Comparison of Performance in Weed Detection with Aerial RGB and Thermal Images Gathered at Different Height

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Abstract*— Weed detection is a crucial aspect of reducing the usage of phytosanitary products. Most studies about weed detection have been performed with linear crops; few studies can be found in crops with high soil coverage. In this paper, we have evaluated the effect of drone flying height on wild species detection. We have gathered images in a golf course from 4 to 16 m above ground. A non-professional drone with a camera with 1.5 megapixels was used to gather the pictures. The images are composed of red, green, and blue bands. Images were gathered in three zones with a very high infestation, high infestation, and low infestation of *Daucus carota*. To evaluate the effect of flying height, we calculate the percentage of the affected area and compare the obtained rates for different height, assuming that the rate at 4 m is 100% of detection. To determine is a pixel represent the wild plant or the grass, a vegetation index is used. Our results indicate that the error in estimating the affected area is relatively low, from 8 to 10 m; in some cases, overestimation errors are detected. Nonetheless, the relative error beyond 12 m reaches up to 25% of relative error. In these cases, the error consists of an underestimation of the presence of a wild plant.

Keywords-image processing; drone; turfgrass; green areas; vegetation indexes; wild plants.

I. INTRODUCTION

The green areas are special agroecosystems characterized by the cultivation of a single species, grasses, to maintain a green cover in cities. Several authors pointed out the importance of green areas in cities and their potential benefits for air quality, quality of life of citizens, and enhancing social cohesion [1].

One of the requirements for the green areas is having a homogenous coverage with a low or null incidence of wild plants. This is especially important in green areas intended for recreational purposes. To stop the proliferation of weed plants, periodic mowing and phytosanitary products can be applied. Nonetheless, considering the global efforts to reduce pesticide applications and the particular scenario for green areas, it is essential to minimize the application of phytosanitary.

One of the best ways to reduce the amount of used product is to develop tools for early detection [2]. Thus, the infected area in which products must be applied is small, and a reduced amount of phytosanitary product is used. The use of image processing techniques acquired by different means has become essential in agriculture to identify the proliferation of pest, diseases and wild plants. Nevertheless, using these tools in green areas is reduced since most techniques cannot be directly applied due to the vegetation patterns. While in most cropping systems, the crops are schemed as lines, and the proliferation of green biomass outside that lines can be considered a wild plan, in green areas, there are no lines. Instead, the grass covers all the ground, and the wild plans might appear interspersed with the grasses.

Most of the tools developed for agriculture are based on this linear scheme and the recognition through artificial intelligence of the wild plants. Nonetheless, this requires internet access, and the data cannot be processed in real-time in most cases. On the other hand, some indexes have been developed based on combining the Red-Green-Blue (RGB) components of an image. Initially, those are the most used components since not all drones incorporate thermal images. Moreover, in several cases, the optimal combination of RGB can be used to differentiate between the crop and the wild plants. Although those indexes are not as accurate as artificial intelligence, they can be applied in real-time and in scenarios without internet access. Moreover, this methodology can be used with the appropriate adaptations for other similar crops such as cereals or pastures.

In recent papers, we have established different indexes, based on bands combinations, to determine the presence or absence of wild plants in a green area [3]. Another option is to use the edge detection technique to identify the wild plants [4]. Nevertheless, both techniques have been applied only with images gathered at low height and good spatial resolution. As far as we know, no tests have been done to determine the maximum flying height possible for gathering data with commercial drones. Even that the professional drones might have cameras with better spatial resolution, fixing an average limitation for commonly-used drones with regular cameras is needed. Once we identify the maximum flying height, it will be possible to estimate the required time to monitor an area.

In this paper, we analyze the possibility of detecting wild plan in a green area using images gathered with Bebop 2 Pro drone at a flying height of 4 m to 16 m. We use pictures gathered in an area with the presence of *Daucus carota* L., a wild plant. The band combination is the technique used to determine the weed plant presence. First, we will evaluate the incidence of the wild plant as the percentage of pixels defined as a wild plant in a rectangular area. Then, we will compare the incidence in three areas, with diverse levels of incidence, at different flying heights to determine the maximum height that can be used for monitoring purposes.

