CoFly: An automated, AI-based open-source platform for UAV precision agriculture applications

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Abstract

This paper presents a modular and holistic Precision Agriculture platform, named CoFly, incorporating custom-developed AI and ICT technologies with pioneering functionalities in a UAV-agnostic system. **Co**gnitional operations of micro **Fly**ing vehicles are utilized for data acquisition incorporating advanced coverage path planning and obstacle avoidance functionalities. Photogrammetric outcomes are extracted by processing UAV data into 2D fields and crop health maps, enabling the extraction of high-level semantic information about seed yields and quality. Based on vegetation health, CoFly incorporates a pixel-wise processing pipeline to detect and classify crop health deterioration sources. On top of that, a novel UAV mission planning scheme is employed to enable site-specific treatment by providing an automated solution for a targeted, on-the-spot, inspection. Upon the acquired inspection footage, a weed detection module is deployed, utilizing deep-learning methods, enabling weed classification. All of these capabilities are integrated inside a cost-effective and user-friendly end-to-end platform functioning on mobile devices. CoFly was tested and validated with extensive experimentation in agricultural fields with lucerne and wheat crops in Chalkidiki, Greece showcasing its performance.

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Metadata

Nr.	Code metadata description	Please fill in this column
C1	Current code version	V1.0.0
C2	Permanent link to code/repository used for this code version	`https://github.com/CoFly-Project/cofly-gui`
C3	Code Ocean compute capsule	-
C4	Legal Code License	MIT
C5	Code versioning system used	git
C6	Software code languages, tools, and services used	JS, Python, Electron, Node
C7	Compilation requirements, operating environments & dependencies	>= Node JS v8.0, Python 3.6, pandas =1.2.1, numpy =1.20.3, matplotlib =3.4.2
C8	If available Link to developer documentation/manual	`https://github.com/CoFly-Project/cofly-gui#readme`
C9	Support email for questions	keglezos@iknowhow.com

1. Motivation and significance

Agriculture constitutes a vital component of the economy in many less industrialized countries, leveraging natural resources to yield both income and export revenue. Improving productivity in agriculture not only benefits the economy of individual countries but also contributes to global food production, as food insecurity and poor quality can have negative impacts on public health.

Unmanned aerial vehicles (UAVs) equipped with artificial intelligence and visual analysis capabilities offer a promising solution to the aforementioned challenges faced in agriculture, particularly in the realm of precision agriculture (PA). To this end, commercial closed-source software and research agricultural products have been developed, leveraging digital farming technologies for precision agriculture and farming development. Commercial products, including Pix4D [1], DroneDeploy [2], and Sentera FieldAgent [3], which are drone mapping software that can create UAV flight paths, capture aerial photographs, visualize crop health indices, and provide a timeline view of previous field scans for continuous monitoring. Additionally, Agisoft Metashape [4] employs photogrammetry to create 3D maps including crop yield and plant health maps. Botlink [5] is a UAV-based agricultural software with a flight planning framework that can produce high-definition 2D and 3D outputs and vegetation indices. Lastly, Blue River Technology [6] provides smart farm machines that use computer vision and deep learning techniques to individually monitor each plant in the field, a capability that is currently lacking in integrated UAV products. Table 1 compares these various commercial agricultural products based on their farming technological features.

Software	Path planning	Vegetation indices	Timeline	Weed detection
Pix4D [1]	✓	✓	✓	✗
Drone Deploy [2]	✓	✓	✓	✗
Sentera FieldAgent [3]	✓	✓	✓	✗
Agisoft [4]	✗	✓	✗	✗
Botlink [5]	✓	✓	✗	✗
Blue River Technology [6]	✗	✗	✗	✓
CoFly	✓	✓	✓	✓

Table 1: A competitiveness matrix that compares commercially available products, including CoFly, based on their farming technological features.

