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THE APPLICATION OF UAV AND PHOTOGRAMMETRY FOR SUPPORTING PRECISION
AGRICULTURE AND MONITORING ENVIRONMENTAL PROBLEMS

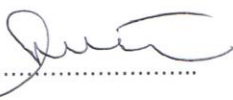
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The difference between a toy and a tool is the value that
users can create with it.

(B. Rijk)

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Abstract

Nel corso degli anni, purtroppo, la terra è stata caratterizzata dal susseguirsi da numerosi disastri ambientali, sia naturali che dovuti alle attività dell'uomo. Questi hanno comportato e comportano un'alterazione dell'equilibrio dell'ecosistema e danni alla salute umana. Il termine problema ambientale è comunemente usato per definire gli atti che danneggiano flora, fauna e genere umano. Da ciò si comprende la necessità fondamentale di mettere a punto delle tecniche in grado da un lato di determinare le caratteristiche e l'entità di tali problematiche, e dell'altro di monitorarle nel tempo. Nel corso dell'attività di ricerca del corrente dottorato due diversi problemi ambientali sono stati affrontati. Il primo incentrato sullo sviluppo di una tecnica innovativa per l'individuazione dei terreni inquinati da rame, ed il secondo, invece, relativo alla scelta del metodo migliore per poter stimare le proprietà strutturali e biochimiche dell'ecosistema grassland.

La presenza dei contaminati nei suoli agricoli rappresenta una delle maggiori criticità ambientali del territorio italiano in generale e della regione Campania in particolare. Quest'ultima, da sempre nota per la bellezza dei suoi paesaggi, si è ritrovata al centro dell'attenzione mediatica a causa della presenza di ben 6 dei 55 siti di interesse nazionale. Infatti, gli inquinanti presenti nei terreni agricoli danneggiano la qualità del cibo e, di conseguenza, la sicurezza della salute umana. Infatti, a seconda del tipo di contaminante, gli effetti sulla salute umana sono sostanzialmente differenti e, di conseguenza, è fondamentale conoscere la loro reale distribuzione e la loro concentrazione. Al fine di sviluppare una tecnica innovativa, in grado di sostituire la metodica correntemente utilizzata per l'individuazione degli inquinanti, si è scelto di fondere tecniche comunemente applicate in altri settori e a scale differenti e di trasferirle a scala di campo e in tale settore di ricerca. Infatti, la tecnica proposta si basa sulla fotogrammetria aerea da UAV, sugli indici per la predizione delle zone umide e sulla geostatistica. Al fine di validare tale metodo, il campo sperimentale nell'area di Trentola Ducenta, appartenente al SIN agro-aversano, è stato scelto come campo test. Tale area è stata campionata con una maglia regolare 5*5 m e, per ogni campione, la è stata analizzata concentrazione del rame.

Confrontando la mappa della reale distribuzione del rame con quella predetta mediante l'applicazione del metodo suddetto, si evince che ben 5 aree, caratterizzate da una concentrazione superiore ai limiti di legge, su 7 sono state predette dal metodo. Di conseguenza, i risultati risultano promettenti, anche se, prima che quest'ultima possa entrare a pieno titolo nell'organizzazione dell'attività di campionamento è necessario che venga sperimentata su campi di altre dimensioni e localizzati in altre aree.

L'ecosistema grassland, invece, è stato scelto in quanto esso ricopre circa il 40% della superficie terrestre e perché le sue caratteristiche risentono fortemente della posizione geografica e delle attività umane. Pertanto, lo sviluppo di una metodica in grado di ottimizzare i piani di gestione di tale ecosistema, fino ad ora organizzate sulla base dell'esperienza dei contadini, con informazioni quantitative sembra fondamentale per migliorare il suo stato di salute e per l'individuazione del punto ottimale di raccolta o di concimazione. L'obiettivo di tale applicazione è quello di testare i diversi metodi statistici al fine di individuare quello più performante nella stima delle caratteristiche strutturali e biochimiche della grassland dalle immagini iperspettrali acquisite da UAV.

Ambo i metodi confrontati, gli indici vegetativi e il PLSR, presentano dei risultati promettenti anche se il più performante è il PLSR. Anche in questo caso, come in quello precedente, per poter affermare la validità universale di tale tecnica sono necessarie ulteriori sperimentazioni.

