A smart beekeeping platform based on remote sensing and artificial intelligence

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ABSTRACT

Honey bees play an essential role in the food chain, being responsible for one third of the global food supply due to pollination. Thus, preserving the health of beehives is of paramount environmental and economic importance. Unfortunately, at present a decline in bee populations is reported, attributed to factors such as climate change, environmental disasters, use of pesticides, etc. The SmartBeeKeep (https://smartbeekeep.eu/) research project, co-funded by EU and Greek funds, builds on the latest developments in remote sensing and AI technologies to provide a holistic platform (currently at the integration stage) that offers services addressing different needs of beekeepers, facilitating their work and contributing to the study of biodiversity. Such services can improve current beekeeping practices, reduce costs, and create a new distribution channel for beekeeping products. Specifically, an automated mapping service was implemented that runs periodically in the backend and uses the freely available multitemporal multispectral Sentinel-2 data to estimate and update information regarding the beekeeping flora (including blooming detection), based on state-of-the-art AI models for semantic segmentation. Moreover, a WebGIS app and a mobile (progressive web) app were developed that make extensive use of modern remote sensing and AI technologies. In particular, the WebGIS app displays freely available data layers that provide crucial information for beekeepers and enables them to view and edit their own data layers, manually entering information regarding the beekeeping flora near their apiary. On the other hand, the mobile app provides three functionalities: a) viewing and editing information regarding the beekeeping flora at a user's current location, b) automated AI-based identification of beekeeping plants from photos captured by the mobile phone, and c) tools for beehive inspection and management, which allow beekeepers to keep track of honey bee colonies development, applied treatments and/or feeding actions.

Keywords: Remote Sensing, phenology monitoring, smart beekeeping, biodiversity, WebGIS, participatory mapping, artificial intelligence, machine learning

1. INTRODUCTION

In recent years there has been a significant decrease in the populations of bees and other pollinating insects, which is due to various factors such as climate change, environmental disasters, the use of pesticides, etc.[1]

In recent years, the European Community has made systematic efforts to study the phenomenon, understand the causes and reverse the situation*. Unfortunately, recent relevant research concludes that the phenomenon is complex and there is a significant lack of knowledge. In Greece in particular, the reduction of the bee population

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*https://rea.ec.europa.eu/news/eu-funded-projects-helping-protect-bees-across-europe-2022-05-20_en

in recent years has been dramatic and the losses during the winter months, according to the Federation of Beekeeping Associations of Greece, even reach 40%. In addition, the sector also faces problems from endogenous factors (introversion, financial crisis, lack of modernization of production). A characteristic feature of professional Greek beekeeping is the continuous and long-distance movements of the bees. Adverse weather conditions force beekeepers to move the hives to ensure the growth and survival of the bees, but also to increase production. This process increases the cost of running an apiary. However, such hive transfers are typically based on experience or hearsay, so they are often unsuccessful. The ability to systematically locate beekeeping plants and particularly collecting information regarding their flowering period will greatly reduce costs and travel time.

In order to deal with these challenges, SmartBeeKeep aims to combine recent developments in remote sensing and machine learning to serve the needs of the beekeeping community, including beekeepers, general public interested in beekeeping procedures and products and Laboratories performing analyses of beekeeping products. The main contributions can be summarized as follows:

1. **Beekeeping flora mapping and monitoring:** The free availability of high resolution Earth Observation (EO) data at high revisit frequencies, through the Copernicus (Europe, ESA) and Landsat (United States, NASA/USGS) programs, represent valuable resources for numerous remote sensing applications, including precision agriculture and beekeeping. Specifically, they also enable the creation new methods that can properly identify crop phenology, i.e. the periodic changes in plant life cycles.[2,3] Recently, Transformer-based deep learning approaches exploiting temporal attention have demonstrated great efficiency for crop classification with Sentinel 2 imagery.[4–7]Smartbeekeep will build on these advances to create new automated modules for beekeeping plant identification and mapping as well as blooming period monitoring based on free satellite data. Furthermore, the Smartbeekeep web app will give the beekeepers the ability to either personally or collaboratively map beekeeping flora at their regions of interest

