Infrared Thermal Monitoring of Intelligent Grassland via Drone

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Abstract – **The aim of the study was to investigate the possibility of using infrared thermography (IRT) as a tool for thermal monitoring of intelligent grassland via drone. A low resolution sensor was used. Real experiments were performed. Several typical cases of grass observation from two distances have been considered. Statistical processing of the results was performed.**

Keywords – **infrared thermography, intelligent grassland.**

I. Introduction

Permanent productive meadows, high mountain pastures and grasslands with low productive potential occupy significant agricultural areas in Bulgaria. They occupy the largest share in the Western and Central Stara Planina, Vitosha, Rila, Pirin, Western Rhodopes, as well as in some higher parts of Southwestern Bulgaria.

Permanent grasslands are the only land use that can both contribute to biodiversity conservation and reduce the carbon footprint of agricultural production, as required by the EU's 2030 Biodiversity Strategy [1].

In addition to providing fodder for livestock, permanent grasslands perform various functions and ecosystem services that make them extremely important. The most important are carbon conservation, biodiversity, water purification, erosion control and landscape conservation. Keeping them in good agricultural and ecological condition is extremely important for animal husbandry - animal products are low cost, pure and have good taste. The traditional low-intensity agricultural practices in this direction are grazing and haymaking, as well as surface measures with low levels of fertilizers and pesticides. In line with the concept of sustainable development, biodiversity and landscape protection requires moderate, distributed exploitation [2-5].

In this regard, these areas are provided for interventions in climate and environmental schemes, which will be included in the Strategic Plan for Agricultural and Rural Development for the period 2021 - 2027.

Pastures and meadows are "high nature value" ecosystems that provide natural food (green mass and hay) to pasture animals.

The composition of meadows and pastures in Bulgaria includes plant species from different botanical families with different nutritional value. The quality and quantity of the plant mass are directly dependent on the geographical location, the natural conditions, the ratio between the different species and the way of land exploitation. Pastures and meadows are the main source of fodder, which is why they are the subject of constant research on productivity, botanical composition, development of grassland, presence of pests and pollution, nutritional value, effect on productive and reproductive indicators in animals and others.

The productivity and quality of pasture biomass can be assessed using both conventional methods and remote sensing technology.

Conventional methods for assessing pasture productivity and quality are subjective, time-consuming and feasible (or applicable) only for assessing and monitoring pastures on a small scale.

In recent years, a number of methods have been developed to assess pasture productivity, based on data from satellite remote sensing. In some of the pasture monitoring publications, data from a multispectral scanner in the air were used to map the leaf area index, and in others hyper spectral images were used.

The methodologies for estimating pasture biomass can be categorized into three groups: 1) using vegetation indices, 2) biophysical simulation models and 3) machine learning algorithms.

According to the Industry 4.0 concept, the basic basis for improving the quality of crops are intelligent systems that support the automated management of technological and management processes. With the help of artificial intelligence, it is possible to analyze the various parameters of the field, refine the necessary care activities, monitor weather conditions, predict the quantity and quality of yield and more [6-15].

II. Hardware realization

The Lora WiFi v2 board is used for the realization of the device. It is based on the ESP32 microcontroller, has a built-in display and a battery charging module. The presence of a module for charging and using batteries allows the battery to be connected directly to the board without the need for an additional module to convert the voltage from the battery to what is needed to power the board. The presence of a display allows the relevant error information to be displayed on the display in the event of an error when starting the device. The Lora module allows real-time image sending on request (Fig.1).

Fig. 1. DJI Phantom 3 drone with mounted boards with Melexis MLX90640 sensor during the flight

A Melexis MLX90640 sensor is used, which is connected to the microcontroller via an I2C interface. A module for reading and writing micro SD cards is connected to the microcontroller via SPI interface. The data received from the sensor is recorded directly on the micro SD card. To ensure synchronization, the relative time at which it is taken is recorded at the beginning of each report. The relative time is taken into account from the moment the circuit is switched on. An LED is provided for the circuit to fall within the field of view of the drone camera. The moment the LED flashes, it is recorded at the beginning of the file and this allows the two videos taken by the IR camera and the drone camera, respectively, to be synchronized in time (Fig.2).