Gli esempi esplorati hanno permesso quindi di confermare gli enormi vantaggi introdotti dall'uso della fotogrammetria aerea da drone nell'ambito del monitoraggio ambientale e nel settore dell'agricoltura di precisione, nonché di introdurre delle tecniche innovative in grado di migliorare le metodiche attualmente adoperate.

Abstract

Currently, the earth surface is damaged by natural disaster and any human activities, that causes seriously problems to the well-being of humans and the balance of our ecosystem. Therefore, in order to conserve the human health and protect the environment, the detection and the monitoring of the environmental problems are necessary. In particular, two different examples of environmental problems are explored. The first is focused on the development of an innovative method for detecting copper contaminated soils while the second is related to the choice of the best statistical method for estimating grassland traits in order to conserve the different grassland ecosystems.

The knowledge of pollutants concentration and distribution should be a priority for the community since they strongly affect the human health. Indeed, the pollutants presented in soils are commonly absorbed by crops that are usually eaten by human. The health problems are different according to the pollutant taken into account (Oliver, 1997; Muchuweti et al., 2006). This problem has been selected because it is one of the most widespread Italian criticality, due to the combination of geogenic and anthropogenic elements (Cicchella et al., 2005). The heterogeneity of Italian territory has generated an extremely diverse and complex situation (Vito et al., 2009), whereby also difficult to detect. Indeed, Campania region, known for the beauty of its territory, is currently involved in the area with more environmental problems since 6 of the 55 sites of national interest (NIPS) have been selected in this area. For this reason, it is essential to develop a new technique able to replace the method commonly used to detect pollutants accumulated in agricultural soils too expensive and time consumive. Thus, in the present work, approaches commonly applied in other research sectors and at other scales have been merged and transferred to field scale in order to predict copper accumulation in agricultural soils. The proposed technique is based on photogrammetry using UAVs, the indices for predicting wetland and geostatistics. In addition, to validate this method, an experimental field in Trentola Ducenta, in NIPS Agro-Aversano, has been selected as test field. So, in order to know the amount of the pollutants in the soil, the field was sampled using a regular grid of 5*5 m.

By comparing the map of the real distribution of copper and the map of predicted values, it is clear that 5 areas on 7, characterized by a value greater than legal limit, were identified. Consequently, the results of the method appear promising and the information extracted from this method have to be integrated in the sampling activity.

Grassland ecosystem has been selected because it covers 40% of the earth surface and because its features are affected by the geographical position and human activities. Therefore, it is required the development of a new grassland management plans able to integrate the qualitative information, due to farmers experience, with the quantitative data. Thus, the goal of this method is to test the different statistical approaches and identify the most performant approach for predicting the structural and biochemical grassland traits from hyperspectral images acquired by UAVs. Both tested methods show promising results, even if PLSR is the best.

The explored examples show a lot of advantages introduced by photogrammetric technique from UAVs in the field of environmental monitoring and precision agriculture supporting.

Chapter 1

Introduction

1.1 Environmental problems

Nowadays, the environment suffer from natural disaster and any human activities, that result in changes in the habitat, greatly damaging the well-being of humans and the balance of our ecosystem. This means that only when a problem endangers flora and fauna enough to ruin the balance of the ecosystem, it can be defined as an environmental problem. Thus, to not damage the human health, protect and preserve the environmental wellbeing, the activities of detection of the problem features and monitoring are essential. In particular, in the current study, two different examples, the first related to the pollution detection and the second focused on the grassland ecosystem conservation, have been selected and analyzed.

Detection of contaminated sites and knowledge of pollutants concentration should be a priority since, both by means of crops and air, they compromise environmental and human health. Generally, the contaminants accumulated in agricultural soils are absorbed by crops and, consequently, they get in touch with human body, causing serious health problems (Oliver, 1997; Muchuweti et al., 2006). In addition, among the several environmental problems, this topic has been selected also because it is one of the most widespread Italian criticality, due to both geogenic elements and anthropogenic factors (Cicchella et al., 2005). The diversity of the contributing factors has generated an extremely heterogeneous and complex situation on the Italian territory (Vito et al., 2009), whereby also difficult to tackle. Although the distribution of geogenic pollutants is essentially known and predictable, the mapping of anthropogenic elements is difficulty cognizable, if not applying laborious and expensive procedures. Therefore, priority of the Italian government should be the development of the new methodology, able to detect the contaminated soils, reducing the time – consuming and the operation costs. The introduction of the new technologies, such as drones and small RGB cameras that can be mounted on them, has allowed to significantly improve the landform mapping and, consequently, to obtain more precise information regarding earth surface. Therefore, their application could result essential in pollutants detection.