2. **Smart inspection app:** An innovative smart inspection mobile app was developed to facilitate and better organise the Beehive inspection tasks. This app is able to record all necessary information, including beekeeper activities such as hives' relocation, disease treatment or feeding and provide any required related notifications. It also allows the automated recognition of beekeeping flora from captured photos of mobile phone based on Convolutional Neural Networks (CNNs).

3. **Identification of pollen grains/pellets** A palynology-as-a-service application is offered to Laboratories responsible for this task. It allows users to upload of i) a microscope image with pollen grains (from honey or pollen pellets) or ii) a camera image of pollen pellets. The server then detects the locations and classification of each grain or pellet using deep learning object detection techniques, and returns a report with the findings.

4. **Innovative e-Markeplace** A sophisticated e-Marketplace will also be offered to beekeepers using the system. Each store will leverage SmartBeeKeep's database to automatically provide detailed information on beekeeping products produced using the SmartBeeKeep tools, such as botanical and geographic origin of product, beekeeping flora/biodiversity and production processes (e.g. inspections made, disease history), etc. Furthermore, the final version will also support crowdfunding of organic beekeeping with a specific origin and production/certification/packaging procedures.

2. METHODOLOGY AND PLATFORM

The ultimate goal of SmartBeeKeep methodology is design and develop a set of required units and integrate them in a common *SmartBeeKeep Platform*, whose architecture is illustrated in Fig. 1. The platform front-end consists of a web and a mobile app, whose functionalities are described in the following subsections.

2.1 Online mapping unit

The recording and mapping of the beekeeping flora, which is necessary to ensure food for the bees, is required for documenting the identity of the beekeeping products, highlighting the special local characteristics and for the protection of the consumer, as well as the beekeeper. This unit of the web app includes data in two different