The rest of the paper is structured as follows; Section 2 outlines the related work. The materials and methods are described in Section 3. Section 4 analyzes the results, highlighting the implications of the flying height. Finally, conclusions and future work are summarized in conclusion.

II. Related Work

In this section, we are going to summarize the existing efforts for detecting wild species and the different options for grass monitoring with drones.

First of all, we differentiate the options for remote sensing. According to Huang et al. [5], we can divide the remote sensing into four systems attending to the distance from the ground and the used equipment. Images gathered at least 5 m height are usually collected by ground-based systems and considered proximal remote sensing. Images gathered with drones are collected between 10 and 200 m. Each method has each own characteristics, restrictions and limitations. In our paper, we are using a drone, but according to the flying height, we are in-between both systems described by Huang et al.

In [6], Hassanein and El-Sheimy used an Inspire 1 drone from DJI with an X3 RGB camera to determine the presence of wild species in crops (canola and bean). Authors shave selected as flying height 20, 40, 80, and 120 m. Their methodology consists of segmenting the image and generate vegetation indexes for each segment. Then, they apply a threshold to determine if in this grid there are wild plants or not. Their methodology offered good results at high height (80 and 120 m). Nonetheless, the authors do not provide the used threshold or equations for detecting the wild plants in their paper. The employed camera has a higher resolution than our camera (they used a professional drone). Moreover, they do not indicate the size of the wild plant sports detected. In this case, their methodology can be applied in a large area where a high proliferation of wild plants is expected.

Barrero and Perdomo proposed image fusion for gramineous detection in rice fields in [7]. They combine two cameras for obtaining images and fuse the data. The first camera was an RGB camera with 12.1 megapixels; the second one was a multispectral camera with 1.2 megapixels. Their methodology, fuse data using neural networks, was efficient with images gathered at 60 and 70 m. Although authors have proven their methodology at a higher height than us, they have better cameras and professional drones. In our case, the drone and camera stability are not as accurate as in their case since their drone has a gimbal. In addition, our camera has 1.5 megapixels for RGB image.

The effect of pixel size, which directly relates to flying height, over the accuracy of wild species detection was studied by Tamouridou et al. in [8]. Authors used machine learning to determine the presence or absence of wild plants in an abandoned field, previously used for cereals cropping. First, the authors applied the Maximum Likelihood classifier. Their images had a pixel size of 0.1 m. Next, they study the effect of reducing the pixel size on accuracy. Their results indicate that similar accuracy is found for the pixel size of 0.1 to 1.5 m. Still, a substantial reduction in the accuracy is found for 2 m (the largest evaluated pixel size).

Another study, presented by Zou et al. [9], shows the accuracy of wild species detection in crops. The authors used a DJI, MAVIC 2. They have an image of the pixel size of 5 mm obtained with a flying height of 20m. The authors obtained good accuracies by combining different artificial intelligence techniques. In our case, the acquired images have a pixel size of 3mm (at a flying height of 4 m) to 8.5 mm (at a flying height of 16 m).

As far as we know, no paper has evaluated the effect of incrementing the flying height using non-professional drones in green areas. Most studies are developed for linear crops using professional drones, heavier gimbal, and higher spatial resolution.

III. Materials and Methods

In this section, we are going to detail the procedure followed for gathering and processing the data, as well as the employed hardware and software to obtain the results.

A. Data gathering process

In order to test the effect of flying height on the quantification of infection by wild plants, images of grass were gathered in a golf course. The photos were taken in one of the green areas, which was suffering from an infection of *Daucus carota* L., one of the common wild plants. The green was composed of *Agrostis stolonifera* L. T1, mowed periodically at 3.8mm. A picture of the data gathering process can be seen in Figure 1 (a).