Several research studies have also developed systems-level software for various agricultural practices, primarily focused on crop health and yield monitoring. According to a recent review paper [7], these systems mostly utilize commercial usage-based pricing models (Table 1) for their flight planning and photogrammetric services, thereby hindering their customization for agricultural applications, as it requires a certain level of expertise for consolidation and overall management. Additionally, most of them aim to improve specific workflows such as estimating plant volume [8], monitoring vegetation canopy reflectance [9] and evaluating chlorophyll levels in rice paddies

[10]. Other practices include periodic crop status inspections, pH level, and acidity calculations, as well as vineyard monitoring and mapping [11, 12, 13]. Regarding motion planning, while numerous options are available for flight control and mission planning using open-source UAV flight controllers and simulators [14], [15] none of them extend their capabilities beyond flight control to include data post-processing, and they do not cater to the unique characteristics of each field, such as no-fly zones and automatic UAV-based weed detection.

Owing to the lack of some advanced features, in this article, a novel UAV-based, low-cost, and user-friendly precision agriculture platform, named *CoFly*, has been developed providing an open-source alternative while integrating pioneering functionalities with custom-developed robot-related services in a UAV-agnostic system. The CoFly-GUI platform is a field management tool for UAVs that generates tailored field monitoring paths to assist decision-making objectives and ensure optimal management of crop growth. The primary objective is to simplify the process of scanning, imaging, and parametric analysis of crops using UAVs, making it accessible even to non-experienced in UAV flight end-users without the need for complex manipulations such as autonomous control, precision flight control, obstacle avoidance, etc. The user interface (UI) was designed with the user workflow in mind, aiming to provide the operator or farmer with a cost-effective and end-to-end integrated system that provides valuable information on seed yields, quality, and health. At the same time, the platform is capable of identifying problematic locations, identifying crop health deterioration sources, and providing targeted, on-the-spot inspections. Finally, a weed detection module is also integrated, providing detailed weed classification. These steps are adequate for everyday agriculture needs that require surveillance of a new crop, analysis of photometric indices, and detection of intrusive plant species with minimal hardware requirements to ensure cost-effectiveness. CoFly as a UAV-agnostic PA software, allows the integration of various robot-related and software-dependent systems, as well as multiple UAVs utilizing open-source or SDK-ready firmware. At the same time, we provide the research community with a tool that enables them to create and evaluate customized solutions for several agricultural applications. The technical specifications of the developed field management system are outlined in Section 2.

2. Software description

CoFly-GUI is a hybrid user interface application that has been designed to facilitate easy installation on any computer system, regardless of the operating system. It employs HTTP [16] and MQTT [17] communication protocols for communication with the UAV and its sub-modules. The software features a user-friendly interface that enables users to effortlessly manage and modify settings through the use of graphical representations and instructions that enable them to operate the individual subsystems within the software without the need for specialized knowledge. The user interface has been implemented in JavaScript using the Node JS software development platform and the Electron framework [18]. The design of the software places a strong emphasis on ease of use and user-friendliness.