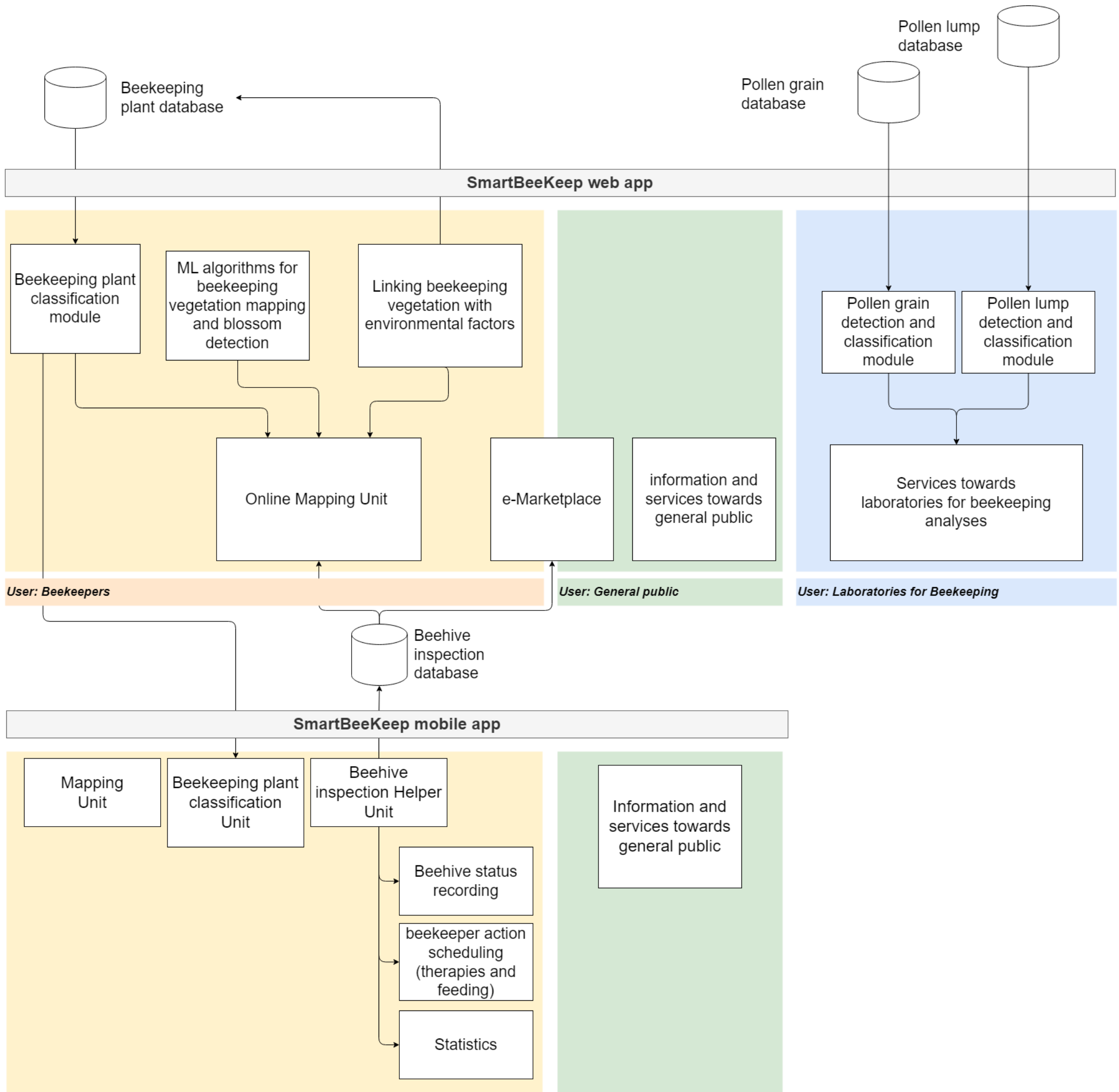


Figure 1. The SmartBeeKeep Platform architecture

sources: a) manual mapping by contracted users (amateur or professional beekeepers) and b) automated mapping by using satellite data.

Manual mapping allows users to manually or collaboratively create and update their own maps by identifying the two prevailing beekeeping plants at a specific location, out of a list of the most common beekeeping plants and trees. An interface allows the user to enter this information in a dynamic canvas map, where the size of cells can be increased or decreased by changing the zoom factor. Cells are coloured based on the user's choice for the prevailing beekeeping plant. This mapping interface can also be activated from the Smartbeekeep mobile app, while the beekeeper is in the field.

Automated mapping is based on using pre-trained deep learning models based on multitemporal and multichannel satellite images for predicting the dominant beekeeping plants in a specific region of interest. For this reason, we opt to use deep learning techniques for semantic segmentation suitable for multitemporal and multi-channel satellite data. Specifically, a highly optimised transformer-based architecture based on temporal self-attention, namely Lightweight Temporal Encoder Transformer (LTAE), was integrated within a U-NET-like architecture, namely U-TAE(U-Net with Temporal Attention Encoder), in[8] to be used for semantic segmentation of multispectral satellite time series. This model encodes a multitemporal image sequence in the following steps: (1) a shared multi-level spatial convolutional encoder embeds each image in a simultaneous and independent way, (2) a temporal attention encoder creates a single feature map for every level by stacking the temporal dimensions of the resulting sequence. Specifically, in order to reduce the memory and computational requirements, for every pixel it produces temporal attention masks at the lowest resolution, which are then spatially interpolated at all resolutions. (3) A convolutional decoder calculates features at every resolution level and the final predicted segmentation mask is produced as the output of the highest resolution level.