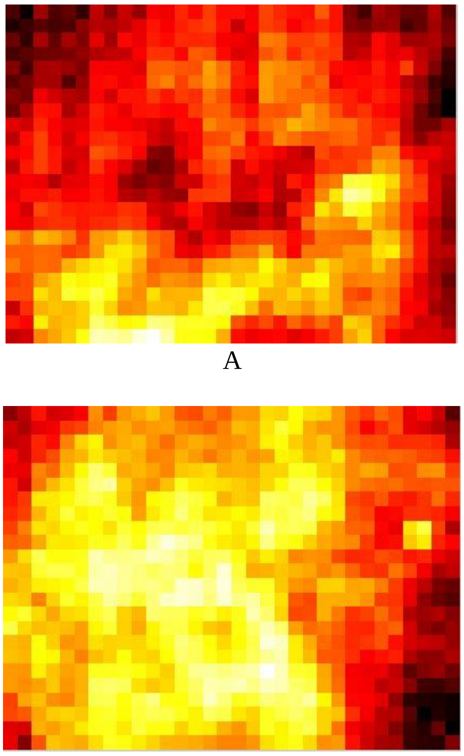
Fig. 2. DJI Phantom 3 drone with mounted boards with Melexis MLX90640 sensor close look

In case of connecting the circuit to a computer, the data will be transmitted in real time via the serial port and they will be able to be viewed on the computer screen. For this purpose, Matlab software is written, which takes the data and visualizes them after pre-processing.

The part where the image can be transmitted in almost real time on request via the Lora interface is also planned for completion. This function will be useful if you need to monitor the condition in a specific, pre-known location. The use of Lora interface is preferred to Bluetooth or Wi-Fi, due to its significantly larger range. Image transmission will only be on request, as Lora's data rate is limited and does not allow real-time continuous transmission.

III. Numerical investigation and processing of the results

For the initial processing of the results, two approaches were chosen - visual and analytical. In the first case, a visual representation of the captured thermographic images from the infrared sensor can be obtained, as seen in Fig. 3.



A

B

Fig. 3. Visual representation of the captured thermographic images of Ex1 (A) and Ex2 (B)

In the study we photographed three different species of plants, which we will call Ex1, Ex2 and Ex3.

In order to be able to evaluate the obtained results, we performed a histogram analysis of the extracted data.

The studied objects were photographed under the same conditions from a distance of 0.5 and 1 meter, and the aim of this experiment was to evaluate the effective distance for extracting a high-quality thermographic image. Fig. 4 and Fig. 5 show the results of the histogram analysis of the obtained experimental images at distances of 0.5 and 1 meter.

It can be said that at a distance of 0.5 meters we have a more accurate recognition of the various objects of study than at a distance of 1 meter, which is evident from the results obtained. At 0.5 meters, the objects can be clearly distinguished, and their histograms can be used to identify the various objects studied. While at 1 meter there is a merging of the histograms due to the influence of thermal radiation from the air and so it is not possible to give a clear recognition of the individual objects.

From this we come to the conclusion that in order to recognize the studied objects it is appropriate to study them from a distance of 0.5 meters.