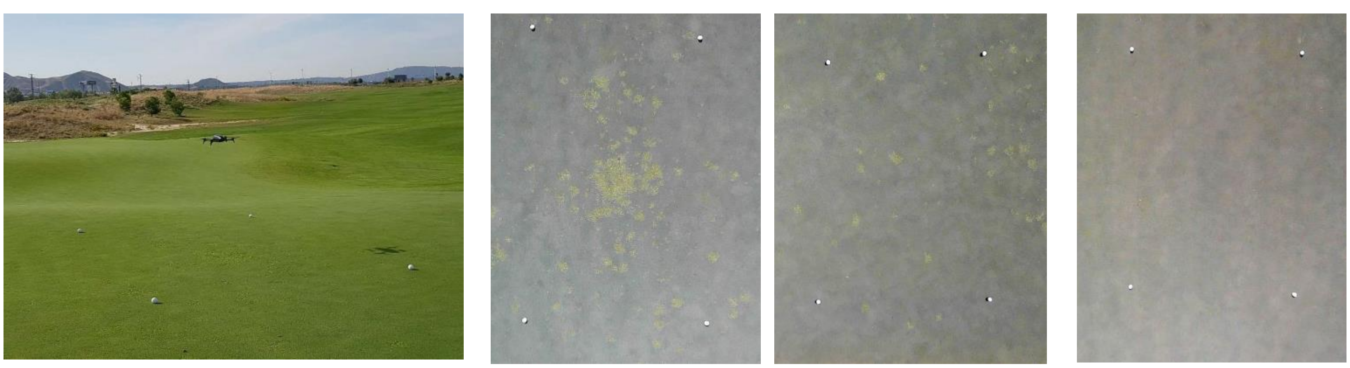
(a) (b) (c) (d)

Figure 1. Images of the data gathering process, (a) picture taken during the data gathering, (b) to (d) data gathered for each studied area.

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Along the same green, three study areas were delimited according to different incidence levels of the wild plant. To delimit the areas, four golf balls were used to define the 4 vertexes of a polygon. The three areas were described as “Very High Incidence”, see Figure 1 (b); “High Incidence”, see Figure 1 (c); and “Low Incidence” see Figure 1 (d).

The area delimited by the four balls has an average surface of 3x7 m. Images were gathered at 5 different flying heights, from 4 m to 16m height. In Figure 1 (b) to 1 (d), we show the data gathered at 4 m height. All the images were collected on the same morning and with the same meteorological conditions. The data gathering process had a duration of less than 1 h

B. Drone and image characteristics

To gather the data, we have selected a commercial drone with typical characteristics. The chosen drone is the Parrot Bebop 2 Pro [10]. It has a flying autonomy of 20 min and a weight of 504 g. In addition, it has a peak velocity of 60 km/h and four helixes.

The drone has two different cameras. One of them has a fixed position, and the second one can be moved. For these tests, we need to use the zenith pictures to use the second camera. It is essential to consider that for this drone, and this is the camera with lower resolution. The gathered images have 1080x1440 pixels and 24-bit colour.

C. Image processing

To process the image, specific software (generally used for remote sensing) is used. We have selected ArcGIS 10.5 for its versatility. Once the photos are included in the ArcMap, from ArcGIS software [11], they are converted into 8-bit colour images to simplify the operations.

First of all, a vegetation index based on RGB data can differentiate pixels with grass from pixes with the wild plant. The vegetation index is a linear combination of the two or more bands of the picture, which produce different values according to the presence or absence of wild plant; more information can be found in [3]. In past papers [3], we have developed vegetation indexes. Nonetheless, those indexes were used for mixed lawns composed of two or more grass species. In this case, as we have a single grass species, we will try to simplify the existing indexes. After calculating the vegetation index, the threshold to differentiate the type of cover is determined. Then, the image is reclassified [12], the pixels without wild plant are classified as 0, and the pixels which values indicate the presence of wild plant are classified as 1.

