natural disasters, profoundly altering regional geographies [1]. Climate change could lead to a 17% Gross Domestic Product (GDP) drop across Asia and the Pacific region by 2070 under a high-end emissions scenario, which could rise to 41% of GDP by the end of the century. The projected climate effects of sea level rise and labor productivity losses will be the most damaging - with lower-income economies and the region's poorest set to be the hardest hit [2]. These underline the urgent need for a shift toward more sustainable agricultural practices. These practices must focus on reviving soil, producing more and better-quality food with less water, and contributing to climate change mitigation.

Regenerative Agriculture or Climate-Smart Agriculture (CSA) has gained considerable global traction as a response to these challenges. Supported by organizations like FAO, the World Bank, and CGIAR, proposing a set of innovative practices and technologies, underpinned by well-conceived policies and regulations [3]. In Pakistan, several initiatives supported by international donors are promoting regenerative agriculture. For example, USAID is focusing on developing a low-carbon livestock sector, while the Asian Development Bank (ADB) is promoting sustainable rice farming through the Sustainable Rice Platform. Additionally, Better Cotton Pakistan has signed a Memorandum of Understanding (MoU) with the All Pakistan Textile Mill Association's (APTMA) Cotton Foundation (ACF) to enhance sustainable cotton production. These efforts collectively reflect a growing interest in advancing regenerative agricultural practices in the country. In India, modern rice and wheat varieties have saved approximately 39 and 37 million hectares of land, respectively, while zero-till agriculture saved Rs.100 crores in 2002-03 alone [4]. Brazil's ABC (Agriculture, Biodiversity, and Climate) program promotes integrated crop-livestock-forestry systems, reducing emissions by 20%. New Zealand's "Pastoral Greenhouse Gas Research Consortium" supports similar initiatives. The study provides a global review of Regenerative Agriculture as a panacea for emerging issues highlighted by climate change.

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II. REGENERATIVE AGRICULTURE AND ITS BUILDING BLOCKS

Regenerative Agriculture is grounded in core principles like minimizing soil disturbance, maximizing cover crops and crop diversity, keeping living roots year-round, and integrating livestock, as illustrated in Figure 1. These practices, elaborated further in the sections below, essentially enhance soil health and biodiversity, leading to better water retention, reduced irrigation needs, and increased carbon sequestration. These benefits contribute to climate resilience and reduce the energy-intensive processes associated with conventional agriculture.

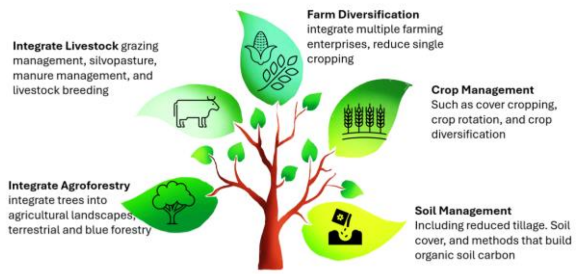

Figure 1. Building block of Regenerative Agriculture.

A. Soil Management

A cornerstone of Regenerative Agriculture is soil management, encompassing practices like no-till or reduced tillage, the use of organic amendments, and methods for building organic soil carbon [5]. These approaches collectively improve soil structure and sustainability. Globally, several countries have successfully implemented regenerative practices. For instance, New Zealand has applied these methods to over 1 million hectares [6], focusing on soil health and biodiversity, which has significantly boosted agricultural productivity and environmental outcomes. In Australia, conservation agriculture covers over 40% of agricultural land, achieving notable reductions in soil erosion and increased carbon sequestration [7]. In Africa, regenerative practices vary across regions based on local needs and priorities. In Kenya, conservation agriculture practices, such as minimum tillage and cover cropping, have improved soil fertility, reduced erosion, and helped farmers adapt to climate change, enhancing food security [8]. In Ghana and Niger, practices like intercropping, crop rotation, and the use of organic manure have seen adoption rates exceed 80%. However, challenges such as the perceived inappropriateness of certain technologies [9], lack of information dissemination, limited technical ability, and prominent levels of illiteracy among farmers hinder widespread adoption.

Effective soil management and precise nutrient application are crucial to maximizing agricultural productivity and minimizing environmental impact. When poorly managed, soil and nutrient inputs—whether organic or inorganic—can contribute to greenhouse gas emissions and heighten diffuse pollution risks, impacting surrounding water quality. Conversely, a single teaspoon of healthy soil holds billions of bacteria, kilometers of fungal networks, and thousands of microscopic organisms, all contributing to a resilient ecosystem [10].

B. Crop Management

Regenerative Agriculture emphasizes diversified cropping systems, crop rotation, intercropping, agroforestry, cover cropping, organic amendments, and integrated pest management. These strategies improve soil structure, reduce pests and diseases, and promote ecological balance. The Sustainable Rice Platform (SRP), a global alliance, aligns with these principles by promoting sustainable practices in rice farming, improving smallholder livelihoods, and reducing environmental impacts. SRP's standards, which encourage resource efficiency and climate resilience, are now applied in over 20 countries in Figure 2. France, for example, promotes agroecology through diversified cropping systems and organic amendments, supported by the "4 per 1000" soil carbon sequestration program. China has implemented large-scale agroforestry programs to reduce soil erosion and enhance biodiversity, supporting sustainable land use and ecosystem health [11]. In Indonesia, crop rotation and intercropping have reduced soil degradation and increased crop yields across millions of hectares. Costa Rica has implemented agroforestry on over 20% of its agricultural land [12], enhancing biodiversity, water regulation, and carbon sequestration. In Mali, CSA technologies such as drought-tolerant crops, micro-dosing, organic manure, intercropping, contour farming, agroforestry, and climate information services keep soil fertility and improve resilience against climate change [13]. Despite these achievements, challenges remain in policy, fiscal support, and the adoption of greener technologies, with obstacles like unclear policy indicators and inadequate monitoring and evaluation systems.

C. Farm Diversification

Farm and crop diversification are essential for enhancing ecological interactions, promoting biodiversity, and improving resilience within agricultural systems. Cuba has advanced Regenerative Agriculture by implementing polyculture and agroecological zones across millions of hectares, promoting biodiversity and stabilizing agricultural ecosystems. Kenya has adopted crop and farm diversification, integrating crops and livestock, which has improved food security and provided multiple income streams [14]. India’s "National Mission for Sustainable Agriculture" encourages crop diversification and organic amendments, enhancing soil health and productivity. Zero budget farming is also gaining ground through supportive government policies [15]. Despite these efforts, a study in West Africa (Ghana, Niger, and Mali) revealed that crop diversification has seen limited adoption compared to other practices [13]. The key strategies include crop diversification, farm diversification, agro ecological zones, poly cultures, and cover cropping. These practices reduce dependence on single crops, integrate multiple farming enterprises, and use ecological synergies for a more sustainable and resilient farming approach.

Role of Sustainable Crop Platform in Promoting Regenerative Agriculture– case of Rice

The Sustainable Rice Platform (SRP) is a global alliance of over 100 stakeholders from various sectors, working to transform the rice industry by improving smallholder livelihoods, reducing the social, environmental, and climate impacts of rice production, and ensuring a steady supply of sustainably produced rice. SRP promotes resource efficiency and climate resilience in rice farming, focusing on both on-farm practices and across the entire value chain. Through voluntary market transformation, SRP develops standards, indicators, and incentives to encourage widespread adoption of sustainable practices. In 2015, SRP introduced the first voluntary standards for sustainable rice farming, and SRP-Verified rice is now available in over 20 countries as detailed below

Figure 2. Sustainable Rice Platform.

D. *Integrating Livestock*

Integrating livestock into agriculture through programs like zero or rotational grazing, which mimic natural systems, is crucial for enhancing ecosystem services. Global experiences show the potential of livestock integration in reducing agriculture's carbon footprint. New Zealand leads in this area, with over 1 million hectares focused on grazing management and soil health, promoting soil carbon sequestration and biodiversity [16]. Silvopasture systems provide shade and habitats, while the "Pastoral Greenhouse Gas Research Consortium" [17] reduces methane emissions by 10-20%. Europe's "Low Carbon Beef" project reduces beef production emissions by 15% through improved grazing, feed, and breeding practices [18]. In Pakistan, USAID, in coordination with the Government of Pakistan, the Global Dairy Platform, and other stakeholders, is engaging the Green Climate Fund (GCF) to initiate a large-scale methane emission reduction program in the dairy sector. Africa's "Livestock for Sustainable Development" aims to cut emissions by 30% through better feed quality and grazing management.

Small adjustments in livestock management can lead to substantial financial savings and a lower carbon footprint. For example, dairy farmer John Kerr, part of the Farming for a Better Climate initiative, saved £63,000 and reduced emissions by 6% over four years [19]. Key regenerative agriculture strategies include grazing management, silvopasture, agro-pastoralism, manure management, and selective livestock breeding.

E. *Promoting Forestry - Terrestrial and Blue Forestry*

Both terrestrial and blue forestry play critical roles in climate change mitigation through carbon sequestration. Agroforestry integrates trees into agricultural landscapes, providing shade, improving microclimates, enhancing soil health, and creating habitats for beneficial organisms. This approach boosts ecosystem services like pollination and pest control while sequestering carbon in both trees and soils. Terrestrial forests absorb approximately 2.4 billion metric tons of CO2-equivalent annually through tree growth, soil carbon accumulation, and wood production. However, forest-related activities release about 1.3 billion metric tons of CO2-equivalent each year, resulting in a net positive carbon balance of 1.1 billion metric tons annually [21].

Brazil's agroforestry and regenerative agriculture projects focus on soil conservation and biodiversity, restoring degraded lands, and creating sustainable agricultural systems [22]. The Brazil Investment Plan (BIP) is an initiative endorsed by the Forest Investment Program Subcommittee to support Brazil's Nationally Determined Contribution (NDC) commitments, focusing on sustainable land use and improved forest management in the Cerrado Biome. The plan aims to reduce GreenHouse Gas (GHG) emissions and enhance carbon sequestration through environmental conservation, restoration practices, and the adoption of low-carbon emission agricultural methods.

The BIP employs an Integrated Landscape Management (ILM) approach to balance human needs with biodiversity, emphasizing long-term sustainability and the efficient use of land. Key strategies include recovery of degraded pastureland; integrated crop-livestock-forestry systems; no-tillage farming; biological nitrogen fixation; cultivated commercial forests and treatment of animal waste [23]. The project has significantly increased the adoption of sustainable practices, providing extensive technical assistance and training to thousands of producers. It has also led to the restoration of substantial land areas and increased the adoption of low-carbon technologies. Notably, the project has encouraged economic returns, promoting wider adoption among rural producers.

Coastal ecosystems, including mangroves, tidal marshes, and seagrass meadows, are equally crucial for climate change adaptation. These ecosystems protect against storms, prevent erosion, regulate water quality, and provide habitats for fisheries and endangered species, contributing to food security for coastal communities. Despite their importance, coastal ecosystems are among the most threatened globally, with 340,000 to 980,000 hectares lost annually. If current trends continue, up to 40% more could disappear within the next century, turning them from carbon sinks into major

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TABLE 1. COMMON FRAMEWORK OF ADAPTATION STRATEGIES [25].