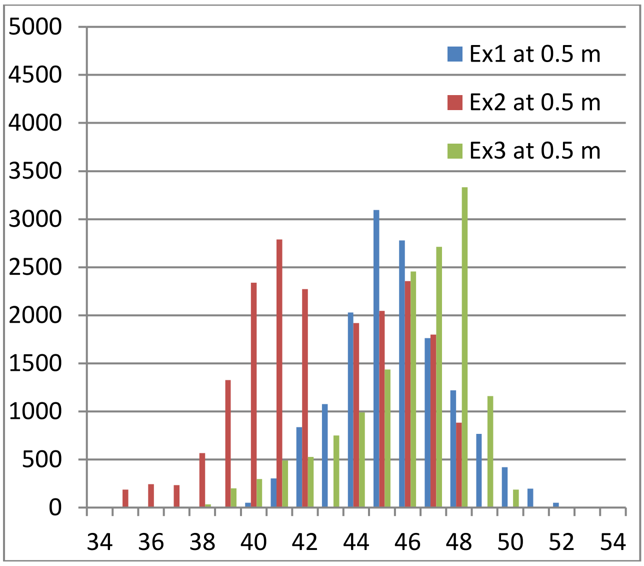


Fig. 4. Histogram analysis of the studied objects at a distance of 0.5 m

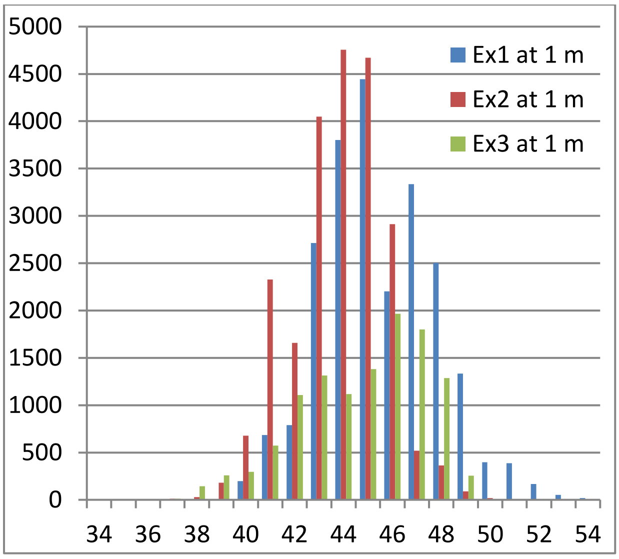


Fig. 5. Histogram analysis of the studied objects at a distance of 1 m

After evaluating the effective shooting distance of the studied objects, we made a series of surveys of the three objects and after processing the results we can say that we have a clear recognition of the three objects. This can be seen from the histogram analyzes of FIG. 6, FIG. 7 and FIG. 8.

As can be seen in Ex1 we have a peak around 44-46 degrees of temperature, in Ex2 we have a relatively equal distribution in a larger temperature range from 39 to 47 degrees, and in Ex3 we have peaks in high temperatures around 48-49 degrees.

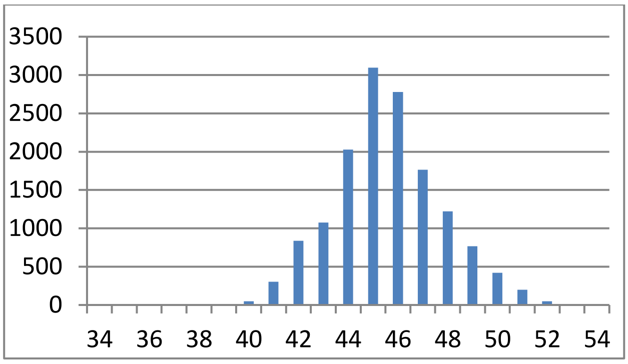


Fig. 6. Histogram analysis of the studied object Ex1 at a distance of 0.5 m

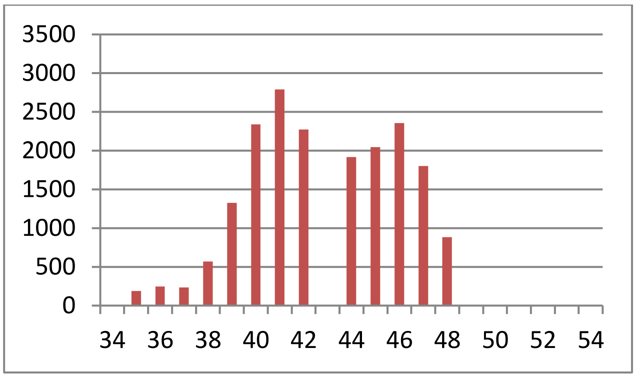


Fig. 7. Histogram analysis of the studied object Ex2 at a distance of 0.5 m

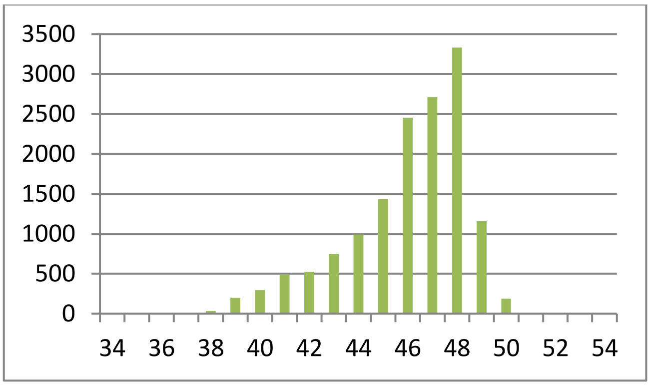


Fig. 7. Histogram analysis of the studied object Ex3 at a distance of 0.5 m

IV. Conclusions

An essential factor for the analysis is the extraction of knowledge per unit of agricultural area and the application of intelligent means for their cultivation.

From the derived results it can be said that this method is suitable both for research and for recognition of different objects in relation to their thermal radiation.

This is possible due to the possibility of automated monitoring, most often with the help of computer vision, collection of sufficient data and the application of appropriate machine learning algorithms on them, in order to take appropriate action.

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