Following, for each image, we generate a vectorial layer formed by a polygon that delimits the studied area. As the flying height increases, the size of the polygon (in pixels) decreases. To define the polygon, the inner extreme of each one of the balls is used.

Once the image is classified as “Infected Pixel=0” and “No Infected Pixel=1”, the tool Zonal Statistic as a Table [13] is used to obtain the summary of data in each studied area. The most critical data are the summation, the mean, and the standard deviation from the statistics. The statistics summary of each polygon is exported to Excel. Finally, in Excel, some other parameters are calculated. The % of affection is calculated using the total number of pixels in the studied area and the number of pixels with values = 1 (obtained through the summation).

We consider that the data gathered at 4 m is the most accurate one. Thus, we consider that this data has no error in their results. This is 100% of detection. The percentages of detection obtained at other height are compared to identify maximum height that offers accurate values.

IV. RESULTS

In this section, we are going to analyze the obtained data. First, we will see if previously used indexes might be used for this case or if indexes can be simplified in order to accelerate the calculations. Secondly, we compare the results in terms of accuracy at different heights.

A. Obtention of vegetation index

We have considered the two indexes presented in [3]. Among the proposed indexes, the first is the one that detects the wild plant. A modification of this index is proposed for this paper. The new index is defined in (1). The soil removal coefficient is removed from the index, and the mathematic operations have been modified.

$$Vegetation\ Index = B1+B2-B3 \qquad (1)$$

where B1 is the red band, B2 is the green band, and B3 is the blue band.

Theoretically, the index can have values from -256 to 512. Nonetheless, the found values go from -29 to 260. After analyzing the vegetation index values of the 15 evaluated images, we have established the threshold as 190. While values higher than 190 are defined as will plant, the values lower equal or lower than 189 are defined as grass. This is a significant improvement concerning the previous indexes, in which the definition of wild plant or grass is based on natural breaks (or Jenks), and no fixed value can be used.

In Figure 2, we can see the results of applying the index to the images gathered at 4 m in all the studied areas. We can see for each studied area the RGB picture, the results after applying the index, and the classified raster once the threshold is applied. The polygon that defines the studied area is visible for index images to facilitate the interpretation of results.

We have compared the results of applying this index with the index defined in [3], and the results are similar. Thus, we keep with the index of (1).

B. Comparison of incidence of wild species at different height

This subsection will analyze the differences in the obtained incidence of images gathered at a different height. First of all, we include a short summary of the statistical information obtained for each image in Table II. The Zones are identified by the Id: 1 = Very High Infestation, 2 = High Infestation, and 1 = Low infestation. The height indicates the flying height at which the picture is obtained. The area and sum are the numbers of pixels of the studied area and the number of pixels classified as a wild plant. Those are the values used to calculate the % of the affected area. Finally, the Mean and the Standard Deviation (STD) indicate the variability of data in the studied areas. If there is no effect of flying height on a wild plant mean and STD detection, each zone should be similar. Nonetheless, we can see that the values decrease as the height increase. Therefore, we can affirm that there is an effect of flying height over the wild species detection.

In order to identify the maximum flying height, we are going to consider not only the mean and the STD but also the error in the estimated affected area. For that purpose, we are going to compare the estimated affected area with each one of the images. Figure 2 shows the calculated affected area according to the number of pixels of the studied area and the number of pixels classified as a wild plant. We can see that the zones with Very High Infestation are the ones with a higher % of the affected area (3.66% to 2.04% from 4 to 16m). The zone with High Infestation has an affected area of 0.39 % to 0.12 %, and the Zone with Low Infestation from 0.05% to 0%.