Adaptation Drivers	Farm Production Practices	Productivity	Adaptation	Mitigation
Soil Management	• No till • Use organic amendments • Building soil organic	Improves soil fertility and productivity	Reduces deep percolation of fertilizers and subsequent water pollution and eutrophication.	Lowers the production and emission of methane and other gases from irrigated rice ecosystems
Crop Management	• Adopt new crop varieties; • SRI, DRI and AWD in rice • intercropping, organic amendments • Pest management	Increases productivity through improved soil quality and water availability.	In-situ soil moisture conservation by water retention. Prevents erosion.	Promotes carbon sinks through increased accumulation of dry matter.
Farm Diversification	• Crop diversification, • Farm diversification • Agroecological zones and cover crops	Intercropping with legume may bring new income- or covering cost (sugarcane or others).	Reduces temperature in tree canopy, which can increase crop productivity and quality. By introducing fruit and/or woody trees (as a diversification strategy), it can contribute to increased resilience.	Contributes to carbon sequestration in the system, especially when woody species are introduced in agroforestry systems.
Integrating Livestock	• Zero Grazing • Rotational Grazing • Fodder banks • Manure composting	Enhances resilience Increases milk and meat production.	Reduces heat stress through shading, increasing the efficient use of pastures and other natural resources.	Increases digestibility of feeds and reduces GHG emissions such as methane (CH_4).
Agro Forestry	• Terrestrial forestry • Integrate; provide shade, improves soil health, create habitat	Enhance farm productivity and diversify income	Reduces water runoff and soil erosion. Produces sticks for beans, fodder, and fuel wood at farm level.	Maintains or improves soil carbon stocks and soil organic matter content. Can also promote carbon capture if using woody species.
Agroforestry – Blue Carbon	Mangroves, tidal marshes, and seagrass meadows	Enhance productivity	Enhance carbon stock Produce Biochar	High-efficiency carbon sequestration

carbon sources [24]. Marine and coastal ecosystems sequester about 1.5 billion metric tons of CO2 annually, while coastal development activities contribute to 0.5 billion metric tons of CO2 emissions, resulting in a net removal of 1.0 billion metric tons annually.

Pakistan has a strategic advantage in tapping into the global carbon market, estimated at nearly a trillion dollars. By certifying carbon credits or offsets, the country can generate significant revenue by supporting projects that reduce emissions, such as forests and renewable energy. Experts suggest that Pakistan could generate between $2 billion and $5 billion from carbon markets by 2030 if effectively managed and developed. In Sindh province, Pakistan is advancing two major carbon credit projects: Delta Blue Carbon (DBC) 1 and 2, aiming to restore over 300,000 hectares of degraded mangroves in the Indus Delta. This project, with a potential to create $12 billion in carbon credits by 2075, involves partners like the Government of Sindh and the Climate, Community & Biodiversity Alliance. The initial phase has already seen the replanting of 86,409 hectares, issuing 3.1 million voluntary carbon credits. The project is expected to yield over 250 million blue carbon credit units over its 60-year lifespan, providing environmental and social benefits, including habitat protection for endangered species, and improved local livelihoods [24].

TABLE 2. COMMON FRAMEWORK FOR ADAPTING MITIGATION STRATEGIES GOING FORWARD

Mitigation Drivers	Farm Production Practices	Productivity	Adaptation	Mitigation
Infrastructure – grey or blue	• Feeder roads • Irrigation • markets	Investments in climate resilient infrastructure may increase	Cope with short-term and long-term climate risks	Reduce GHG emissions.
Renewable energy	• Low cost-efficient technology	Enhances long term productivity	Better with local solution Water on demand	Efficient irrigation systems; weather information systems; Farm-level practices
Recycling of crop and livestock residues or waste	• Biogas plants run by crop and animal waste • Energy or evasive crops	Enhance productivity and income through circular economy	Work as circular rather linear economy	Major force in methane reduction
Agro-Forestry and range management	• Install forestry structures (terraces, shelter belts, tree planting)	Livelihood diversification, high potential for income generation	Generated microclimates, water regulation, soil conservation	Increased carbon reserves and sequestration.
ICT-Based Weather Forecasting, Meteorological Information	• Farm based • Community Based • Private-public partnership	Adequate and timely weather information can help farmers take decision on timing and variety of crops increasing productivity	Better manage the negative impacts of weather-related risks in poor seasons while also taking greater advantage of average and better than average seasons.	By better matching the use of fertilizer and other production inputs with year-to-year climatic conditions
Policy Engagement	• Through national and regional strategies and with other actors, farmers, private, and civil society	Clear massage that enhancing productivity is central	Simple and clear raod map making key resources available	Prioritize low-cost mitigation options
Insurance Index – cover weather related risk	• Uses weather index Less administrative cost with lower premiums	take added risks and to invest in improved practices that increase productivity	explicitly designed to manage short term risks	Improved production practices which either enhance carbon sequestration or reduce greenhouse gas (GHG) emissions
Incentive policies	Regulations, Taxes, Caps and Carbon trading Carbon Credits and offsetting	Encourage farmers to reduce carbon footprints and enhance productivity	Incentive is created to adopt	Use as major tool to reduce carbon footprints

By 2030, the Sindh Forest Department plans to complete restoration on 450,000 hectares, offsetting an estimated 240 million metric tons of CO2 equivalent. However, to capitalize on the carbon market, Pakistan must ensure effective management, transparency, and equitable distribution of benefits. Challenges include establishing robust regulatory frameworks and transparent governance to ensure that revenues benefit local communities and enhance climate resilience. With the right strategies, Pakistan can leverage the global carbon market to foster sustainable development and climate adaptation [24].

III. CREATING ENABLING ENVIRONMENTS FOR REGENERATIVE AGRICULTURE

Enabling environments for Regenerative Agriculture are the foundational conditions that promote and support the adoption of climate resilient technologies and practices. These environments encompass policies, institutional frameworks, stakeholder engagement, gender considerations, infrastructure, insurance mechanisms, and access to weather information and advisory services. By providing the necessary laws, regulations, and incentives, an enabling environment ensures that the shift towards RA is both effective and sustainable. It also strengthens institutional abilities at all levels and mitigates risks that might prevent farmers from adopting modern technologies and practices. Experience has proven that investing in these enabling environments is crucial for scaling up the implementation of RA.

For the adoption of Regenerative technologies or practices highlighted above to make economic sense, enhanced production with better quality must bring profits for the marketed produce, which is often not the case. It requires investments in the entire value chain. Farmers find it very exciting to know if they can reduce costs and increase yield and income, but they would like to see evidence. We suggest a well-designed study that lists prioritized technologies and practices and work out detailed cost-benefit analysis and then prepare small extension material to share the tradeoff. Farmers are more interested in economic outcomes.

Data science plays a key role in supporting RA by making critical information accessible, reducing waste, and offering advanced climate prediction models. These tools enable farmers to make informed decisions, optimize strategies for sustainability, and enhance farm resilience to changing weather patterns. Accurate climate predictions are particularly valuable for planning crop planting and managing daily operations, ensuring that farmers can better expect and mitigate climate-related risks. Advocacy for sufficient financial and technical resources at both national and sub-national levels is essential for effectively managing these risks, and Artificial Intelligence (AI) can further augment these efforts.

To comprehensively address the challenges of productivity, adaptation, and mitigation, RA must consider not only the technologies and practices involved but also the broader outcomes of these interventions. This requires evaluating the synergies and trade-offs among these three pillars and understanding their interactions within various socio-ecological systems. While the following sections provide a broader approach to RA interventions, it is essential that these strategies be designed and implemented in a region-specific and site-specific manner. Most of the proposed interventions offer dual benefits for both adaptation and mitigation, though the emphasis may vary, as elaborated in Tables 1 and 2.

IV. CONCLUSIONS

The paper highlights the importance of planning and addressing challenges when adopting Regenerative Agriculture (RA) using Climate-Smart Agriculture (CSA) criteria to achieve sustainable productivity growth, enhance climate adaptation, and reduce greenhouse gas emissions. It may be noted that many of proposed climate-smart crop production practices generate co-benefits that require time to manifest themselves. Because of this, effective risk management strategies need to include social protection mechanisms for the small farmers.

Regenerative agriculture fosters sustainable farming through diverse cropping, organic amendments, and integrated pest management, all of which enhance soil health and biodiversity while reducing chemical dependency.

Effective soil management and precise nutrient use are foundational to sustainable agriculture, enhancing productivity while protecting the environment. Healthy soils support rich microbial diversity, which boosts resilience and nutrient cycling. Prioritizing these practices can reduce pollution risks and greenhouse gas emissions, contributing to long-term ecosystem health.

Standard Crop Platforms be promoted for strategic crops as they promote resource efficiency and climate resilience in farming, focusing on both on-farm practices and across the entire value chain. Through voluntary market transformation, SRP develops standards, indicators, and incentives to encourage widespread adoption of sustainable practices.

Small adjustments in livestock management can lead to substantial financial savings and a lower carbon footprint. Key regenerative agriculture strategies include grazing management, silvopasture, agro-pastoralism, manure management, and selective livestock breeding.

Both terrestrial and blue forestry are vital for carbon sequestration, helping to mitigate climate change by storing carbon in trees and soils. Agroforestry further enhances ecosystem services, improves soil health, and supports biodiversity. Initiatives like Brazil's Investment Plan illustrate the impact of sustainable land-use practices, fostering greenhouse gas reductions and economic returns through integrated crop-livestock-forestry systems and other low-carbon agricultural methods. These efforts demonstrate how balanced land management can address both human and environmental needs.

The study though provide broader approach to RA interventions, it is essential that these strategies be designed and implemented in a region-specific and site-specific manner. Most of the proposed interventions offer dual benefits for both adaptation and mitigation, though the emphasis may vary, as elaborated.

To encourage the adoption of Regenerative Agriculture (RA) practices, it is essential to provide financial incentives and access to soft loans, particularly for smallholders. Tailored financial strategies and social business models can enhance farmers' abilities to invest in sustainable technologies and practices, driving the transformation toward low-carbon agriculture.

Given the delayed benefits of regenerative practices, effective risk management strategies must include social protection mechanisms for vulnerable groups, particularly women and youth, to ensure they are not left behind in the transition.

Data science plays a key role in supporting RA by making critical information accessible, reducing waste, and offering advanced climate prediction models. These tools enable farmers to make informed decisions, optimize strategies for sustainability, and enhance farm resilience to changing weather patterns.

Policymakers should carefully prioritize investments by considering the economic and environmental trade-offs associated with different crops and production systems. Tailoring RA programs to regional advantages or site specific while considering farmers' experience, education, and risk tolerance is crucial for long-term success.

Legal and Institutional Support: Adoption of nature-based approaches in RA can be helped through supportive legal frameworks, economic incentives, capacity building, and effective communication strategies. Strong agricultural institutions and policies, along with improved infrastructure and market conditions, are vital for encouraging sustainable farming practices.

Global Collaboration and Continued Research: Scaling RA and integrating it into mainstream agriculture requires global collaboration, ongoing research, knowledge sharing, and supportive policies. Embracing RA is essential for building a resilient, sustainable food system for future generations.

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Regenerative Agriculture: A Systematic Review of Contributions to Social, Economic, and Environmental Sustainability, and Stakeholder Roles

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***Abstract* — Agriculture has a significant impact on the environment and is responsible for the change in landscape use worldwide. In response, new forms of agriculture have been proposed, such as Regenerative Agriculture (RA) to offer sustainable food production methods. Although there is no clear definition of what it is and what practices it encompasses, RA is now attracting a great deal of interest for all stakeholders, most importantly farmers and policy makers. The current systematic review aims to identify how do RA practices and standards foster economic, social and environmental sustainability and the impacts of stakeholders in accelerating or hindering the adoption of such practices. Results show a concentration of research in countries where large scale farming is very prominent. There is a lack of research into the social and economic viability of RA practices and standards. Thus, multidimensional studies are required to better guide, mainly policy makers, and help with the transition or adoption of regenerative agriculture practices.**

Keywords - Regenerative agriculture; Farming; Environment; Sustainable.