Although this approach can also be applied for automated mapping of beekeeping vegetation, the use of satellite image time series as input has significant disadvantages: a) this data can be very noisy due to clouds, calibration errors, etc. and b) memory requirements are significantly increased as the number of input images and channels increases. To address these issues, we propose to preprocess satellite data within a specific time range, in order to create image composites with reduced noise, by using a temporal median filter. Furthermore, we modify the U-TAE approach to use channel attention for calculating weights to different channels, instead of the temporal attention used in the original approach.

Both approaches have been implemented and tested using a custom database of crops (including Levander) in southern France, as it was not possible to obtain similar precise annotations from Greece. More details regarding the database and the results obtained are presented in the Results section.

Visualisation interface: The application interface presents a series of processed thematic data and indicators related to the beekeeping activity, which may aid the beekeeper in making a decision regarding the relocation of his hives. As seen in Fig. 2, these include: a) areas with a particular type of vegetation, b) areas where enemies of bees live, such as bee-eaters or bears, c) inland waterways, as well as buffer areas around of them based on the expected distance that a bee can travel (5km), d) boundaries of NATURA areas and e) altitude zones. The specific interface will also be accessible to the general public, to increase the visiblity of the project.

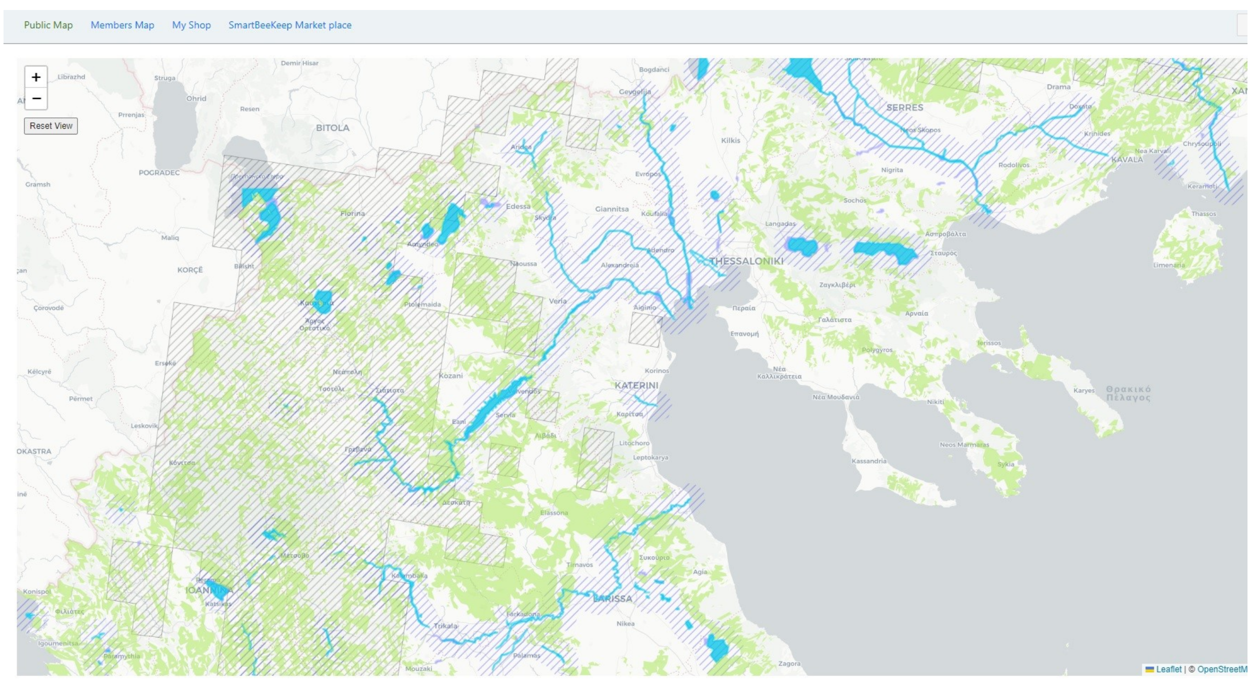
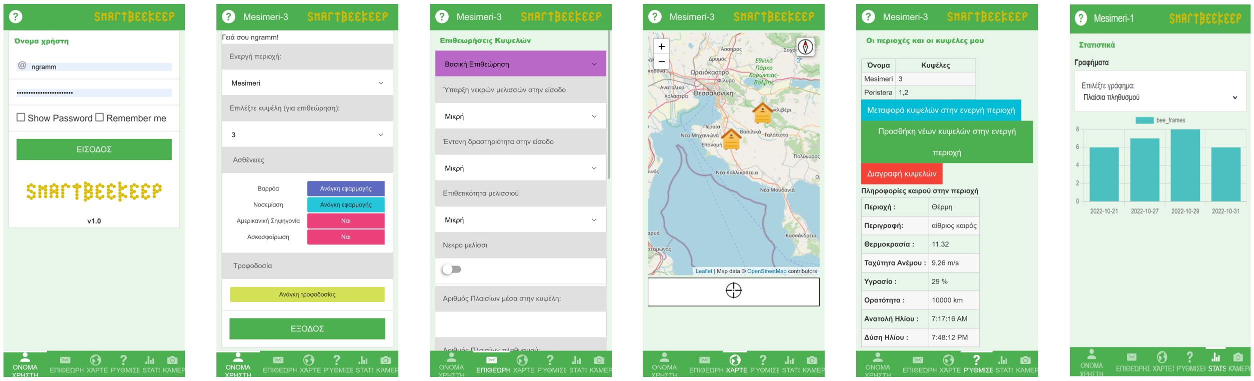