TABLE I. REPRESENTATION OF RGB PICTURE, THE INDEX AND THE CLASSIFIED RESULT

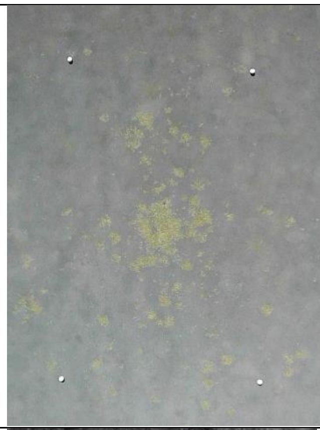
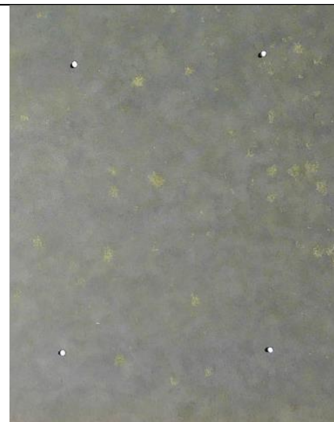
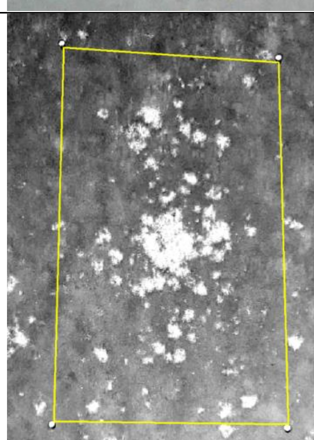
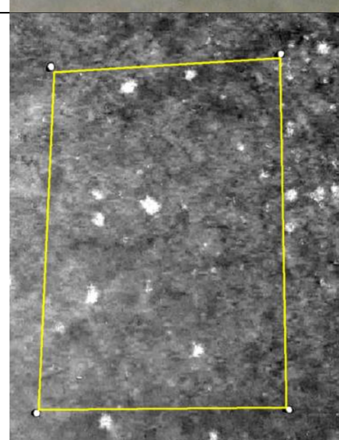
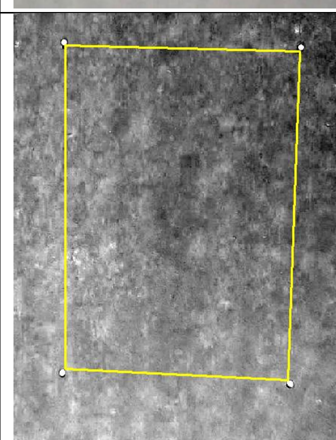
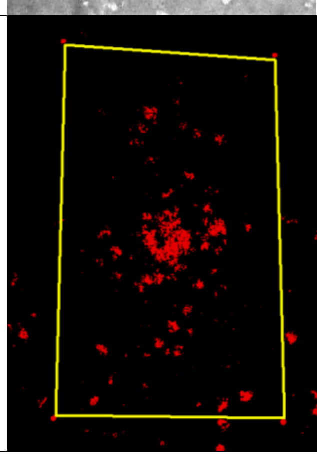
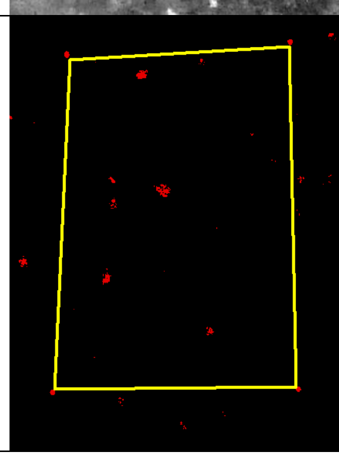
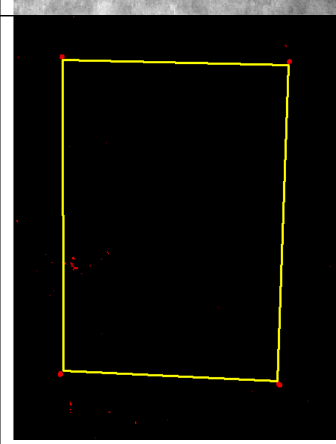
RGB Picture			
Index			
Index with threshold Infected pixels = Red Non-Infected pixels = Black			