I. INTRODUCTION

Agriculture bears a considerable impact on the planet. It is associated with approximately a third of worldwide land use and is an important cause of land use change internationally, especially in the biodiverse tropics [1]. Food production also generates approximately 15% of global greenhouse gas emissions. Meanwhile, global food needs are expected to grow, as a result of increases in population and per capita consumption [2]. In response to these various pressures, stakeholders are seeking more sustainable ways of producing food [3].

The Regenerative Agriculture (RA) has been suggested as an alternative mean of producing food that may have lower—or even net positive environmental and/or social impacts [4]. Various assertions have been made by multiple stakeholders claiming the potential of Regenerative Agriculture to improve the sustainability of the agrifood scene, including the idea that it may be adopted as a strategy to mitigate climate change, satisfy people's needs and sustain farmers livelihoods [5][6]. However, there is a lack of consensus around a common definition to draw a clear distinction between regenerative, organic and other 'alternative' agricultures [7] and how does it align with sustainability and agroecological practices [7].

Therefore, the current systematic review will: i) Identify existing agricultural standards and practices based on their contributions to social, economic, and environmental factors, ii) and define the specific roles played by various stakeholders involved in the shift towards Regenerative Agriculture.

The remainder of the abstract is structured as follows. Section 2 presents the search and selection process of the articles used for the review conducted according to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) system. Section 3 discusses the results that emerged with regard to the economic, social and environmental spheres plus the role that stakeholders play with regard to RA. Section 4 expresses conclusions and gaps for future research.

II. METHODOLOGY

The search for articles has been performed using two online databases: Web of Science and Scopus [8][9]. They both feature high-quality, peer-reviewed journal publications as well as contributions to scientific conferences. The review focused only on peer-reviewed articles. The possibility of extending the review to publications from other sources has also been explored; yet it was deemed that these publications would not meet the scientific requirements of this review due to a lack of an independent revision process.

The following algorithm has been applied: ("regenerative" OR "conservative") AND "agriculture" AND ("environment*" OR "economic*" OR "soci*" OR "sustain*" OR " develop*" OR "ecosystem services"). An asterisk (*) has been attached to most word stems to find all articles which include terms starting with that word stem.

The search was limited to the title, abstract and keywords, and constrained to publications from 2014 to 2024. The entire search and analysis process was undertaken following the PRISMA Statement for Reporting Systematic Reviews and meta-Analyses [10][11]; and thus the 27-items checklist structure [12].

As there is no common definition for RA, in this study we based our selection criteria based on the definitions provided in [7]. All evidence from studies dealing with RA standards and practices and its contribution to social, environmental, and economic development have been collected. Specific inclusion and exclusion criteria have been set following the research questions, to strictly define the eligibility of the articles to be included in the database. In detail, inclusion criteria were:

- Papers published in the last 10 years (from 2014 to 2024). The literature search was concluded on the 7th of June 2024.
- Papers written in English.
- Papers published on peer-reviewed scientific journals.
- Papers that focus only on RA impacts and standards, excluding studies only on biological effects.
- Papers that provide information to our research questions.
- Papers that did not deal with the multidimensional benefits and trade-offs associated with RA practices were instead excluded.

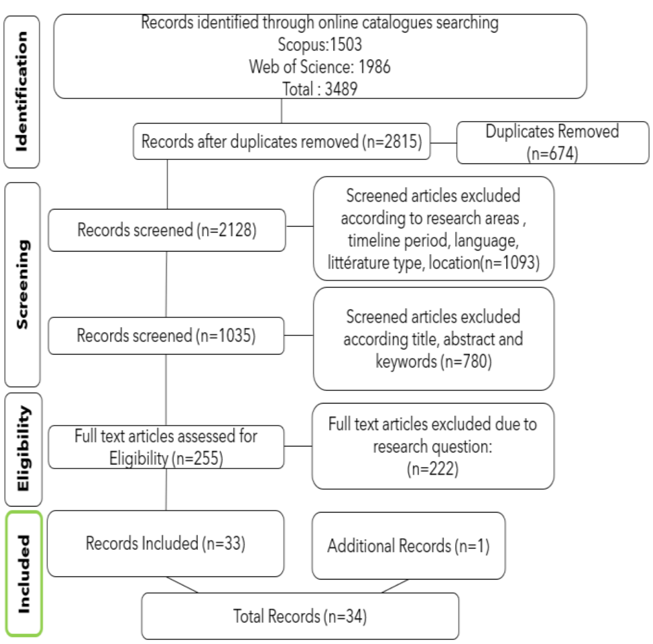

Figure 1. Article selection process.f

A total of 3,489 papers were identified at the first step: 1,986 from Web of Science and 1,503 from Scopus. Then, duplicates (n=674) were removed from the dataset. Afterwards, studies that were not relevant to the specific research areas, timeline period, language, literature type and location were excluded (n=2,128). Notably, the time span from 2014 to 2024 has been chosen to investigate and offer an overview of the latest studies. It also included most of the relevant literature. Subsequently, a three-step screening procedure was applied: i) 1,093 articles were excluded on the basis of search area, publication period, language and article type; ii) 780 articles were excluded on the basis of title, abstract reading and keywords; iii) a total of 255 publications required full-text review. Of these, 222 were excluded due to irrelevance to the research questions and an additional article was identified through cross-referencing, resulting in a final selection of 34 articles. The selection process is illustrated in Figure 1.

III. Results

The final papers that were included in this review were summarized, and the essential data including article information (title, authors, year of publication), study characteristics (study design, sample size, category of participant(s), country of interest), and major findings were gathered (impact on stakeholders, standards/practices treated, relevance to social contribution, relevance to economic, relevance to environmental). Then, in this review we categorized the insights based on the sustainability pillars defined by [13]. Our objectives were twofold: first, to categorize current standards and practices, according to their social, economic, and environmental contribution; and second, the respective roles of diverse stakeholders engaged in the transition towards RA. Economic sustainability refers to practices that support long-term economic growth without negatively impacting social, environmental, and cultural aspects of the community [14]. Social sustainability encompasses the human rights, labour rights, social cohesion, and inclusion and social justice issues that impact the quality of life. It includes providing fair access to resources, ensuring community participation and empowerment, and fostering healthy, just, and resilient societies [15]. Environmental sustainability is about the responsible interaction with the environment to avoid the depletion or degradation of natural resources and allow for long-term environmental quality and it involves the maintenance of ecosystem integrity, natural resource management, and the reduction of waste and pollution [16].

Results marked a concentration of research pertaining to Regenerative Agriculture within specific geographical regions, notably the United States, Australia, and Canada. This concentration underscores a potential limitation in the global understanding of RA's applicability and efficacy across diverse agricultural landscapes. Notably, the prevalence of RA practices on a large scale in these regions contrasts with the dominance of small and medium-sized farming in areas like the European Union (EU). This disparity highlights the need for nuanced investigations into the adaptability and effectiveness of Regenerative Agriculture within varying agricultural contexts worldwide. While existing research predominantly emphasizes the environmental dimensions of RA, including its impacts and benefits, there is a lack of understanding regarding its social and economic ramifications. This knowledge gap represents a critical barrier to fully comprehending the implications of Regenerative Agriculture adoption and implementation. As such, multidisciplinary studies are imperative to define the broader spectrum of impacts associated with Regenerative Agriculture practices, encompassing social, economic, and environmental dimensions.

RA presents a significant avenue for fostering economic sustainability, particularly for farmers. That is where carbon markets step in, offering farmers a chance to earn more by adopting practices that lock carbon into the soil and cut down on emissions [17]. But for those doing mixed farming, especially on a smaller scale, it's not always easy to turn a profit—especially in years when cereal prices are down. That's where Regenerative Agriculture comes into play [18]. Farmers consider RA to give their products a boost in new markets where people really care about quality [19]. By using agroecological methods, they can keep costs low, produce top-notch goods that fetch a premium price, and even sell directly to customers [20]. Plus, diversifying what they grow helps them stay resilient in the face of unpredictable weather and market ups and downs. RA also contributes to the social sustainability of agricultural landscapes by promoting community engagement, biodiversity, and healthy ecosystems. For instance, practices like agroforestry provide habitat for wildlife while improving soil fertility [21]. Collaborative efforts, such as Community-Supported Agriculture (CSA), strengthen connections between farmers and consumers, fostering local resilience [22][23].

By reducing chemical use and promoting healthier environments, Regenerative Agriculture also enhances public health and fosters a sense of responsibility towards the land. RA significantly contributes to environmental sustainability within agricultural settings by prioritizing soil health and biodiversity [24][25]. Integrating agroforestry not only boosts biodiversity but also aids in carbon storage, mitigating the impacts of climate change [27]. Moreover, by minimizing chemical inputs and promoting natural pest control methods, Regenerative Agriculture reduces pollution and safeguards water quality [28][29].

IV. Conclusion

An examination of stakeholder engagement and roles within the context of Regenerative Agriculture adoption reveals a gap in current literature. Understanding the dynamics and contributions of diverse stakeholders, including farmers, policymakers, researchers, and consumers, is therefore paramount to fostering the successful integration of Regenerative Agriculture practices into existing agricultural systems. Yet, existing studies often overlook the intricate interplay between stakeholders and fail to comprehensively assess their respective roles in facilitating or hindering the uptake of RA practices.

Addressing these knowledge gaps necessitates a concerted effort to embrace interdisciplinary research approaches and methodologies. By utilizing frameworks such as the Agricultural Knowledge and Innovation System (AKIS) [30], participatory action research throughout cocreation processes, researchers can enhance collaboration and knowledge exchange among stakeholders, thereby facilitating the adoption and dissemination of RA practices.

Acknowledgment

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Efficient Water Use in Citrus Orchards in the Context of Water Scarcity: A Comprehensive Approach with the AquaCitrus Model

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***Abstract*—Efficient water use in irrigated agriculture is essential, particularly in water-scarce regions. Accurately measuring and managing crop water requirements is key to enhancing water use efficiency. This research presents a new approach implemented in the AquaCitrus model, which separately calculates crop transpiration using the basal crop coefficient and soil evaporation through the Ritchie model. The proposed methodology was applied to calculate the water requirements of drip-irrigated mature citrus trees (*Citrus sinensis*) during the 2015 irrigation season in the semi-arid climate of eastern Spain (Valencia), one of the country's major citrus producing regions. Key parameters, including crop coefficients, transpiration rates, evaporation rates were compared with values from alternative approaches and previous studies, showing high concordance and underscoring the robustness of the developed approach. A significant finding was the clear differentiation between beneficial water use (transpiration, 83.7%) and non-beneficial water loss (evaporation, 16.3%), which is crucial for optimizing irrigation water management in arid and semi-arid areas. The results demonstrate that this methodology is both valuable and practical for improving water use efficiency due to its simplicity and minimal data requirements, making it feasible for calculating local values effectively.**

Keywords-water scarcity; irrigation management; water use efficiency; prennial crops.

I. INTRODUCTION

Agriculture is the largest consumer of freshwater, accounting for approximately 70% of global freshwater use. With increasing water scarcity driven by population growth, industrialization, intensified agriculture, and climate change, the need for efficient water use in agriculture is more urgent than ever. Optimizing water use in agriculture is essential in water-scarce regions, such as much of the Iberian Peninsula. A key element in achieving this optimization is accurately quantifying crop water requirements, specifically crop EvapoTranspiration (ET_c), which balances irrigation needs while conserving water resources [1].