Figure 2. Visualisation of digital map with a) areas where bushes or grass exist, b) inland waterways and 5km buffer around them and c) Bear appearance area.



(a) (b) (c) (d) (e) (f)

Figure 3. Screenshots from the mobile application: a) Login screen b) Main tab for selecting the active area and hive as well as any treatment or feeding action, c) inspection tab, d) Map tab showing user's apiaries, e) settings/information tab for modifying/transferring hives, f) graph depicting bee population vs time

2.2 E-marketplace

To facilitate the management and monitoring of his/her production and sales, each beekeeper can create and operate his own online shop through the SmartBeeKeep E-marketplace web application. The user can add or change the products displayed in his store as well as see information about the orders that have been placed up to the given moment. Furthermore, crowdfunding campaigns for new products will also be supported in the final version of the E-marketplace.

2.3 Smart inspection app

The smart inspection app facilitates the beehive inspection procedure for the beekeeper and greatly simplifies the management of the associated information. The user of the application is first authenticated through a user name and password (Fig. 3a) and then the user selects the apiary which will update and the desired action: inspection, diseases or feeding (Fig. 3b). In the case of inspection, the user first selects the beehive to inspect and fills in a series of information, which are finally recorded in the inspection database (Fig. 3c). Two inspection modes are available: either basic (includes only the most important parameters) or extended (includes all supported parameters). The map tab (Fig. 3d) shows a map of all the user's apiaries, while the Settings tab (Fig. 3e) allows moving/adding/deleting hives from the active area, while also displaying weather information regarding the current location. The Statistics tab (Fig. 3f)presents graphs related to parameters of the last inspections (e.g. number of population frames, brood, honey and pollen). Finally, using the last tab, the user can capture an image of an unknown beekeeping plant, which is then sent to the server. Then, the server uses a CNN classification module trained with the most common beekeeping plants to identify the plant and return as a response the type of plant identified as well as the corresponding matching scope.