2.1. Software architecture

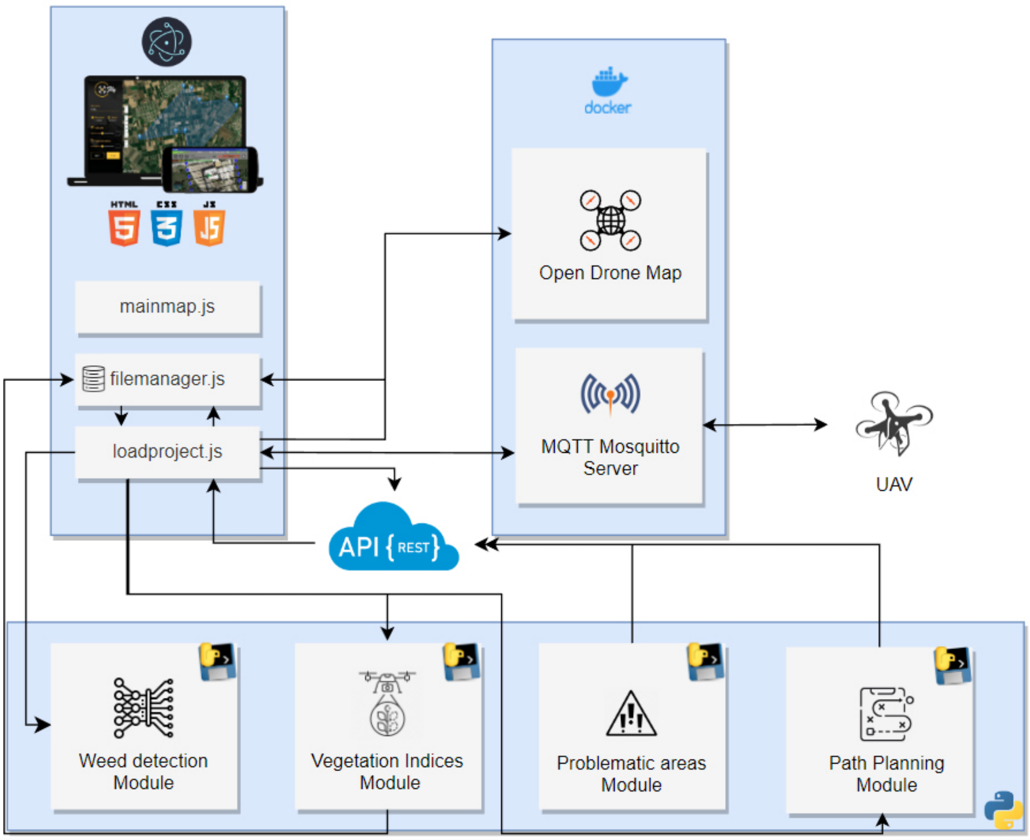


Figure 1: Workflow of CoFly-GUI & Sub-modules.

As sketched in Figure 1, the proposed precision agriculture platform consists of three main components: a graphical user interface, four robotic-related software capabilities, and a bidirectional communication system that enables message interactions and real-time communication between the proposed software and the UAV. As to the graphical interface, the first part concerns the class that creates, visualizes, and manages a world map providing detailed information about geographical regions and sites worldwide (**mainmap.js**). This service has been implemented using the Leaflet library [19], OpenStreet Maps [20], and one extra open-source add-on (draw tool [21]) to generate polygons and markers while simplifying the handling of imported/exported polygons, ultimately resulting in a user-friendly data visualization experience. The **second class** that surrounds the UI is the class that manages, saves, creates, and deletes the files required for the smooth operation of the software (**mainfilemanager.js**). This **file database management class** has been developed to facilitate the recording of information and data of each drone mapping project so as to enable auto-save and local history command actions (*Timeline*). For example, when a user creates a new project with specific parameters (e.g., polygon, UAV mission details e.t.c), the system automatically creates folders and log files so that it can be reloaded in the future either in the same or in another system while keeping a history of the specific drone mapping project. All the parameters created and used by the system can be found in three settings files with the following names: **field_settings.json** (contains useful information such as geographic polygon describing the area of interest, drone's initial position, coverage path, UAV mission parameters, etc.), **map_data.geojson** (contains the name of the field entered by the user and all the information of the geographic polygon of the field), **disabled_paths.json** (contains geographic polygons related to the obstacles defined by the user). Finally, the third and most important class of the CoFly software is the load-communication field (**load-project.js**) which creates a communication node (HTTP API) to facilitate the management and communication of the UI environment with the different sub-modules. The communication of data among different modules is implemented by a Restful API Service [22] which allows the different sub-systems to connect and interact with each other by retrieving the necessary data for their execution. The main communication channel between the sub-modules is reached through the address *localhost:8081* and the data transmission is done via .json files with single post requests.