Several methods are used to determine water requirements in irrigated agriculture, including energy balance, eddy covariance, remote sensing, and crop coefficient approaches [2]. Among these, soil water balance (SWB) models based on the FAO56 method [3] are widely recognized and used. The FAO56 method estimates ET_c by multiplying the crop coefficient (K_c) with reference evapotranspiration (ET_o), calculated using the FAO Penman-Monteith equation [4]. Since the publication of FAO24 in the early 1980s, numerous SWB models have been developed, establishing a foundation in the field of crop water requirements and irrigation scheduling [1]. Most of these models are based on the FAO K_c-ET_o approach, with notable examples including ISAREG [5], BUDGET [6], MOPECO [7], and swbEWA [8]. Although effective, the single crop coefficient K_c, which assumes a unified value for both crop transpiration (T_c) and soil evaporation (E_s), can lead to inaccuracies by not adequately capturing the E_s component, particularly in arid and semi-arid climates where soil evaporation is significant.

To address this limitation, a dual crop coefficient approach ($K_c = K_{cb} + K_e$) was developed [1], [3], which separates the basal crop coefficient (K_{cb}) for transpiration from the soil evaporation coefficient (Ke), thus allowing independent estimation of E_s and T_c. This approach enhances the accuracy of ET_c estimation and better reflects field conditions and irrigation practices [1]. Although various models, such as AquaCrop [9], SALTMED [10], and SIMDUALKc [11], implement this dual approach, most are designed for annual crops, with few options tailored for woody crops like citrus. Additionally, K_{cb} values can be highly site-specific, limiting their transferability [12]. To improve accuracy, [13] developed a method to estimate K_{cb} based on factors like crop height, stomatal control, and canopy cover fraction, making it more adaptable to different orchards and locations.

In this study, we developed a methodology to accurately estimate the water requirements of citrus crops, a critical consideration given the high irrigation demands and growing pressures from climate variability. This approach, implemented in the AquaCitrus model [14], separately calculates E_s using the Ritchie model [15] and T_c based on Allen and Pereira's method [13] for estimating site-specific K_{cb} values. This model is designed to meet the specific needs of citrus crops in water-scarce environments, such as Valencia, Spain—a major citrus-producing region that contributes over 56% of the European Union's citrus production [16].

This article is organized as follows: after the introduction, the materials and methods section describes the AquaCitrus model and its approach to calculating crop water requirements

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(ET_c). This is followed by a presentation of the results and a discussion of key findings. Finally, we conclude with important insights drawn from the study.

II. MATERIALS AND METHODS

A. *AquaCitrus Model*

AquaCitrus is a soil water balance model explicitly designed for citrus cultivation. It aims to enhance irrigation efficiency by simulating water fluxes within the soil-plant-atmosphere system. Key components considered by AquaCitrus include effective precipitation, infiltration, runoff, soil evaporation, drainage, and crop transpiration, while accounting for soil heterogeneity. This model contributes to optimizing water use efficiency in water-scarce regions, computes irrigation requirements, evaluates a given irrigation schedule, and aids in simulating climate change scenarios. The is currently under development, incorporating production function that account for various factors, including the physiological characteristics of citrus crops.

To accurately calculate the citrus evapotranspiration, the model AquaCitrus combines the equations proposed by Allen and Pereira [13], for crop transpiration estimation and the model introduced by Ritchie [15], for soil evaporation determination.

B. *Crop Transpiration Approach in AquaCitrus*

Crop transpiration (Tr, mm.d^{-1}) in AquaCitrus is estimated using the crop coefficient method. The potential transpiration of citrus crops is determined by multiplying K_{cb} by the reference evapotranspiration (ETo, mm.d^{-1}) as illustrated in equation (1) and (2). The model considers various factors like plant physiology, development stages, and environmental conditions to calculate the basal crop coefficient.

$$T_r = K_{cb} * ET_o \quad (1)$$

K_{cb} is computed by multiplying the density coefficient (K_d) by a maximum basal coefficient representing full cover conditions (K_{cb_full}), following the formula proposed by Allen and Pereira [13]:

$$K_{cb} = K_{c\,min} + K_d * (K_{cb\,full} - K_{c\,min}) \quad (2)$$

where, $K_{c\,min}$ is the minimum crop coefficient for bare soil, approximately equal to 0.15 under typical agricultural conditions, as suggested by Allen and Pereira [13]. The $K_{cb\,full}$ is the maximum crop transpiration coefficient during peak plant growth with nearly full ground cover. This coefficient is initially calculated based on the crop height, accounting for climatic variations, and subsequently adjusted for stomatal control in trees using a reduction factor (F_r) derived from mean leaf stomatal resistance [13]. Allen and Pereira's study [13] provides extensive insights, for a detailed understanding of these equations.

C. *Soil Evaporation Approach in AquaCitrus*

The model computes soil evaporation (E_s, mm.d^{-1}) using the Ritchie model [15]. This approach divides the process of evaporation into two stages, distinguishing between the evaporative processes of wet and dry soil zones and recognizing the irregular distribution of soil moisture resulting from localized irrigation practices.

Mathematically:

$$E_s = \begin{cases} E_{s,pot} & if \quad \sum E_s \leq U \\ \alpha(\sqrt{t} - \sqrt{t-1}) & if \quad \sum E_s > U \end{cases} \quad (3)$$

where, $\sum E_s$ is the cumulative soil evaporation, $E_{s,pot}$ (mm.d^{-1}) is the potential soil evaporation amount, t (days) is the time since the start of stage two, and α (mm.d$^{-0.5}$) is the Ritchie coefficient and it depends on soil hydraulic characteristics.

The model accounts for irrigation and precipitation events that re-wet the soil surface, potentially causing a transition back to stage one from stage two. The potential evaporation in stage one is calculated as follows:

$$E_{s,pot} = [\Delta / (2.45 * (\Delta + \gamma)] * R_{ns} \quad (4)$$

where, Δ (kPa ºC^{-1}) is the saturated water vapor pressure slope, R_{ns} (MJ.m^{-2}.d^{-1}) is the net radiation at the soil surface, and γ (kPa ºC^{-1}) is the psychrometer constant.

III. RESULTS AND DISCUSSION

A. *AquaCitrus Model Evaluation*

AquaCitrus was evaluated using soil moisture data from various depths within a citrus plot in Valencia (Spain), a region known for its Mediterranean climate and Spain's main citrus-producing region. The model's performance was commendable, demonstrating a significant correlation between the simulated and observed values (Fig. 1). The results showed high levels of agreement across different soil depths, with coefficients of determination (R^2) ranging from 0.78 to 0.91. These findings validate the model's ability to predict water balance in citrus crops accurately, confirming its potential as an effective tool for irrigation management and water conservation in arid and semi-arid regions, particularly under the challenges posed by water scarcity.

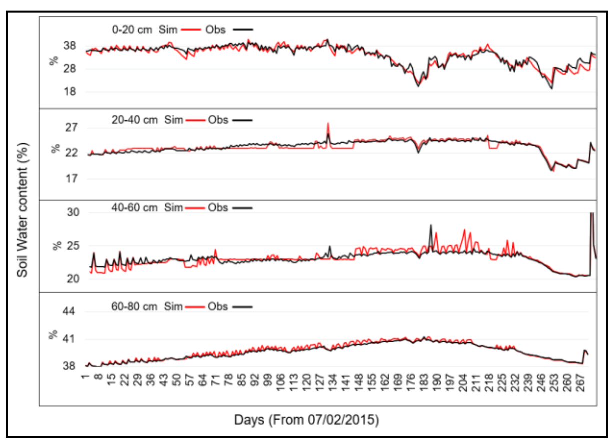

Figure 1. Simulated and observed soil water content at various depths: 10 cm, 30 cm, 50 cm and 70 cm.

B. *Crop Evapotranspiration*

The citrus basal crop coefficient (K_{cb}) was calculated daily using the methodology developed in this study, with monthly averages computed for comparison. These values ($K_{cb\ sim}$) were compared with FAO standard values for citrus crops under similar conditions (50% canopy cover, 3-meter crop height, and no active soil cover): 0.60 at the initial stage, 0.55 at mid-season, and 0.60 at the late season (Fig. 2). Unlike the FAO values, which represent generalized standards, the calculated Kcb values in this study are site-specific.

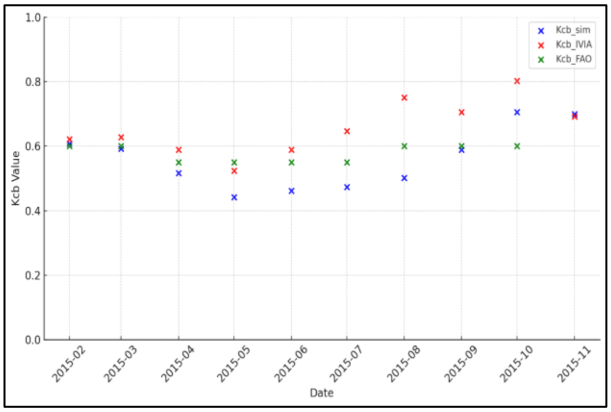

Figure 2. Monthly Kcb values from diffrent approaches.

The study also compared the calculated $K_{cb\ sim}$ with values provided by the Valencian Institute of Agricultural Research (IVIA) ($K_{cb\ IVIA}$) [17]. Despite similar edaphoclimatic conditions between the study and IVIA plots, $K_{cb\ IVIA}$ values were consistently overestimated, particularly during late spring and summer when temperatures are higher. This discrepancy is attributed to two factors: (1) $K_{cb\ IVIA}$ assumes a canopy cover of 70% or more, whereas the canopy cover in this study was 50%; and (2) the methodology developed in this study incorporates an adjustment factor (F_r) to account for the plant's stomatal regulation, which reflects citrus crops' ability to control stomata under conditions of high humidity, wind, and elevated temperatures. This stomatal adjustment enhances the accuracy of the proposed method, making it highly applicable for calculating citrus water requirements.

In addition, crop evapotranspiration (ET_c) was evaluated using research data from the Valencian Institute of Agricultural Research (IVIA) [17], ET_c values simulated by the model were compared with observed values under conditions similar to those of the study plots. This comparison demonstrated a strong correlation, with a coefficient of determination (R^2) of 0.86 (Fig. 3), further affirming the model's reliability in replicating actual agricultural water use scenarios.

During the 2015 irrigation season, the evaporation fraction determined in this study accounted for 16.3% of the total crop evapotranspiration (ET_c), while transpiration represented 83.7%. Evaporation constitutes a non-beneficial water loss for the crop, emphasizing the importance of accurately quantifying this component of ET_c. Such quantification is essential for devising strategies to minimize evaporation losses, thereby enhancing overall water use efficiency in irrigation management.

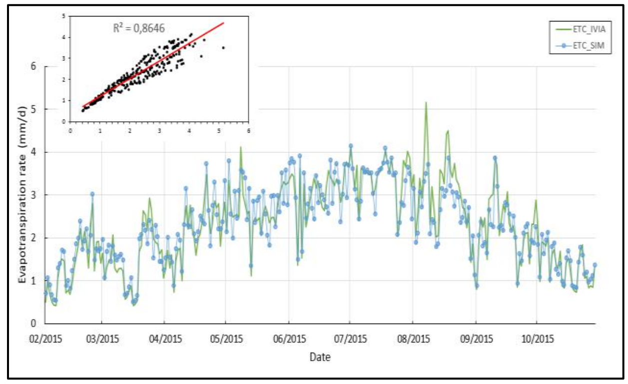

Figure 3. Daily values of ETc sim and ETc IVIA.