The other environmental problem considered in the current research activity has been selected in the field of precision agriculture. The term precision agriculture (PA) is related to farming management and is based on the measurements and observations regarding crop traits, in order to identify the best plan for its conservation and improve its health status. Among the different type of crops, grassland has been chosen since it covers roughly 40% of the total world (Whie et al., 2000) and, consequently, its traits are completely different according to topographic location, extension and in particular, to anthropogenic effects, like fertilization treatments. In addition, up until now, the grassland schedule is organized on the base of qualitative information, resulting to farmers experience. Surely, in order to identify the best strategy and adapt it to the grassland ecosystem features is required to integrate the already existing plans with the quantitative data, obtaining by spatial observations. These variables can be implemented thanks to the development of new sensors and technologies, such as Unmanned Aerial Vehicles (UAV) and hyperspectral cameras that can be mounted on them.

1.2 UAV systems

The term “Unmanned Aerial Vehicles” (UAV) is used to describe the remotely controlled, semi-autonomous or autonomous vehicles. Its most significant characteristic is the absence of the pilot. However, this do not imply that it flies itself autonomously, because, the people responsible for a UAV are several, such as the pilot, the operator and backup pilot, and more than that aircraft.

Firstly, they were built and applied for military purposes, and only, in the last few years, they has become widespread also in other field of investigation, like the civil one or scientific disciplines, thanks to their features and the possibility to mount on it several kind of sensors, (Nex & Remondino, 2014). For these reasons, the development of instrumentations, suitable to be mounted on them is becoming more and more important over the years. The evolution has interested both technical electronic tools for aerial platforms and sensors that can be mounted on them. In particular, the evolution of the integrated circuits and radio-controlled systems has allowed to reach difficult to access areas, since no pilot is on them, and to reduce the flight altitude, compared to traditional aircraft, incrementing, consequently, the spatial resolution. Additionally, it is possible to acquire aerial images in flexible data, eliminating cloud cover problems.

Moreover, the size and the weight of sensors used for capturing aerial photos have been modified in order to adapt them to UAV size. Indeed, big UAV can be equipped with very heavy weights, otherwise the weight must be reduced. Also the introduction of small digital multispectral

sensors has allows to extend the field under investigation to grassland monitoring. Indeed, several studies (Von Bueren et al., 2015) have shown the limitations of RGB cameras and the superiority of multispectral sensors in grassland traits estimation. Subsequently, Sakamoto et al., (2012) has showed that there is a good relationship between vegetation indices, calculated from multispectral images, and grassland bio-chemical variables, able to investigate temporal changes and monitor crop growth. This has allowed the miniaturization of hyperspectral sensors and their application on UAV. The combination of UAV platforms with small RGB cameras or (and) hyperspectral sensors has improved the results in supporting precision agriculture and monitoring environmental problems.

1.3 Advantages and limitations in the use of UAVs

UAV platforms have several advantages compared to the traditional aircraft. First of all, it allows to completely eliminate risks for the pilot, since the vehicles haven't a sitting place for him, but they are remotely controlled, semi-autonomously, or autonomously driven (Eisenbeiß, 2009). This aspect is extremely important since it is the only practical alternative for flying over difficult access areas, or characterized from natural disasters, for example, such as volcanic areas and scenes of accidents (Nex et al., 2013). Moreover, it allows to drastically reduce the flight altitude, improving the images resolution and adapting it to the size of object under investigation (Capolupo et al., 2014; Capolupo et al., 2015). UAV allows also to improve the aerial photos quality, removing the problems caused by weather conditions. Indeed, thanks to low flight quota and the possibility to realize the campaign in flexible data, aerial photos don't affect by cloudy and drizzly weather conditions (Nex et al., 2013). Additional advantages are related to the capacity to see the aerial images in real time, in order to verify if they are taken in the correct position and they are blurry, to acquire and transmit the picture in fast way. The implementation of a global position system (GPS) and a navigation unit allow to accurately plan the flight path, guaranteeing sufficient image coverage and overlap.