Additionally, **load-project.js** is also responsible for message interactions and real-time communication with the UAV. This bidirectional communication is done by the MQTT communication protocol over the port 9090 and the Eclipse Mosquito MQTT Server [23] running on docker images. To handle all messages generated by both the UI and UAV, CoFly creates drone topics and connects to them (by listening and subscribing). Specifically, these topics ensure commands to the UAV (start/abort/stop mission), the indication of the exact position of the drone marker on the world map, and its current mission status. Besides, through these topics, the UAV transfers in real-time the collected data to the software. In particular, the open-source library piexif [24] has been used for image handling, which converts the image from base64 encoding to .jpg and assigns to it metadata that will be needed afterward to extract the orthomosaic photo of the field. To display the orthomosaic photo on the world map we also used the piexif library that allows us to convert the exported ODM's [25] .tiff image to .jpg with channel A enabled for transparency.

To ease both the installation of the overall CoFly software and the utilization of the robotic-related and computer vision services, each and every sub-module has been packed into an executable python file (.exe) with the usage of the PyInstaller [26] library without the need of any prerequisite and dependency. The overall framework of the CoFly-GUI program is developed using HTML, CSS, and JS web technologies.

2.2. Software functionalities

Once CoFly-GUI is installed and running, the end user is presented with a set of options including **Load project** (view an existing project), **Create project** (create a new project), or **Import project** (import an existing project). Let us assume that the user selects the second option **Create project**. The first step is to input basic mission attributes, known as Coverage Mission Details, such as the area polygon to be surveyed, flight altitude, and scanning speed.

Once the necessary attributes are defined, the user can select the "calculate path" button to initiate the *Path Planning* utility for the designated polygon, as shown in Figure 2. To cover a continuous field, the well-known Spanning-Tree Coverage [27] algorithm is utilized, which is proficient in handling Coverage Path Planning (CPP) [28] operations, determining a collision-free trajectory that mitigates the limitations of UAVs, and ensuring the most energy-efficient path to comprehensively survey the given area. Once the computation is completed, the flight path is returned to the UI and superimposed on the map. As long as the users are satisfied with the computed flight path, they can proceed with initiating the mission by selecting the "Start Scanning" button. This action initiates the UAV adaptor topic and establishes a direct communication channel with the drone via an HTTP service, enabling the transmission of images captured by the drone without any intermediary processes. Concurrently, the drone's real-time location on the global map is displayed to apprise the user of its precise position over the field and facilitate its supervision in real-time (Figure 2).

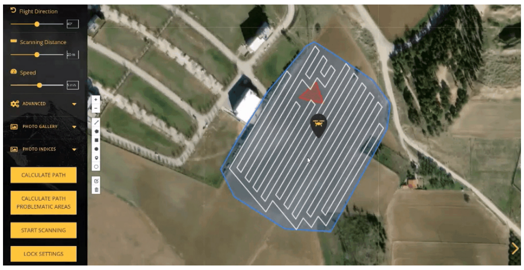
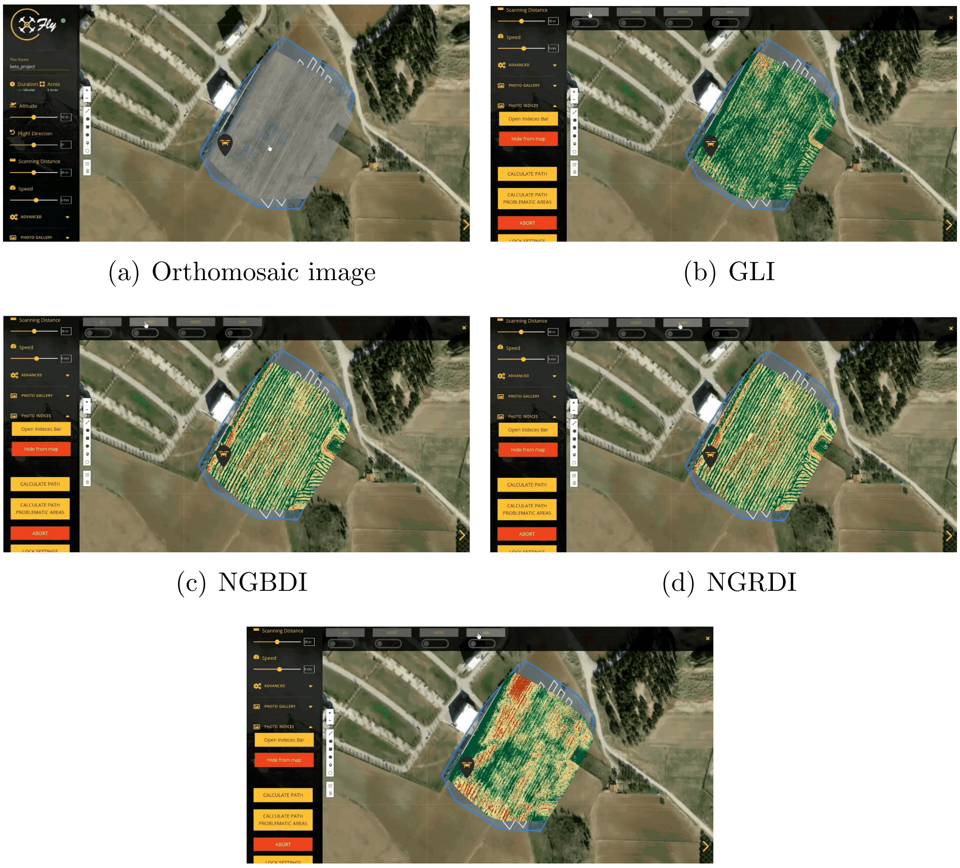