IV. CONCLUSION AND FUTURE WORK

Accurate measurement and management of crop transpiration and soil evaporation are critical for improving water use efficiency, particularly in arid and semi-arid regions where water scarcity pose significant challenges. The methodology developed in this study offers a more precise understanding of citrus crop water requirements, enabling the implementation of targeted and efficient irrigation strategies.

One of the key advantages of this method is its simplicity and minimal data requirements, making it practical and accessible for diverse agricultural contexts. This approach is integrated into the AquaCitrus model, which also incorporates key factors such as root distribution and soil heterogeneity to calculate the soil water balance and optimize crop water use. While the model shows promise, its development is ongoing, and further testing and refinement are necessary to address additional challenges such as site-specific parameterization and model validation under diverse climatic and soil conditions. Future work will focus on enhancing the model's functionality and usability to support sustainable water management in citrus orchards. The final version of AquaCitrus will be made available upon completion.

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Testing the Variation in Performance of a Coil-Based Soil Moisture Sensor with Soil-Core and Air-Core Deployments

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Abstract*— Soil moisture monitoring is crucial for irrigated and rainfed crops. Multiple sensor solutions have been proposed in the last decades, and recently, coil-based sensors have been proposed. In this paper, we evaluate the hypothesis that the performance of a coil-based sensor with an alternative setting will not diminish its performance. This new setting supposes an easier deployment in which the core of the coil is not filled by soil but with air. The tests were conducted on a sensor composed of two copper coils with 40 and 80 spires. The sensor has been calibrated with two settings, with the core filled with air or with soil. For the calibration, four different soil moistures were included. Calibration models were obtained for each of the settings. The following metrics are considered for each regression model to evaluate the performance of the two sensors' settings: correlation coefficient, R2, and p-value. The results indicate small differences between both sensors; R2 were 0.95 and 0.93 for soil-core and air-core sensors. Additional tests and metrics have been considered to compare the performance. A T-student test of paired data indicates that there are no significant differences between data gathered with air-core and soil-core sensors. Finally, the coefficients of variation between multiple data gathered in the same conditions were 0.43 and 0.25 % for air-core and soil-core sensors. The obtained results indicate that even though the performance is slightly lower in air-core sensors, the simplicity of the deployment justifies this slight reduction since its impact on the measurements is almost null.

Keywords-Coil-based sensor; Precision Agriculture; Conductivity Sensor; Digital Agriculture.

I. INTRODUCTION

Soil moisture is essential to numerous ecological and agricultural processes, making it a key component in understanding and managing the environment. Recent research has underscored its importance in studies related to climate change, agricultural productivity, and ecosystem health. As a vital indicator of climate change, soil moisture is utilized by researchers to examine patterns and predict future developments [1], [2]. In agricultural environments, precise soil moisture monitoring allows for timely irrigation, minimizing water waste and reducing plant stress [3]. Additionally, soil moisture content greatly affects the formation of condensation water, which can serve as a vital water source in arid regions [4]. The relationship between soil moisture and vegetation also influences surface-air temperature, shaping local climate patterns [5]. Innovative methods, like transfer learning and remote sensing, are being developed to enhance soil moisture forecasting and improve measurement accuracy [6], [7].

Recent breakthroughs in biological humidity sensing have created new and innovative opportunities for moisture detection. Recent studies showcased the detection of relative humidity, presenting different, promising methods [8]. Many recent advances, highlight the increasing interest in utilizing biological systems for humidity measurement, potentially providing benefits in sensitivity, biocompatibility, and environmental sustainability [8], [9].

On another note, progress in humidity sensing technologies has broadened the methods for precise and dependable moisture measurement. Optical sensors, including the ones using optical fibers with adjustable temperature and humidity sensitivities, present promising options for accurate humidity detection [10]. Another study revealed that the use of metal ions-based sensors, have shown selectivity in sensing relative humidity, opening new possibilities for material-based methods [8]. Additionally, incorporating humidity sensors into Internet of Things (IoT) systems and smart building applications has facilitated distributed measurement networks for thorough environmental monitoring.

Another approach to evaluate soil moisture is the use of coils as humidity sensors. Humidity sensing technology has investigated the use of coils as effective measurement devices. Coil-based humidity sensors provide benefits in sensitivity, response time, and durability over traditional methods [9]. These sensors generally rely on changes in the coil's electrical properties, such as impedance or resonant frequency, to detect variations in ambient humidity levels [11]. Some other designs use hygroscopic materials coated on the coil surface to improve sensitivity and selectivity [12].

Soil-filled coils pose distinct challenges in scientific research and engineering. The heterogeneous nature of soil can result in uneven electromagnetic properties within the coil, impacting its performance and dependability [13]. Moreover, changes in soil moisture content can lead to fluctuations in the coil's inductance and quality factor over time [14]. There are not many studies that specifically focus on the problems that coils have when measuring the soil,

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nevertheless, it is known that the measuring instruments suffer variations when samples are taken within a difference of minutes [15], [16].

The aim of the study is to test whether the performance of the soil sensor proposed in [14] is affected by the reduction in the volume of sensed soil (soil-filled coil or air-filled coil). We have based our study in one of the prototypes previously developed and tested in [14]. To evaluate the variation in the performance, we have compared the results of a calibration conducted with a soil-core and an air-coil sensor. The calibration was conducted, including four soil moisture values. Commercial organic substrates have been used as soil with different water volumes. Multiple metrics and tests are considered to evaluate the loss in performance due to the new setting.

The rest of the study is divided into five sections. Section II details the most relevant reported studies, whereas Sections III and IV describe the proposal and the used materials and methods. The results are presented in Section V, followed by a conclusion and future perspective in Section VI.

II. Related Work

This section summarizes the current use of sensors to measure the moisture of the soil and their benefits and limitations.

Recent studies on moisture sensors have aimed to enhance their accuracy, affordability, and suitability for different soil types and moisture levels. In 2023, Schwamback et al. [17] compared low-cost and commercial soil moisture sensors, examining the balance between price and precision. Their research emphasized the promise of automated, inexpensive sensors for broad agricultural applications. The following year, in 2024, Nandi et al. [18] assessed the performance of both low-cost and high-end soil moisture sensors across various moisture levels and soil textures. Their study offered important insights into the accuracy and reliability of sensors in different environmental conditions, supporting the ongoing effort to create more versatile and affordable moisture-sensing technologies.

In a field study, Marković et al. [3] assessed the performance of low-cost capacitance and resistance-based soil moisture sensors in an irrigated apple orchard. They observed that although the sensors generally followed soil moisture trends, discrepancies emerged between sensor readings and gravimetric measurements, especially at higher moisture levels. The authors stressed the need for proper sensor calibration and positioning to ensure accurate readings. According to what was studied in the previous article, Kim et al. [19] compared soil moisture variations based on different sensor installation positions in Korean orchard soils. The study revealed that sensor placement relative to irrigation emitters and tree roots influenced readings, with sensors nearer to emitters showing greater variability. Their findings underscore the importance of strategic sensor positioning for accurate soil moisture monitoring. Both articles are proof that due to the heterogeneity of the soil, and its properties, moisture measures can fluctuate in the space where the sample is taken.

Another study in 2021, Basterrechea et al. [20] discusses the design and calibration of a soil moisture sensor using inductive coils and electromagnetic fields. The prototypes, which vary in coil characteristics and wire dimensions, were tested in commercial and agricultural soils providing a significant voltage difference between wet and dry soils. While it is useful to differentiate between dry and wet soils, this study does not clarify what would happen if the soil entered the coil's core differently, thus not proving other ways of measuring the electromagnetic field.

III. Proposal

In this section, the details of the soil moisture sensor are included. First of all, the sensor is characterized. Then, the signal conditioning circuit, which has been used to allow the sensor to operate in microcontrollers, is described. Following, the circuit used to power the coil and the test to seek the peak frequency of the proposed system is presented. Finally, the two possible deployments of the system, air-core and soil-core, are explained.

A. Description of the assembly and operation of the conductivity sensor

The conductivity sensor consists of two coils, the primary coil with about 80 turns and the secondary coil with about 40 turns, as shown in Table 1. This consists of a signal generator feeding the primary coil with a sinusoidal signal, generating a variable magnetic field. From this, the secondary coil is induced with this field where, depending on the medium in which the coil is located, it will be one voltage or another due to changes in soil moisture. With this principle, we can calibrate the sensor to detect changes in the medium depending on the amplitude of the signal obtained. The magnetic field obtained is solenoidal since the coils are mounted on a tube with a diameter of 25 mm. Given the direction of the ascending current, a magnetic field is generated in an anticlockwise direction. It must be noted that this coil-based sensor is one of the prototypes previously studied in [14].

TABLE I. TABLE OF CONDUCTIVITY SENSOR MOUNTING CHARACTERISTICS

Features	Secondary coil	Primary coil
No. of coils	40	80
Layers	1	1
Copper diameter	0.4 mm	0.4 mm
Covering	Epoxy	Epoxy
Ratio	2	0.5
Coil diameter	25 mm	25 mm

B. Signal conditioning circuit description

The process for filtering the signal of the values obtained in the sensor consists of the rectification of the AC-DC signal. The first step is transforming the Vin signal, where the V1 signal is received. The second step is rectifying the signal from alternating to direct using a diode bridge. The third step is the filtering of the lobulation signal of the V1 signal so that it is a signal with a more stable amplitude over time. The fourth step is regulating V3 of the signal in direct current to provide further stability to the already filtered signal V2. Finally, the voltage obtained from the Vout regulation stage is captured to process and send to the server, as seen in Figure 1.

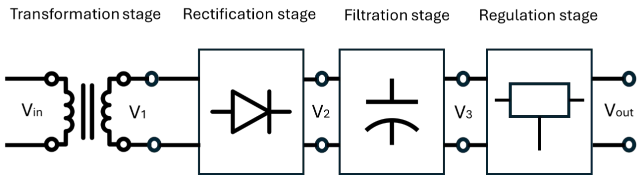

Figure 1. Diagram of signal filtering stages.

Figure 2 illustrates the electrical circuit integrated into the node to support the aforementioned stages. It is important to note that the input signal to the primary coil is supplied by a signal generator, which provides a sinusoidal signal. This allows the primary coil to generate a varying magnetic field, inducing an electric current in the secondary coil.

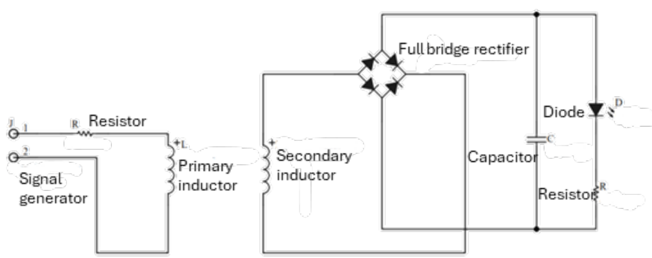

Figure 2. Sensor circuit diagram.

C. Peak frequency and sensor power supply

As mentioned earlier, the primary coil is powered by a function generator, providing a consistently stable sinusoidal signal with an amplitude of 9 volts. The signal frequency is chosen based on the coil's resonance peak. A frequency sweep, as shown in Figure 3, is conducted to determine this peak.