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TABLE II. SUMMARY OF OBTAINED INFORMATION OF EACH AREA

Zone (Id)	Height (m)	Area (number of pixels)	Wild plant	Mean (pixel value)	STD
1	4	326956	11953	0.036558	0.187675
1	8	178129	6585	0.036968	0.188682
1	10	124936	4135	0.033097	0.17889
1	12	47070	1251	0.026577	0.160845
1	16	29356	601	0.020473	0.141611
2	4	245417	958	0.003904	0.062356
2	8	127101	740	0.005822	0.076081
2	10	67318	339	0.005036	0.070784
2	12	35319	101	0.00286	0.053399
2	16	19955	25	0.001253	0.035373
3	4	266248	137	0.000515	0.022678
3	8	147082	31	0.000211	0.014516
3	10	89412	9	0.000101	0.010032
3	12	35570	5	0.000141	0.011855
3	16	20203	0	0	0

Comparing the percentages at different heights, the data gathered at 4 and 8 m offer almost identical data in Zone 1, while the calculated areas at 10m are slightly lower. For Zones 1 and 2, the percentage increase in some cases at 8 and 10 m due to the increment of size pixel and the reduced number of pixels that contain wild species. This is a common effect when the flying height increase and the number of interesting pixels (pixels classified as a wild plant) are low. This effect was not found in Zone 3.

We consider the Absolute Error (AE) in our estimations, assuming that the results of the image obtained at 4 m represents 100% of the affected area. Thus, we calculate the AE of each image having the % of affected areas at 4 m as a reference. The more evident results can be seen for Zone 1 (Very High Infestation); in this case, the AE is almost null for 8 m (-0.04%). The AE reaches 0.34, 0.99, and 1.6 1 % the 10, 12, and 16 m. For the other areas, the errors are much lower since the affected areas are smaller.

In Relative Error, see Figure 3, the errors can be compared among areas. Those errors with positive value indicate an overestimation of the infestation; meanwhile, errors with negative value indicate an underestimation. As detailed before, For Zones 1 and 2, there are some points, with low height, with an overestimation of the incidence. Nonetheless, after 12 m, in all the cases, there is an underestimation. Note that the error at 12 m is almost the same for Very High Infestation (-27.3%) and High Infestation (-26.7%). It is important to remark that with Low Incidence, there is no overestimation.

Considering the negative effect of underestimation in the proliferation of wild species and the delay of phytosanitary products application, we consider that 10 m should be the established threshold for monitoring with this sort of drones.

C. *Limitations of proposed technic and implications of established threshold*

In this section, we are going to analyze the limitations of our study and the implications of the established threshold for the flying height.

First of all, there is a bias in our tests given the used drone. Each camera has a different resolution parameter, which affects the resolution of the obtained pictures. Moreover, the fact of having the image in 8-bit to simplify the analyses affect the accuracy of our results. Nonetheless, these biases can be assumed since the specialized drones with cameras with high resolution (in terms of pixels) still have a high cost, and their weight can be a limiting factor according to the national or regional regulations. Moreover, cameras with higher resolution are used with professional drones, with a higher cost (almost 10 times more), which the enterprises cannot readily assume. The 8-bit constriction has an effect on the accuracy of the proposed vegetation index, but this is necessary if we want to keep the image processing in real-time or nearly real-time.

It is essential to consider that this threshold, established for cameras with similar resolution than the used one, might be helpful in different wild species. Nonetheless, the threshold must be re-evaluated to detect grass diseases such as *Fusarium* or Dollar spot. The main reason is that the affected areas by the diseases are smaller than with wild species.