Figure 2: Creation, parameterization and calculation of the coverage path.

After the coverage mission is completed, the user can proceed with launching the *Vegetation Indices* services. By selecting the "Photo Indices" button, the UI forwards the UAV captured images to the corresponding services and obtains the geo-referenced stitched image along with the calculated vegetation index images, as illustrated in Figure 3. Specifically, an accurate orthomosaic map is acquired by deploying the robust OpenDroneMap (ODM) toolkit [25, 29] for the stitching process, while the vegetation index images correspond to 4 efficient indexes, that are widely employed in precision agriculture [30, 31], namely Green Leaf Index (GLI) [32], Normalized Green-Blue Difference Index ($NGBDI$) [33], Normalized Green-Red Difference Index ($NGRDI$) [34], Visual Atmospheric Resistance Index ($VARI$) [35]. Each one of the employed indexes utilizes different characteristics of the vegetation's light reflectance and thus, it quantifies different aspects of crop health. This can be clearly conceived in Figure 3 where vegetation indexes present spatial variations in terms of crop health, while the combination of all of them can provide a concrete overview of the vegetation's health status. Leveraging the acquired knowledge of vegetation, the system will automatically engage the *Problematic Areas* detection service to detect areas within the agricultural field that may pose difficulties, as demonstrated in Figure 4.

Towards assessing the extracted problematic locations, by selecting the "Calculate Path Problematic Areas" button, a UAV-based inspection mission is designed. The process of determining a path for visiting a finite set of points is a motion planning problem, where the objective is to identify the most efficient route that results in the minimum realization cost. For the visual on-site inspection, the Travelling Salesman algorithm [36], a renowned method for finding the shortest path within an undirected graph, is applied. It should be noted that the end-user possesses the ability to interfere with the identified problematic locations via the user interface by differentiating them and adding or removing specific points to formulate a custom site-specific mission that caters to their requirements.

Following the acquisition of aerial imagery, the captured visual data are



(a) Orthomosaic image

(b) GLI

(c) NGBDI

(d) NGRDI

(e) VARI

Figure 3: Visual representations of the geo-refenced orthomosaic and VI maps.

forwarded to the *Weed detection* service for further processing and analysis. In specific, existing weeds among the crop are automatically detected and highlighted for the end-user. The deployed module is employing the robustness of DeepLabv3+ [37], a well-known deep-learning architecture for semantic segmentation, trained and evaluated in previously collected crop data [38]. Towards this direction, the visual input is processed via the deep-learning model, and the depicted weed instances are annotated at pixel-level. As illustrated in Figure 5, *Weed detection* service outputs the visualization of weed species to the UI, superimposed on the geo-referenced map, while the pixel-level annotation (pink) provides accurate spatial information regarding the detected weeds.