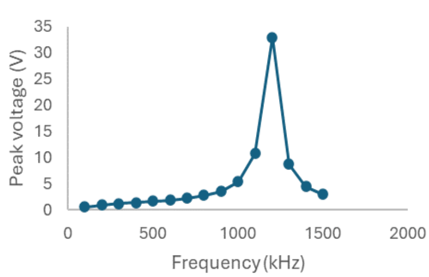

Figure 3. Arrangement of the coil in the ground with or without earth in the core.

The primary coil is supplied with a wide frequency range, with the resonance peak being identified at 1200 kHz, a crucial value in our process of determining the resonance peak frequency.

D. Deployment of the coil in the ground with or without soil in the core

As shown in Figure 4, a detailed arrangement of how the conductivity sensors would be in the proposals can be seen, in our case, by introducing earth into the core of the coil that we can measure or not.

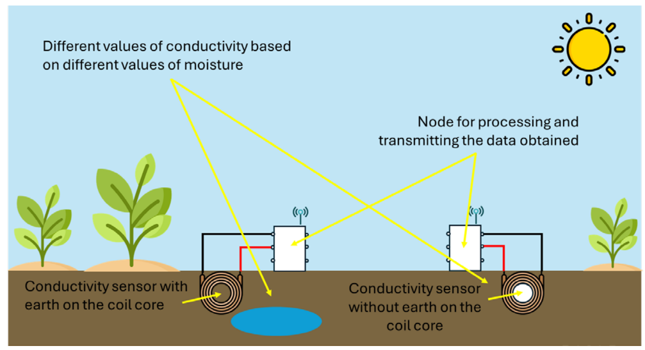

Figure 4. Explanatory drawing of the sensor settings.

Another aspect is that the sensors are placed underground, and through wired transmission devices, we send the data to nodes that process and transmit the collected values. When the coils are inserted into the soil, they detect varying conductivity levels caused by different moisture content (the amount of water per volume of soil in a given area) over time.

IV. MATERIALS AND METHODS

In this section, all the elements and procedures for conducting the tests aimed at evaluating the performance of the sensor are described. First of all, the materials, including the soil, water, and pots, are identified. Then, the different soil moisture concentrations and their generation are characterized. Finally, the employed mathematical methods and metrics to evaluate the performance of the two sensor configurations are explained.

A. Used Materials

The materials used to conduct the tests include pots, soil, water, beakers, laboratory balance, and the soil moisture sensor.

The used tapered pots have a variable diameter, are narrower at the base, and expand towards the top. The pots were made of polypropylene, measuring 13 cm in height, 9 cm in minimum diameter and 13 cm in maximum diameter. Three pots are used in order to have experimental repetitions of the results.

The used soil was commercial soil composed of peat and manure. The soil was a universal organic substrate, widely sold in gardening stores, composed of German peat, enriched with NPK fertilizer and perlite, and suitable for a broad range of plant species mainly used for horticulture and gardening purposes. This soil is characterized by a high water-retention capacity, a pH of 6 and 97 % of organic matter. In each pot, we included 700 g of commercial soil, which constituted 10.5 cm of soil. The amount of soil was measured with a laboratory balance Series 5161 (NAHITA BLUE). This balance has a precision of 0.1 g and a capacity of 5000 g.

Water was added to the pots to generate a variable range of soil moisture values. The used water was deionized water. A crystal beaker was used to weigh the water with the above-described laboratory balance. The beaker from Fisherbrand (Waltham, MA, USA) has a capacity of 250 mL.

B. Generated samples

The generated samples aimed to represent different irrigation regimes or different soil moisture levels in rainfed crops. Four soil moisture levels were considered in the experiments that were conducted.

The moisture levels range from adding 0 to 100 mL of water to the pots. Since organic soil was stored in an open bag for a long time, it is possible to assume that this soil is characterized by 0 mL of added water. Besides this, 50, 75, and 100 mL of water were added to each one of the pots. We can also express the added water as a Gravimetric Water Content (GWC) (% weight or % mass), Volumetric Water Content (VWC), and centimetres of water per meter of soil (cm or mm). All these different options are summarized in Table 2.

TABLE II. TABLE TYPE STYLES

Added water (mL)	GWC (%)	VWC (%)	Liters of water per meter of soil (L/m^2)
0	0.0	0	0
50	7.1	5.2	3.7
75	10.7	7.8	5.6
100	14.3	10.4	7.5

C. Data gathering system

This experiment was based on a prototype in which we constructed two coupled coils to measure changes in soil moisture by detecting variations in conductivity through the induced electromagnetic field. The coils were attached to a tube and connected to a rectifier circuit, which was linked to an Arduino Analog-to-Digital Converter (ADC). From there, we obtained readings of environmental changes. Under natural conditions, if it were necessary to prevent soil from entering the tube, the core would be sealed with two plugs.

D. Data gathering procedure

For data gathering, the sensor was introduced in the pot to ensure that the soil covered the total height of the sensor. The sensor's core was filled with soil in the data gathering of a soil-core sensor. Meanwhile, to obtain data on the air-core sensor, the core of the sensor was left empty. In real conditions, plastic taps are used to seal the core of the soil full of air to ensure that no soil falls into the air core.

After the sensor was exposed to each soil moisture, data was gathered. The sensor gathered data every 45 seconds. In each pot, an average of 5 data sets were gathered and stored in an Excel file for processing. These kinds of data allow us to generate additional results linked to the noise in the signal.

E. Data processing and used metrics

First of all, two regression models were generated with averaged data from each experimental repetition for the air-core and coil-core sensors. For this analysis, the metrics used to compare the results are the correlation coefficient and the adjusted R2. Moreover, the p-value for the regression model is also considered as a metric.

A paired samples t-test was conducted to determine whether there were significant differences between the soil moisture sensor readings in the two settings. This test is commonly used to compare the two series of data with a common origin to determine the magnitude of differences. The metric used in this case is the p-value. The comparison was conducted using the averaged data.

Additional analyses include the comparison of data gathered with the two settings by means of paired data tests. In this case, the employed metric will be the p-value of a T-student test. Finally, and with the aim of evaluating the differences between replicas, the data were compared using the coefficient of variation.

F. Statistical analyses

In order to compare the gathered data with the two alternative uses of the sensor, the following statistical methods are used. First of all, regression models for each calibration process are extracted, and metrics to compare the results include the correlation coefficients, the R2, the p-value and the coefficients of the models a and b values that define the slope and the y-intercept. The generated models corresponded to linear regression models and were obtained with Statgraphics Centurion XVIII [21]. For the generated models, confidence and prediction intervals are identified. Then, to confirm if the behaviour of both ways of using the sensors is comparable, a test of paired data, using the T-student test, is conducted. Finally, the coefficients of variation of gathered data are compared to compare the performance of both calibration tests.

V. RESULTS

In this section, the results obtained were gathered to analyze the performance of soil-core and air-core coils are presented. First of all, a comparison of the calibration for both sensors is analyzed.

A. Comparison of calibration curves

In this subsection, the calibration curves obtained with soil-core and air-core sensors are compared. On the one hand, Figure 5 depicts the calibration of the soil-core sensor, which is the version of the sensor currently used in [14]. The calibration curve follows a linear regression model. In Figure 5, the confidence is shown in dotted green, and the prediction intervals in dotted grey. On the other hand, Figure 6 portrays the calibration when the core of the sensor is not filled with soil. As in the previous case, the presented calibration follows a linear regression model. The metrics for these calibrations, as well as the values of a and b in the mathematical model, are summarized in Table 3. Besides the two calibration models, an additional model has been added, including data for both settings.

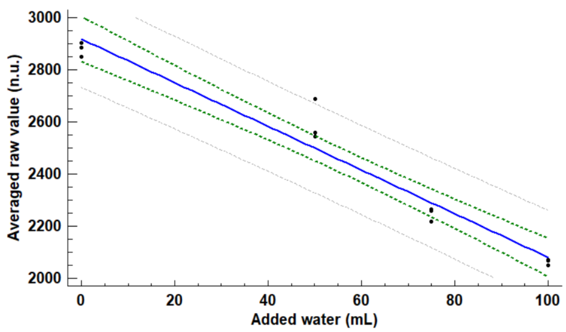

Figure 5. Calibration curve of the sensor with soil-core.

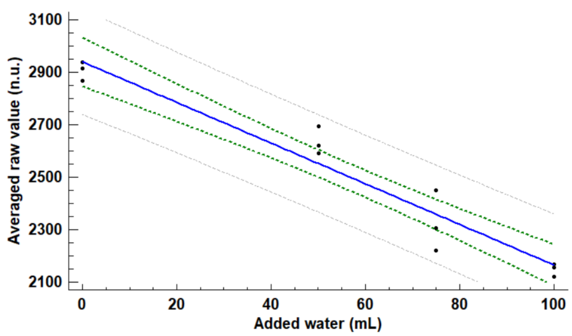

Figure 6. Calibration curve of the sensor with air-core.

TABLE III. DATA OF CALIBRATION REGRESSION MODELS

Data	Correlation coefficient	Adj. R2	*p-value*	*a*	*b*
Soil-core	-0.977	95.03	<0.0001	2918	-8.38
Air-core	-0.969	93.31	<0.0001	2940	-7.76
All data	-0.968	93.51		2929	-8.07

After analyzing the obtained data of the calibration models, it is possible to conclude that even though the metrics are a bit inferior with the air-core sensor, the simplicity of its deployment can justify accepting lower metrics. It must be noted that in this calibration, special efforts have been conducted to ensure that the soil density remains similar in the surrounding soil to that of the core of the sensor by avoiding compacting the soil in the core. Nevertheless, in real deployments, this cannot be ensured due to the difficulties of installing sensors without affecting the surroinding soil. The decrease in the accuracy can be explained by the diminution in the portion of the sensitive volume of the sensor covered by the monitored soil.

B. Comparison of paired data

The result of the T-student test was a p-value equal to 0.002, which indicated that there are no significant differences between both pairs of data. Thus, we can confirm that the use of air to fill the core of the sensors does not alter its performance, and the data obtained can be compared with data gathered with the soil-core.

C. Comparison of differences between gathered data in each pot

The result of comparing the standard deviation between the three experimental replicates of both air-core and soil-core sensors is presented in the following paragraph. We focus on the coefficient of variation for the averaged value of data collected for individual pots considering the pot repetitions for each treatment. This information represents the variability of data due to the experimental replicas. The results can be seen in Figure 7. As in the previous case, the coefficient of variation is very similar, with an average value of 0.8 % in both cases. Nevertheless, in the air-core sensor, it has been possible to achieve values lower than 0.5 % in some of the treatments.

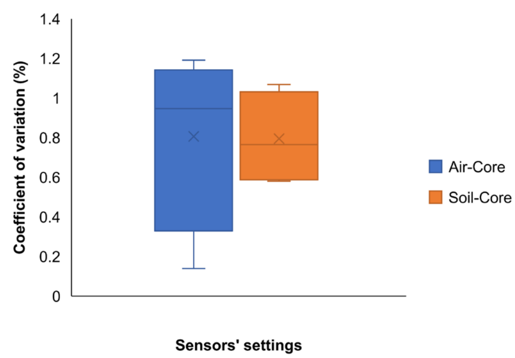

Figure 7. Coefficient of variation of the 3 experimental replicas.

Initially, and considering the gathered data, we can confirm that with the new sensor' settings, it has been possible to achieve similar variability in gathered data. Moreover, some individual results indicate that there is a potential to achieve lower variation in gathered data, but additional experiments are required to confirm this tendency.