On the contrary, the most significant limitation is related to the size and the weight of the sensors that can be mounted on them, often characterized by a small or medium format images. This means that, in comparison of large format camera, a major amount of photos are required to cover the entire area. Moreover, other limitations, regarding the platform configuration, are related to regulation of the country in which they have to be applied.

1.4 UAV-based photogrammetry

Photogrammetry is the science regarding the accurate and metric reconstruction of an object or a scene from pictures (Mikhail et al., 2002). Thus, it allows to analyse the 2D data and establish the geometric relationships between the images and the object under investigation in order to obtain a 3D model. In order to reconstruct the scene, this technique require a minimum of two images of the same objet acquired from two different points of view, but partially overlapped, like the human vision system. Indeed, if a scene is present in at least two images, the different position of an object allows to obtain a stereoscopic view and extract 3D information, essential for the 3D modelling (Remondino, 2011). The performance of this technique has been greatly improved thanks the introduction of UAVs and fifth-generation software for photogrammetry, since they have allowed to acquire aerial images at lower altitude than traditional aircraft and to process hundreds of photos in the mean time and to automatically restitute them (Pierrot-Deseilligny et al., 2011).

The introduction of these elements has allowed to revolutionize the photogrammetric technique, extending the sectors of applications to field scale and opening other opportunity of investigation. So, this new way to do photogrammetry is called UAV photogrammetry (Eisenbeiss, 2008).

1.5 Research goals

Goal of this research activity is to assess the possibility to apply UAV based photogrammetry for solving different environmental problems and to evaluate their ability in these situations.

In particular, two different case studies have been analyzed. The first is related to the development a highly innovative methodology for the detection of copper contaminated soils at small scales. It is based on an “inverse” approach to predict the distribution of copper accumulation hotspots in order to identify the points to be sampled. To reach this goal, techniques commonly used in other contests, such as hydraulic model have been mixed and applied at field scale. It involves indices able to predict wetlands locations and extension at catchment scale, models of transport process, geostatistics and UAV photogrammetry. In contrast, the second case study is focused on the assessment of the ability of hyperspectral images, acquired by UAV, for estimating structural and biochemical grassland traits in order to implement quantitative spatial information to the already existing management plans. In addition, in this research work, the best statistical strategy for predicting vegetation features, the influence of different fertilization types and

grassland plant phenology on the relationships between predicted grassland variables and observed vegetation traits have been explored.

1.6 Outline

Chapter 2 gives an overview regarding photogrammetric technique in order to describe this methodology more in depth and to analyse its evolution over the years. Chapter 3 is dedicated on UAV platforms and in particular, it gives an overview of the UAV platforms and their classification. In addition, it describes also the UAV systems applied in the two case studies, analyzed in this research activity. Chapter 4, instead, is related to the workflow for acquiring and processing aerial images in order to obtain 3D models and orthophotos, and later the final products, required to fit the research goals. Chapters 5 and 6 illustrate the practical applications of the combination of photogrammetry and UAV systems for detecting copper contaminated soils and for estimating structural and biochemical grassland traits, respectively. In the last chapter, chapter 7, the final conclusions are presented.

Chapter 2

Photogrammetry

2.1 Introduction

Photogrammetric technique is based on the extraction of 3D information from photographs or any type of image (satellite, aerial or terrestrial) as long as there is an overlap between the images. Thanks to the development of new digital cameras, computers and software, the photogrammetry has been become attractive and, for this reason, it can be applied to a wider range of situations, in particular in the field of environmental monitoring. Moreover, the introduction of new technologies has allowed to dramatically reduce the cost of the entire process of acquiring, processing and analyzing. Therefore, this technique has become essential in the current research work.

So, after an overview on the historical background at the base of the photogrammetry, this chapter is focused on the description of the photogrammetric technique and its evolution over the years.