Figure 4: Problematic areas detection.

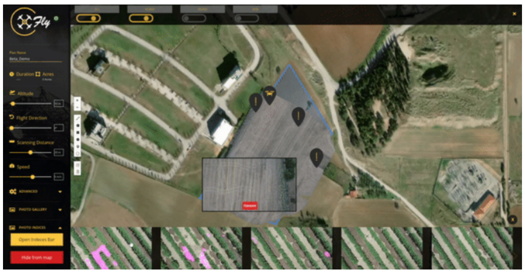


Figure 5: Weed detection module exports upon GLI & NGBDI vegetation indices.

The entirety of this data, retrievable via the **Load** or **Import** feature, is automatically archived in a timeline encompassing the entire crop growth cycle from the fallow period and land preparation, to crop establishment and maintenance, to harvest and storage. More details about the specifics of the developed methodologies can be found here [39]. A video demonstration illustrating the sequence of events among all the aforementioned services is attached to the following link[1].

3. Illustrative examples

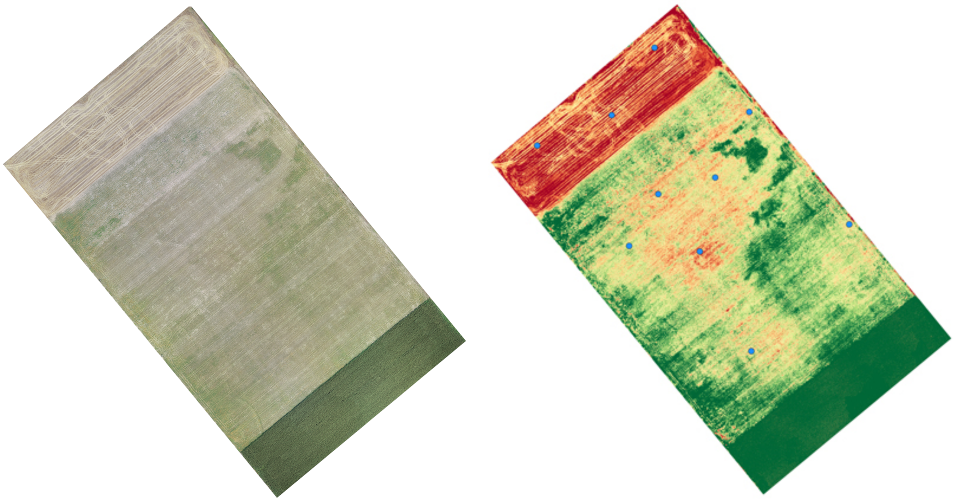
In this section, an experimental evaluation of the proposed software is carried out focusing on the evaluation of vegetation health estimation in a real-life demonstration scenario. The experiment is intended to assess and validate the operational proficiency of the developed software, encompassing both path planning and remote sensing capabilities, leveraging the utilization of the custom-developed robot-related software solutions.

3.1. Evaluation and results

For the experimentation study, a DJI Phantom 4 Pro equipped with an RGB camera was used for image acquisition. The UAV flight planning for

[1]https://www.youtube.com/watch?v=C0hdCu-ZRQk&ab_channel=CoFlyProject

monitoring an agricultural field was done by the developed software. The experiments were carried out in a rural region of Chalkidiki, Greece, featuring fertile soil cultivated with lucerne and wheat crops. To further demonstrate the efficiency of the developed software, we present a set of results acquired from different vegetation fields. In specific, Figure 6 illustrates the orthomosaic of a lucerne (medicago sativa) cultivation with the corresponding VARI index, acquired via the developed tool. The estimated VI map is displayed to the operator by utilizing a red-green color map where regions with low VI values indicating poor vegetation health are displayed in red, and those with high VI values indicating good vegetation health are represented in green. The detected problematic areas are also annotated with blue dots, indicating the center of each area. Results imply that the deployed framework can be exploited to derive a detailed overview of the examined field, accompanied by high-level information regarding crop health and its spatial variation.