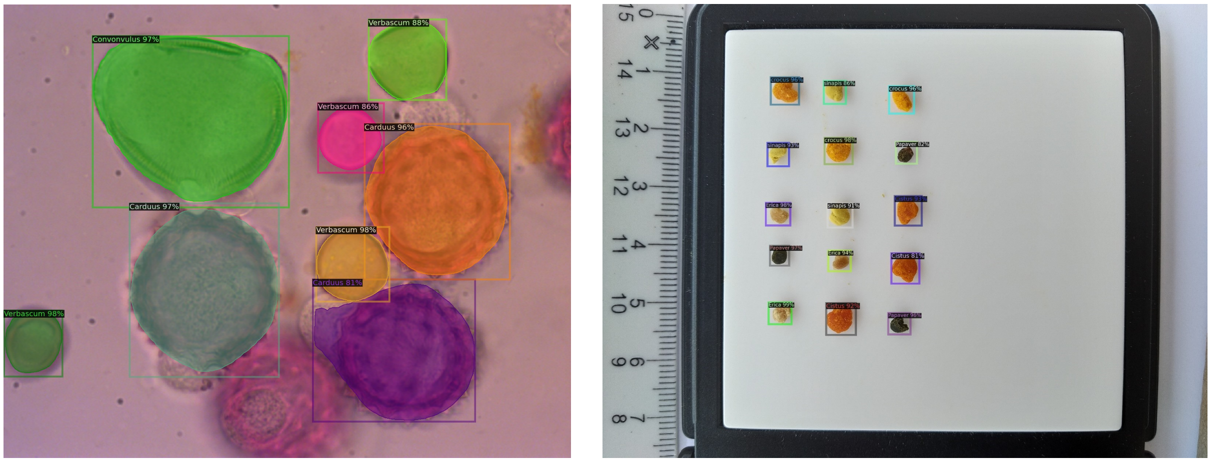
In addition, the beekeeper has the ability to record both the feeding actions in the apiary and the treatments he applied for any diseases (e.g. varroa) and receive immediate notifications via email for any necessary related imminent actions.

In the final version, the Smart inspection app will also support the execution of the manual mapping unit presented above.

2.4 Detection and recognition of pollen grains from honey or pollen pellets

This feature is provided as a service for laboratories performing analysis of beekeeping products (e.g. honey). Specifically, through the Smartbeekeep web app, it is possible to upload a microscope image to the server that detects and recognises the pollen grains in the image using object detection algorithms, returning the corresponding results to the user.

Experiments were conducted using a dataset containing 38 different classes of beekeeping plants, with each plant having a sample size of around 100 microscope images with multiple objects. The dataset consists of



(a) (b)

Figure 4. Results of recognition of (a) pollen grains from microscope images and (b) pollen pellets from camera images

3569 images and was split in three sets as follows: 80% training, 10% validation and 10% test. We evaluated different state of the art deep learning algorithms for object detection to see which performs better. First, we manually annotated the images with masks and trained a Mask R-CNN model[9] using a Resnet101 backbone, with satisfactory results (Average Precision of 67.7% at 0.5 IoU). A sample result is illustrated in Fig 4a. However, using Yolov6,[10] yields an even higher Average Precision of 87% at 0.5 IoU. The Yolov6 model we used had 59.6 million parameters and was trained for 100 epochs.

2.5 Detection and recognition of pollen pellets

This feature can serve both laboratories performing beekeeping analysis as well as beekeepers and researchers. Through the web application, it is possible to upload photos of pollen pellets to the server that detects and recognises the pollen pellets in the image using object detection algorithms, such as Faster RCNN, returning the corresponding results to the user (Fig 4b).

3. RESULTS

In this section, results from the automated mapping Unit for crop segmentation, including lavender, an important beekeeping plant, will be presented. Training data were selected from specific areas in Southern France, which were chosen as they contain a majority of France's lavender fields. Specifically, the database was constructed by 2,420 patches of size 128×128 pixels with 10m resolution for the period January - December 2021. We use Sentinel-2 Level-2A images with 12 multispectral bands (resolutions of 10,20 and 60 meter/pixel) representing Surface Reflectance. However, similarly to,[5] the noisy atmospheric bands, i.e. bands for Aerosols and Water vapor with 60 meter/pixel resolution, are omitted since they can not provide any useful information. All available Sentinel-2 Level 2A images with cloud cover was less than 20% of the total image were used. The selected areas have 153 different plant species, including lavender, but for the database we used 12 most dominant crops, plus a *background* class and an *void* class (including all other species), following.[8] The full list of classes is presented in Table 1. Annotations are provided by the French government through the Land Parcel Identification System (LPIS) [†]. LPIS crop maps rely on the annual declarations from farmers who report the extent of their parcels and the type of crop grown. According to the French Government's on-the-spot checks, the accuracy of the marked parcels is 98%, with a relative error of 0,3%.