2.2 Historical background

The first investigations were performed by Gaspard Tournachon in 1858 by applying a manned balloon in Paris (Newhall, 1969). Over the years, the balloon and other systems, such as kites, Pigeons and Rockets were developed in order to spy the enemies during the world wars (Newhall, 1969). In addition, a tethered balloon was employed in archaeological field in 1967, as shown by Whittlesley (1970). During this experiment, several cameras were mounted on a gimbal, located 9 m below the balloon, and the images were taken at a distance of up to 50 m above the ground. The load of this configuration was of about 2.7 kg while it was able to fly at a distance of about 600 m above the ground. Therefore, this first configuration showed that the flight quota depends on the requirements of the project and system parameters.

The first fixed wing UAV was applied in photogrammetric experiment in 1979 by Przybilla and Wester-Ebbinghaus, (1979). In this case, an UAV of the company Hegi was used. It was 3 m long with a wing span of 2.6 m. It was able to carry a maximum payload of 3 kg. It flew over the

study at flying height of 150 m above ground with a speed of 11 m/s. As explained in the successive chapters more in depth, the flight height was strongly influenced by the size of the plane, the payload and the size of the object under investigation. This experiment showed also that the images acquired in this way were not sufficient because of image motion, caused by the speed and the vibration of the engine. Therefore, in order to reduce the vibrations, Przybilla and Wester-Ebbinghaus (1979) proposed to use an helicopters.

In 1980, Wester-Ebbinghaus employed a rotary wing UAV for photogrammetric purposes. It was able to rise up a maximum payload of 3 kg and it was equipped with a medium format camera like the Rolleiflex SLX, a navigator system in order to verify the altitude, a camera shutter activated via radio link, a pilot in order to control the take off, landing and flying. Due to the success of this experiment, this kind of configuration was used as example for developing the successive models. Indeed, currently, multi rotors are the “gold standard” used in photogrammetry. In particular, the model most used is the quadricopter.

Also the development in computers and electronics have strongly improved the evolution of photogrammetry. Thus, four generations of photogrammetry can be distinguished. The first generation involves the period between the middle and the end of 1800, and it is characterized by the invention of photography by Daguerre and Niepce in 1839. The second generation is related to the analog photogrammetry, referred to the beginning of last century with the invention of stereophotogrammetry by Pulfrich in 1901. Moreover, also the airplanes and cameras became available and the aerial survey techniques were developed. This allowed to developed the basic mathematical theory even if the amount of computational operations was prohibitive for numerical solutions and consequently this method was not appreciate for long time.

Analytical is the name of the third generation photogrammetry, which is characterized by the introduction of the computer. For the first, Schmid employed the adjustment theory to photogrammetric measurements, even if the computers of that period were not adapt to support these operational heavy. Another important innovations of this group were the plotter and block adjustment program developed by Brown in the late sixties. In the fourth generation, digital photogrammetry, the aerial photographs are replaced by the digital images. In addition this phase is characterized by the development of special microprocessor chips and storage devices which permit rapid access to digital images.

2.3 Photogrammetry

In the reality, there is not an univocal definition of the term photogrammetry, which is composed by three Greek words: “phos” that means light, “gramma” that means letter and “metrein” that means measure. It's commonly defined as the “science of obtaining reliable information about the properties of surfaces and objects without physical contact with the objects, and of measuring and interpreting this information” (Shenk, 2005). Indeed, quite simply, it can be considered as a black box, for which the inputs are characterized by any kind of images, acquired with a proper overlap, from which is possible to extract reliable 3D information of the object or study area under investigation. The device used for acquiring photogrammetric data is called sensor and it consists of an optical and a detector system. It can be a digital sensor or an analog sensor. In this case, the pictures have to be digitalized by applying a scanner. On the contrary the tool where is mounted the sensor is called platform. The most common used platform are the airplanes or UAVs. From the digital images can be extracted four types of information:

- Geometric information, consisting of the spatial position and the shape of the object under investigation;
- Physical information, involving the properties of electromagnetic radiation;
- Semantic information, depending of the meaning of the image;
- Temporal information, depending of the change of an object in time.

This data can be obtained by comparing several images of different times.

After having processed the pictures and extracted the information required the outputs are generated. They can be classified in three categories:

- Photographic products: they can be generated from one photo or, alternatively, more pictures, which are merged in a mosaic. This result is called photomosaic. Only when it is rectified, it is geometrical identical with a map. In this case, it is called orthophoto;
- Computational results: the most important application of this field is the aerial triangulation. It allows to deliver 3D position of the points in a ground control coordinate system. The most significant product is the digital elevation model (DEM);
- Maps: these are the most considerable result and they can be distinguished in planimetric (they contain only the horizontal position of the ground

features), topographical (they contain both horizontal and elevation data) and thematic (they underline one particular feature of the ground).