CONCLUSIONS

In this paper, we have assessed the performance of an existing soil moisture sensor with an alternative setting. While the original sensor was previously used and completely buried in the soil, in this paper, we propose the fact of not filling the core of the sensor with soil due to the problems encountered in the past. This new form of using sensors has the potential to facilitate their use by users who are not experts or have limited experience.

The results indicated that even though a portion of the sensor's sensing volume has been filled with air, the sensor's performance is similar to that of soil-core sensors. We have evaluated multiple metrics, including the ones linked to the calibration regression models and coefficient of variation. While the R2 of the regression model for the soil-core sensor was 0.95, the one for the air-core sensor was 0.93.

In future work, and with the aim of testing the effect of filling the core of the sensor with soil, the sensors will be buried and unearthed multiple times to evaluate the coefficient of variation of gathered data in these cases. Moreover, the experiments will be conducted with different soils. Finally, the impact of roots in the data gathering will be assessed.

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The Use of MQx-based System for Characterization and Optimization of Plant-derived Volatile Organic Compounds

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***Abstract*— The agricultural sector faces escalating challenges from pest issues exacerbated by climate change, which alters the distribution and behavior of insect pests, threatening crop yields and food security globally. While traditional chemical pest control methods exist, there is increasing interest in sustainable alternatives, such as plant-derived Volatile Organic Compounds (VOCs), which show potential for environmentally friendly pest management. Certain plants, including rosemary, peppermint, and lavender, emit VOCs capable of repelling pests, aligning with principles of integrated pest management and climate-smart agriculture. Advances in sensor technology now allow precise detection and analysis of these plant-produced VOCs, facilitating research into their composition, concentration, and effectiveness for pest control. Additionally, understanding the dispersal range of VOCs is essential to optimize the placement of aromatic plants in agricultural systems for maximum pest deterrence. This study aims to characterize the gases emitted by rosemary, peppermint, and lavender using various gas sensors, and additionally, to determine the maximum detection range of these emissions to enhance pest control strategies. For data classification, Machine Learning (ML) techniques were employed to enhance the system's performance. With all features, Boosted Trees achieved 77.66% accuracy, while reducing to 5 features improved accuracy to 80.4%. The model effectively distinguishes temperature patterns between distances, though the confusion matrix shows minor misclassifications, suggesting potential for refinement.**

Keywords- pests; aromatic plants; sustainable agriculture; gas sensors; pest repellent.

I. INTRODUCTION

The agricultural sector faces significant challenges due to pest problems, which can severely impact crop yields and food security. As climate change continues to alter ecosystems, the geographic distribution and behavior of agricultural insect pests are shifting, creating new threats for farmers worldwide [1]. To address these evolving challenges, various pest control methods have been developed and implemented, ranging from traditional chemical approaches to more sustainable and ecological management strategies [2].

In recent years, there has been a growing interest in alternative pest control methods that are both effective and environmentally friendly. Among these, the use of plant-derived Volatile Organic Compounds (VOCs) has gained attention as a potential tool for pest management [3]. Plants such as rosemary, peppermint, and lavender are known to produce a variety of gases that can repel or deter insect pests [4]. These natural compounds offer a promising avenue for sustainable pest control, aligning with the principles of integrated pest management and climate-smart agriculture [2].

Advancements in sensor technology have enabled researchers to detect and analyze these plant-produced gases with increasing precision [5]. These sensors can provide valuable data on the types and concentrations of VOCs emitted by plants, offering insights into their potential effectiveness pest control applications [6]. Understanding the composition and concentration of these plant-derived gases is crucial for developing effective pest management strategies based on their repellent or insecticidal properties [7], [8].

The distance that plant-produced gases can reach is an important factor in determining their efficacy for pest control. While the dispersal of VOCs depends on various environmental factors, such as wind speed and temperature, recent studies have begun to investigate the spatial dynamics of these compounds in agricultural settings [9]. This knowledge is essential for optimizing the placement of aromatic plants or their extracts in crop systems to maximize their pest control potential [10], [11].

The aim of the study is to characterize the gases emitted by specific plants (Rosemary, Peppermint, and Lavender) to prevent pest presence, by using different types of gas sensors. Additionally, the study seeks to determine the maximum detection range of these emissions.

The rest of the study is divided into seven sections. Section II details the most relevant reported studies, whereas Sections III and IV describe the proposal and test bench. The Results are explained in Section V, and in Section VI, a

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discussion is presented. Finally, conclusion and future perspective are shown in Section VII.

II. Related Work

This section summarizes the current findings in gas characterization, sensor monitoring and usage, and pest management.

Recent studies on gas detection and analysis in plants by using sensor technologies have gained significant attention in agriculture, environmental monitoring, and plant health assessment. Several studies have explored the use of various sensor types and systems for this purpose. In 2024, Díaz Blasco et al. [12] investigated the use of Metal-Oxide (MQ) sensors which are sensible to different gases. These gas sensors were used for classifying essential oils from *Cistus ladanifer* plants. Their work demonstrated the feasibility of using low-cost gas sensors to differentiate between essential oil samples based on their VOC profiles. This approach shows promise for rapid and in-situ analysis of plant-derived gases. In a related study in the same year, Ahmad et al. [13] developed a LoRaWAN-based network for estimating harvest time in *Cistus ladanifer* crops. While not directly measuring plant gases, this work highlights the potential of integrating sensor networks with long-range wireless communication technologies for agricultural applications.

The importance of monitoring plant gases extends to pest management in sustainable agriculture. Bouri et al. [14] reviewed climate-smart pest management techniques, emphasizing the role of precision agriculture tools, including sensors, in monitoring and managing pests. Similarly, Kanwal et al. [4] discussed the integration of precision agriculture techniques for pest management, highlighting the use of sensors for pest monitoring and detection. Additionally, El-Zaeddi et al. [15] characterized the volatile composition of essential oils from aromatic herbs grown in Mediterranean regions. Their work provides valuable insights into the diverse range of volatile compounds produced by plants, which can inform the development of targeted sensing technologies.

On another note, in 2023, Alabi et al. [16] studied the effects of essential oil blends on rumen fermentation and greenhouse gas emissions in livestock. While focused on animal agriculture, this work underscores the importance of analyzing plant-derived compounds and their impact on gas production in biological systems.

In conclusion, numerous papers and experiments are similar to the research currently in progress. The objective, in comparison to related work, is to collect all the benefits provided by these studies, merging them with the concept of pest detection and plant damage prevention, and incorporating them into our system.

Nevertheless, there are a series of open issues that should be solved, especially the ones related to the cost of electronic devices to be installed in the crops. Additionally, the possibility of developing unassisted sensors is crucial for decreasing, among others, the cost of production of final products (e.g. reducing the amount of fuel required for farmers' displacements). Finally, it is so important to determine the number of devices required for covering a crop to be sure that measurements are significative enough. For this reason, in this paper, we have created a device capable of identifying different profiles of aromatic plants. Additionally, the presence of plants is measured at different distances to know the ratio of action of only one plant. As we already commented, the use of this type of plants mixed with other crops helps farmers to reduce or even eliminate the use of chemical pesticides in crops, protecting then, the environmental from unnecessary pollutants.

III. Proposal

This study aims to develop a low-cost system for identifying aromatic plants using MQ family sensors integrated into a gas monitoring node [12]. In the market, it is possible to find a vast variety of gas sensors with different manufacturing techniques. Most of them require some kind of maintenance [17][18]. However, MQx sensors do not require it [19].

A. Introduction to MQ Sensors

MQ sensors, based on metal oxides, are known for their high sensitivity and rapid response times, making them suitable for applications such as flammable gas detection, air quality assessment, and the identification of compounds in breath. Each MQ sensor model is designed to detect specific chemical components in the air, offering flexibility across various monitoring applications.

B. Selection of Sensors and Cost Efficiency

Seven MQ sensors were selected due to their accessibility and low cost, generally priced between 1.5 to 2 € per sensor. This affordability makes MQ sensors a practical choice for many experimental and environmental monitoring applications. These sensors were selected based on a previous study conducted by Viciano-Tudela et al. [20].

C. MQ Sensor Structure and Functionality

Each MQ sensor contains an electrochemical sensor that changes its resistance upon exposure to certain gases. This resistance change enables the measurement of gas concentrations in the environment. Each sensor includes a heating element, which raises the temperature of a metal wire, typically composed of tin dioxide (SnO_2), to enhance sensitivity to gas. For safe operation, sensors are enclosed in a double-layer stainless steel mesh, preventing the heating element from affecting surrounding materials. The sensor's internal circuits comprise a heating circuit and a measurement circuit, which detect resistive changes indicative of gas concentration.

D. Additional Environmental Monitoring with DHT11 Sensor

A DHT11 sensor was incorporated to monitor temperature and humidity, as these variables can influence the accuracy of gas sensor readings. The DHT11 sensor measures temperature with an accuracy of ±2 °C within a 0 °C to 50 °C range, and humidity with ±5% accuracy within a 20% to 90% range. The sensor operates at a sampling rate of 1 Hz, enabling continuous environmental monitoring.

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E. System Processing and Data Management

The MQ sensors and the DHT11 sensor are managed via an Arduino Mega 2560 microcontroller board, chosen for its high number of analog inputs, essential for processing data from multiple sensors. The board's ATmega2560 processor features 54 digital I/O pins (15 with PWM output capability), 16 analog inputs, and 4 UARTs for serial communication. This microcontroller acts as the system's central processing unit, collecting data from the sensors, processing it, and storing it in a database, as can be seen in Figure 1.

F. Data Storage and Real-Time Monitoring

The prototype system includes data storage in a MySQL database, allowing for real-time review of measurements. Additionally, a real-time clock is integrated to timestamp each measurement, facilitating data analysis.

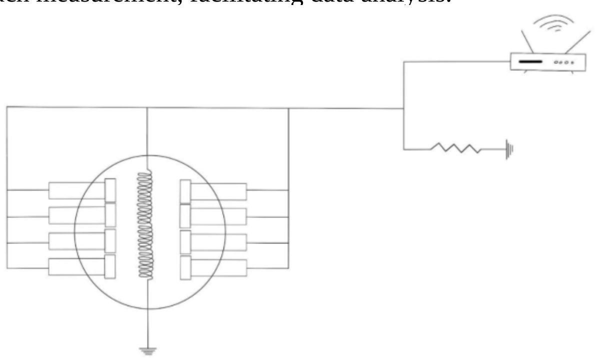

Figure 1. Illustration of the proposed sensor node consisting of 7 MQ gas detector connected to the router.

G. Application for Aromatic Plant Identification

This setup enables precise monitoring of aromatic plants by leveraging the sensitivity and versatility of MQ sensors to detect the unique chemical components emitted by these plants. By analyzing data from the sensors, the system can identify and differentiate specific aromatic plants efficiently and economically.

IV. TEST BENCH

This study uses gas sensors to identify three aromatic plants from the Lamiaceae family: rosemary, lavender, and mint. Emissions from each plant were measured at different distances and times to analyze their effectiveness as pest repellents. Statistical analysis will help differentiate the species and optimize sensor use in aromatic plant monitoring.

A. Plant description

For our tests, three varieties of aromatic plants commonly found in different crops were selected, all belonging to the Lamiaceae family. The first is rosemary (*Salvia rosmarinus*), a woody perennial plant with green leaves and purple flowers. Lavender (*Lavandula angustifolia*) in Figure 2, a perennial plant with lanceolate leaves and purple flowers, was also used. Finally, specimens of mint (Mentha) were included, which are herbaceous perennials with green leaves and white or purple flowers, although, at the time of the measurements, the mint plants did not have flowers.