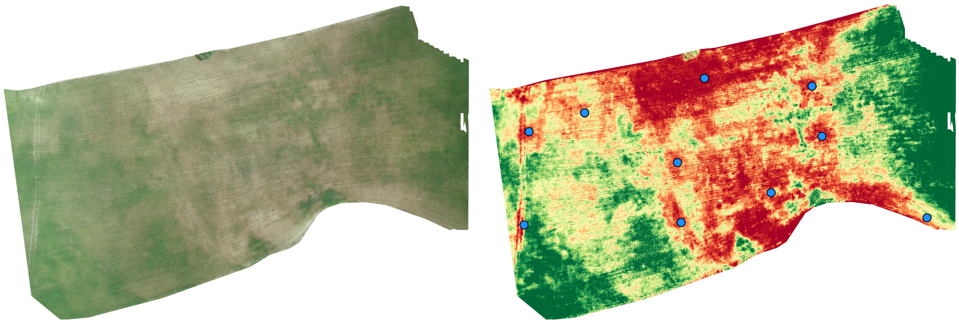
(a) Orthomosaic image

(b) Problematic areas

Figure 6: Visual outcome of the develope framework for a field of lucerne.

Similarly, in Figure 7, the corresponding results for an examined wheat crop are presented. The developed application provides a high-resolution map of the field through the extracted orthomosaic. Additionally, via the deployed analysis tools (demonstrated for the NGBDI index), valuable information regarding the crop health and the local problematic areas is acquired.

Showcasing its performance, the current version of CoFly can proficiently manage the pre-and post-processing stages of a typically precision agriculture software, presenting all the outcomes generated by the sub-plugins.



(a) Orthomosaic image (b) Problematic areas

Figure 7: Visual outcome of the developed framework for a field of lucerne.

4. Impact

All in all, CoFly is an open-source and cost-effective agricultural software, that enables farmers easily acquire, analyze, and continuously monitor their fields. By combining cognitional operations of micro flying vehicles, the system can optimize solutions and mitigate the negative impact of the UAV's limited battery life, improving operational time and energy efficiency, serving, thus, as a tool for monitoring and site-specific precision farming. As demonstrated in the illustrative examples, CoFly retains all the essential characteristics of a typical commercial agricultural software, making it a valuable and highly accurate tool for the farming community to obtain contemporary field management skills. CoFly is designed aiming to maximize the usage of PA by non-experienced UAV flight end-users while, at the same time, offering the research community a tool, through a public release on Github [40], for developing and testing custom solutions for several agricultural applications. An extensive demonstration of the proposed software's practical utility in several real-life experiments can be found at [39].

5. Conclusions

In this paper, an open-source pre- and post-processing framework for precision agriculture named *CoFly* is developed. The proposed system takes into account the sensing and operational capabilities of the UAVs while avoiding any no-fly zones or obstacles within the operational area. It processes aerial data to generate detailed field and crop health maps using vegetation indices, which provide information on seed yields and quality. The framework also includes a pixel-wise processing pipeline to detect and classify sources of crop health deterioration and a novel UAV mission planning scheme for targeted, on-the-spot inspection of potential problem areas. A weed detection module using deep learning methods is also included to classify weeds based on inspection footage. All of these features are integrated into an end-to-end platform that can be used on mobile devices and is designed to make it easy for UAVs to be used in precision agriculture applications, enabling them to be effective tools for site-specific precision farming.

Declaration of competing interest

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

Code & Data Availability

The overall CoFly ecosystem is open-source and publicly available at `https://github.com/CoFly-Project` to the community.

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