2.4 Basic principle of photogrammetry

The generation of photogrammetric outputs is based on the collinearity principle, which defines the relationship between image and object space. Following the equations of that principle is described:

$$\begin{cases} x = -f \frac{r_{11}(X-X_0)+r_{21}(Y-Y_0)+r_{31}(Z-Z_0)}{r_{13}(X-X_0)+r_{23}(Y-Y_0)+r_{33}(Z-Z_0)} + x_0 \\ y = -f \frac{r_{12}(X-X_0)+r_{22}(Y-Y_0)+r_{32}(Z-Z_0)}{r_{13}(X-X_0)+r_{23}(Y-Y_0)+r_{33}(Z-Z_0)} + y_0 \end{cases} \quad (\text{Eq. 2.1})$$

where f is the focal length, X_0 Y_0 Z_0 are the element of the perspective centre, r_{11} , r_{12} , r_{13} , r_{21} , r_{22} , r_{23} , r_{31} , r_{32} , r_{33} are the elements of the rotation matrix, X, Y, Z are the coordinates of the 3D object while x_0 and y_0 are the coordinates of the image point. The collinearity model is related to the metric image coordinate system, while the measurements carried out on the digital images is related to the pixel coordinate system. The points measured in at least two images are commonly called tie points, and for them the collinearity model is applied. The equations for all tie points are merged in a system, which is solved using an iterative least squares method, generally called Gauss-Markov model. In order to obtain the 3D object, firstly it is required to approximate all the unknown parameters and then they are estimated. The name of this method is bundle adjustment. If the interior parameters are known the method is called self calibrating bundle adjustment. The estimation error can be described by the following equation:

$$-e = Axl \quad (\text{Eq. 2.2})$$

where e is the error vector, while A is the design matrix, x is the vector of the unknown parameters and l is the vector constituted by the observations. To weight the observations and the unknown parameters it is used also a weight matrix P . Thus, the estimated x is computed by Equation 2.3:

$$\hat{x} = (A^T P A)^{-1} * A^T P l \quad (\text{Eq. 2.3})$$

Its residual and the standard deviation are calculated with Eq. 2.4 and 2.5:

$$v = A\hat{x} - l \quad (\text{Eq. 2.4})$$

$$\sigma_0 = \sqrt{\frac{v^T P v}{r}} \quad (\text{Eq. 2.5})$$

r is the redundancy of the system.

In order to obtain a 3D reconstruction, at least two pictures of the same object acquired by two different viewpoints are necessary. Indeed, between the two images the baseline (B) and the average camera to object distance (D) are considered and used to calculate the base-to-depth ratio (B/D). Its typical value in photogrammetry is around 0.5, even if it's really difficult to reach this standard in the practical situations. This parameter influences the accuracy of the results. So, the accuracy is increased with the largeness of the baseline. In the mean time, the largeness of B causes problems in finding automatically the correspondences between the images involved. The accuracy of the reconstruction is computed by Eq. 2.6 (Fraser et al., 1996):

$$\sigma_{XYZ} = \frac{qS\sigma_{xy}}{\sqrt{k}} \quad (\text{Eq. 2.6})$$

Where k is the number of pictures, q is an empirical factor, S is the image scale, σ_{XYZ} is the accuracy of the computed 3D object coordinates and σ_{xy} is the accuracy of the measurements. The entire workflow related to the data acquisition and processing are described in Chapter 4.

Chapter 3

UAV systems

3.1 Introduction

The term Unmanned Aerial Systems (UAS) has been coined and adopted by the US Department of Defense (DOD) and the Civil Aviation Authority (CAA) of the UK to describe the whole flight system, composed by the aerial vehicles and the ground control station (Nex & Remondino, 2014). Over the years and depending on the field of investigation, various different names and acronyms have been developed to describe them, such as “Unmanned Aerial Vehicle” (UAV), “drone” or “Remotely-Piloted Aerial System” (RPAS), introduced by the International Civil Aviation Organization (ICAO) in the ICAO Circular 328 (ICAO, 2011). Nevertheless, the most popular terms are drone and UAV (Colomina & Molina, 2014), and, for these reasons, in the present work, the term UAV is commonly used.