Finally, we are going to analyze the impact over the flying time of modifying the threshold between 8, 10 and 12 m. The maximum covered areas with these flying thresholds are 80x60 m for 4m high, 88x65m for 10 m high, and 96x70m for 12 m high. The variation in the flying height increases a 20% and 40% (for 10 and 12 m, respectively). Considering the time required to fly over an area of 60x80 m, the drone will need 20 min at 8 m, 17.5 min at 10 m, and 15 min at 12 m. This increment in the required time to cover a small area must be scaled when an entire golf course or green areas in cities must be evaluated. Thus, we are going to indicate the required time to cover different interesting and well-known areas for the different flying height (8 to 12 m). For example, in a golf course type Regulation Course with turfgrass areas from 350,000 m^2, the required flying time will be 24.30, 21.26, and 18.23hours. For golf course type Par 35 or 36 with a Standard combination (average turfgrass surface of 120,000 m^2, the required flying time will be 8.33, 7.29, and 6.25 hours. For other sports such as polo, which fields have an average surface of 40,134 m2, the time required is 2.7, 2.4, and 2 hours. For soccer or rugby fields, an average surface of 10,800 m^2, the time of flying needed will be 45, 39.37, 33.75 minutes. In the case of the hockey field, an average of 5,027 m^2, the flying time will be 21, 18.3, 15.7 minutes. Finally, for a tennis court, an average extension of 195 m2, less than 1 minute is required regardless of the flying height.

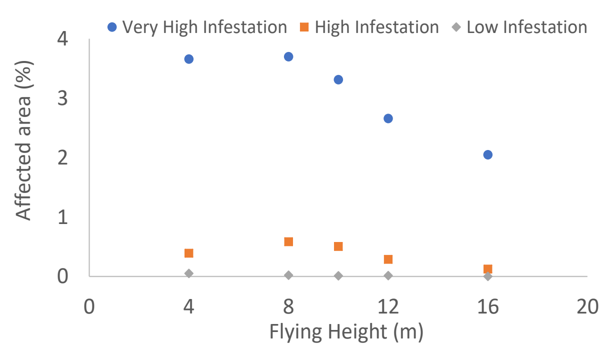

Figure 2. Comparison of estimated affected areas at each height

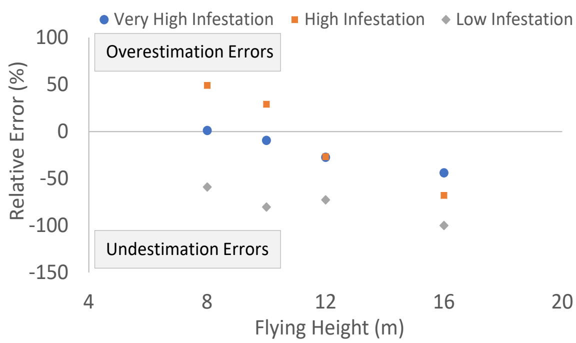

Figure 3. Relative Error of estimated affected area

The other advantage of our proposed method is that controlling the infected areas with pictures will reduce the possible overestimation by the workers and reduce the consumed time. Currently, workers, particularly in green areas with high requirements, have to walk through the area periodically, searching for the apparition of diseases or wild plants.

V. Conclusion and Future Work

In this paper, we have studied the effect of flying height on detecting the infestation of grass with a wild plant (*Daucus carota)*. This is especially relevant in the management of green areas since a fast detection will save phytosanitary products, reducing the maintenance cost and increasing its sustainability.

We need to find a balance between spatial resolution (low flying height had high resolutions) and flying time vs. covered area (high flying height had better relation) in selecting the flying height. We have evaluated the error in determining the percentage of infestation in a green area for different flying heights. Our results indicate that 10 m should be the maximum height given the characteristics of our camera.

In future work, we will include thermal images to evaluate if having a combination of four bands allows having a better index with which we can have a higher threshold for the flying height. Regarding the index, we will work on its standardization for different undesired species in order to simplify the process in the future. In addition, we will compare the flying height for images captures with professional drones. If possible, we will compare the recommended threshold for wild species with a threshold for disease.

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