A) B)

Figure 2. Plant Sample. A. Corresponds to Lavandula angustifolia. B. Corresponds to mint.

B. Data Gathering Methodology

To characterize each plant, the procedure followed is explained as follows. First, the sample plant (*Salvia rosmarinus*, *Lavandula angustifolia*, or mint) was placed inside the measurement device. The sensors were turned on, and, after 24 hours, the data collection process was stopped. Once the data collected was stored, sensors were turned off.

This procedure was meticulously repeated for each plant species in the experiment, and a total of three trials per species were conducted. The measurement device was positioned with exact precision at one centimeter from the plant like in Figure 3. After completing all measurements at this distance, the device was then placed ten centimeters, and finally thirty centimeters from the plant. Throughout, the above process was consistently followed to obtain the required data for each plant species.

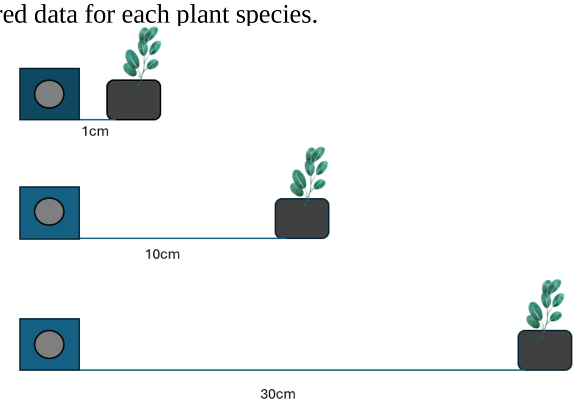

Figure 3. Assembly of the experiment at different distances. A. 0 cm separation from the plant; B. 10 cm separation from the plant; C. 30 cm separation from the plant.

It is important to note that the data collected during the first hour of each trial should be excluded, as this is the estimated warm-up period required for the gas sensors to reach optimal performance.

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C. Data Analysis Procedure

For the data analysis, the first step is to compare the variation in readings based on the type of aromatic plant analyzed and the distance at which gas sensors are positioned at different times of the day. This approach aims to determine whether the plants maintain consistent effectiveness over time or if there are specific periods during the day when their pest-repelling capabilities are more robust. Suppose fluctuations in data are observed at the start of measurement that later stabilize. In that case, it will be considered that the sensor requires an initial warm-up period, which may affect the readings. For this reason, a prolonged measurement period is used for each plant to determine the sensor's stabilization time.

To evaluate each plant's effective range, the sensors are placed at controlled, progressively increased distances, observing any changes in readings. A reduction in values as distance increases could indicate that the plant has reached its maximum effective range in repelling pests.

TABLE I. SUMMARY OF THE ACHIEVED ACCURACY IN CONDUCTED TESTS

Nº of features	Model	Accuracy Training-Validation (%)	Test (%)
38/39 (all)	Boosted Trees	88.87	77.66
9/39 (all)	Ensemble	97.95	72.21
5/39 (all)	SVM	98.23	80.43

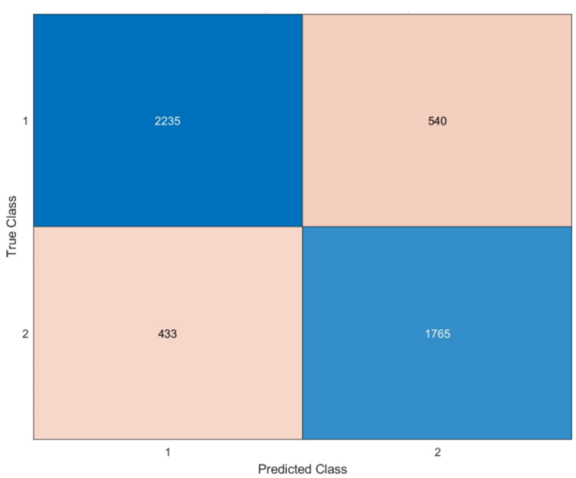

Figure 4. Confusion matrix of selected ML-based classification model.

Once the minimum required measurement time is established, the next critical step is to ensure precise differentiation between the three plant varieties used in the experiment. This differentiation is achieved through the inclusion of controls and statistical methods. The goal is to identify which, or if a combination of sensors, can accurately determine the type of plant present and the effective range of its action. The sensors that have demonstrated the highest accuracy for these parameters will be selected to optimize precision in future measurements and analyses.

V. RESULTS

In this section, we will present the collected data and the results produced by the classification models. The data analysis includes a statistical overview of the collected data. Additionally, the classification outcomes are assessed using established metrics and represent the models that will be included in the node.

A. Data processing and classification

For data classification, the generated dataset is divided into two datasets. Raw values from the data obtained from plants closest and 10 cm to the sensors are used to train the model, and data from 30 cm apart from the sensor is used to test the generated models. The metric selected to test these models is accuracy.

In Table 1, when all features are included, an accuracy of 77.66% is achieved with Boosted Trees. On the other hand, in order to reduce the number of features, up to 9 features, it is possible to reach a 72.21% accuracy, reducing its precision. Nevertheless, when reducing to 5 features, it is possible to achieve the highest accuracy. The classification model achieved an accuracy of 80.4% in distinguishing between temperature measurements taken from plants by a sensor positioned at 0 cm and 10 cm from the plants compared to a sensor placed at 30 cm. This accuracy metric indicates the model's ability to correctly classify the temperature data based on sensor distance. Specifically, an accuracy of 80.4% means that, on average, the model correctly identified the temperature measurement source in 80.4% of the test cases. This suggests a reasonably effective differentiation between the temperature profiles captured at these three distances, though some overlap in temperature readings between the two distances may still exist. The confusion matrix can be seen in Figure 4.

The matrix provides detailed insights into the model's classification performance. The rows represent the actual(true) classes, with "1" and "2" corresponding to temperatures (26ºC and 27 ºC) at 0 and 10 cm compared to 30 cm. The columns represent the predicted classes. In this case, of the samples belonging to Class 1, the model correctly identified 2,235 instances, while misclassifying 540 instances as Class 2. For Class 2, the model accurately classified 1,765 instances and misclassified 433 instances as Class 1. The matrix reveals a balanced distribution of correct classifications for both classes, with high true positive and true negative counts indicating the model effectively distinguishes temperature patterns. However, some misclassifications suggest potential for further refinement, showing the model's strong generalization across sensor depths tested.

VI. DISCUSION

The results of this study demonstrate the potential of using low-cost MQ sensors to detect and analyze the VOCs emitted by aromatic plants such as rosemary, lavender, and peppermint for pest control applications. These findings align with recent research on plant-derived VOCs, supporting their viability as eco-friendly alternatives to

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synthetic pesticides. By leveraging the sensitivity of MQ sensors, we could identify the unique VOC profiles of each plant, providing insight into their repellent properties and practical ranges.

A. Effectiveness of MQ Sensors for VOC Detection

The MQ sensors displayed sufficient sensitivity to detect characteristic VOCs of the studied plants at varying distances, showing promise as a tool for aromatic plant identification. Given the low cost and wide availability of MQ sensors, they present a practical solution for integrating VOC detection into pest management practices, particularly in regions or settings where advanced instrumentation is economically or logistically unfeasible. This study's findings are consistent with work by Díaz Blasco et al. [12] and Ahmad et al. [13], which demonstrated the practicality of MQ sensors in agricultural applications, including crop classification and essential oil analyses remains in enhancing the accuracy and specificity of these sensors. For instance, while the sensors successfully differentiated VOC profiles at proximity (0-10 cm), accuracy diminished slightly at greater distances (30 cm), indicating potential limits in the sensors' effective detection range. This decline in sensitivity may be due to environmental interference or the natural dispersion of VOCs over distance. Thus, further refinement in sensor placement and calibration could improve detection accuracy.

B. Implications for Sustainable Pest Management

This study highlights the potential role of VOCs from aromatic plants in Integrated Pest Management (IPM) strategies, contributing to climate-smart agriculture by reducing the reliance on synthetic pesticides. By characterizing the VOC emission patterns of rosemary, peppermint, and lavender, we can inform farmers on the optimal placement and quantity of these plants within crop fields to enhance their pest-repelling effectiveness. These findings are aligned with the work by El-Zaeddi et al. [15] on the role of Mediterranean herbs in pest management.

C. Environmental and Operational Considerations

Integrating the DHT11 sensor for monitoring temperature and humidity proved essential, as these environmental factors significantly influence gas sensor performance. Data showed that changes in humidity and temperature led to slight variations in the sensors' readings, a well-documented limitation in previous studies on MQ sensors' environmental sensitivity. This suggests that real-time monitoring is crucial to ensuring reliable and consistent data from MQ sensors, particularly in field settings where climate conditions fluctuate.

Future research should consider implementing calibration algorithms that adjust sensor readings in real time based on environmental conditions to address these challenges. Additionally, exploring alternative or supplementary sensor technologies, such as electrochemical or infrared sensors, may enhance the accuracy of VOC detection across a broader range of environmental conditions.

D. Data Analysis and Model Optimization

The machine learning models applied in this study achieved an accuracy of up to 80.4% in distinguishing between aromatic plants based on sensor data, validating the potential of data-driven approaches for plant identification. Notably, the accuracy was highest when using a reduced set of five features, suggesting that sensor data can be streamlined without compromising classification performance. This supports the hypothesis that certain VOC compounds indicate specific plant types and that focusing on these compounds can improve model efficiency.

Nonetheless, the moderate misclassification rate observed in the confusion matrix indicates potential for optimization. Future work could involve experimenting with different machine learning algorithms, such as deep learning models, to enhance classification performance. Additionally, increasing the number of sensor types in the node could provide a more comprehensive VOC profile, potentially improving accuracy further.

E. Limitations and Future Directions

While the findings demonstrate the feasibility of using MQ sensors for plant VOC identification, limitations remain. MQ sensors, while cost-effective, lack the specificity of advanced Gas Chromatography-Mass Spectrometry (GC-MS) used in laboratory settings. This limitation could be addressed by combining MQ sensors with more selective technologies in a hybrid sensing system, providing broader coverage of VOCs with improved accuracy.

Future studies should also investigate the temporal dynamics of VOC emissions throughout the day to understand how plant VOC release patterns vary under different environmental conditions. By establishing these patterns, the effectiveness of VOCs as pest deterrents can be optimized based on real-time environmental monitoring. Furthermore, long-term field trials are recommended to validate these findings under real-world agricultural conditions, as laboratory settings cannot entirely replicate the complexities of open-field environments.

VII. CONCLUSION AND FUTURE WORK

Based on the results obtained, it has been demonstrated that the MQ sensor effectively detects VOCs emitted by aromatic plants. The data collected enables each plant to be characterized using artificial intelligence algorithms, achieving a significant level of accuracy in species identification and distance measurement.

Nevertheless, it is necessary to expand the dataset and conduct further measurements under varying environmental conditions to enhance the precision and consistency of plant characterization. This would allow the models to be fine-tuned and their robustness increased in field scenarios. Additionally, incorporating new variables, such as temporal variations in VOC emissions, could help identify optimal periods for pest control effectiveness.

For future work, once an accurate characterization of the aromatic plants is achieved, estimates of the adequate spatial coverage of each species could be made. This will allow for applying these findings to commercial-scale crops, optimizing the placement of plants in agricultural systems to maximize their repellent effect and contribute to a more sustainable integrated pest management approach.

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