The dataset was split putting 80% of the data in the training set, 10% in the validation set and 10% in the test set. When using temporal attention, all available images are used, while when using band attention, two image composites (one for winter and one for summer) are created, which ideally should provide the same segmentation result. Results from both approaches are presented in Table 2, while sample patches are shown in

[†] https://geoservices.ign.fr/rpg

Table 1. Database classes

0	background
LAV	Lavender
SNE	Temporarily unused agricultural land
VRC	Vine and wine grapes
VRG	Orchard
SPH	Pastoral area - predominantly grass and woody forage resources present
BDH	Winter durum wheat
SAI	Other sainfoin
PPH	Permanent grassland - predominantly grass
PTR	Other temporary grassland of 5 years or less
OLI	Olive grove
SPL	Pastoral area - predominantly woody forage resources
LUZ	Other alfalfa
13	Void

Fig. 5. As seen, the original U-TAE using temporal attention leads to higher accuracy, however the modified U-TAE using band attention has lower complexity.

Table 2. Recognition results for the test set using the two versions of methods

Model	Accuracy
Original U-TAE (temporal attention)	74.52
Modified U-TAE (band attention)	70.13

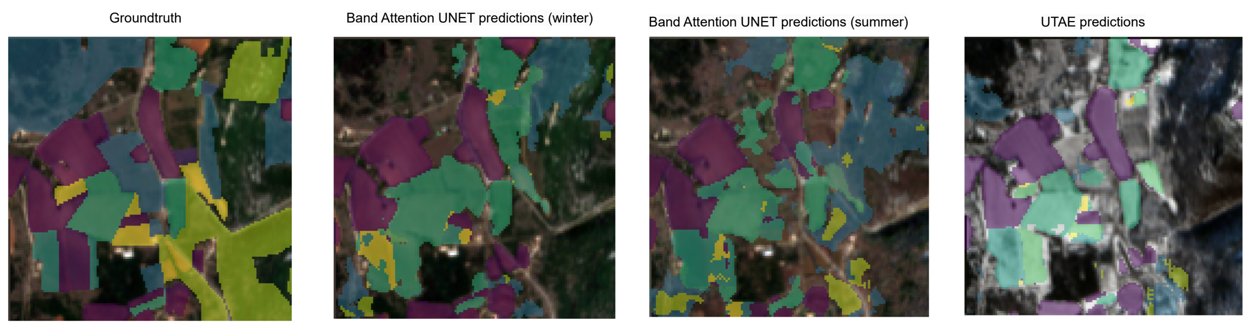


Figure 5. Results obtained by the original U-TAE (temporal attention) and the modified U-TAE (band attention) approaches a) Ground truth, b-c) results of U-TAE(band attention) for winter and summer data respectively and d) Original U-TAE approach.

4. CONCLUSIONS AND FUTURE WORK

In this work, the main functions and services of the SmartBeeKeep platform were presented, aiming to implement a methodology for smart beekeeping. The ambition of the project consortium is to exploit the platform as a whole, as well some of its key components, through a low-cost subscription service, providing significant advantages to its users and contributing significantly to the study of biodiversity as well as to the sustainability of the sector.

ACKNOWLEDGMENTS

This research has been co-financed by the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH – CREATE – INNOVATE (project codes:T2EDK-04396 SmartBeeKeep).

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