This chapter gives an overview of UAV systems, which have been used in photogrammetric applications. In particular, historical background and applications, classification of UAVs, description of UAV platforms applied in the two case studies under investigation, and regulation have been discussed over the following sections.

3.2 Historical background and applications

At first, UAVs were born and developed in the military context, in order to fly over the enemy areas without any risk for the pilot. Just in the late nineteen-seventies, it was evaluated their utility for civil and Geomatics field (Przybilla et al, 1979). Nevertheless, their spread has run up against the distrust of scientific community. Indeed, they have become increasingly popular and widespread in the last two decades thanks to the fast improvement and integration of platforms, of integrated circuits and radio-controlled systems and software applied for reconstructing the surveys.

First investigations dated back to the Carnegie Mellon University, which applied drones in the robotics context. Works related to the study of the potential of the spatial details in the 3D point cloud for urban and natural terrain surveys can be find in 2003, when Thrun (2003) described the results of the combination of helicopter mapping system, Honeywell 3D compass, Garmin Global

Position System (GPS) and Nikon D100 digital SLR camera. However, He didn't take into account the accuracy and orientation of the flight trajectory. The researchers started to move in that direction in 2004 at the ISPRS congress, where a system, including a LIDAR system and CCD-cameras with GPS, for digital surface model generation was presented by Nagai et al (2004). Even if the complete workflow for the digital surface model generation was introduced by Nagai et al., (2008). In this study, the results were obtained by an indirect georeferencing method, which needed the position and orientation at the acquisition time of pictures. So, the images orientation ensued from the use of GPS data and Ground Control Points (GCPs). Recent technical electronic and optical development for aerial platforms and the devices mounted on them have improved the accuracy of UAV trajectory for 3D modelling.

Currently, UAVs are mainly employed in archaeological applications (Remondino et al., 2008) or in environmental problems monitoring, such as traffic supervision (Puri et al., 2007), emergency management (Molina et al., 2012), pollution detection (Capolupo et al., 2014; Capolupo et al., 2015), or in agriculture supporting, like precision farming (Newcombe, 2007).

3.3 Regulation

The necessity to define some security criteria of UAV flights has been warned as essential in order to avoid damage to people and/or things due to the widespread of UAV application in civil context. The regulations for UAV platforms and flights were originally introduced by the cooperation of NATO and EURO control in 1999. This work has not been adopted as standard by the aviation authorities of different countries; indeed, each of them issued a typical guideline according to the characteristics of own Nation. Nevertheless, all regulations have a common thread: the rules are strongly different depending on the size, weight, on board technology of aircraft and their employment.

In particular, in December 2015, the Italian Civil Aviation Authority (ENAC) released the last version of guideline regarding UAVs under 150 Kg. Like the other European countries, it makes a distinction between two types of drones: UAVs characterized by a take-off weight below 25 Kg and UAVs with a take-off weight above 25 Kg and below 150 Kg. This classification is linked to devices critically. On the base of pilot capacity to visually track the drone, the operational condition are organized in *Beyond Visual Line Of Sight (BVLOS)*, *Visual Line of Sight (VLOS)* and *Extended Visual Line Of Sight (EVLOS)*. *BVLOS* comprises the operations in which the pilot cannot have a visually direct contact with the drones; on the contrary, *VLOS* includes the operations in

which the pilot visually tracks the drone; instead, *EVLOS* indicates the situations in which the pilot can visually monitor the drone thanks the help of some devices. On the base of location, the procedures are classified in *non critical* and *critical*. The firsts are referred to *VLOS* operations on non congested areas; all the others situations are considered *critic*. Flying over groups of people is prohibited in any case. The criticality must be assessed by the pilot.

The specific rules for every unmanned aircraft of less than 25 kg of take-off mass impose that they have to be equipped with an electronic identificative device able to transmit and record each data related to the operation in real time. Moreover, both vehicles and ground station need a licence plate in order to identify the system and the operator. It is also necessary a declaration of compliance undersigned by the pilot and submitted to ENAC. For the *critic* conditions further equipments are needed in order to ensure an acceptable level of safety. Indeed, a system to maintain the aircraft control in the case that data link is lost the aircraft, is required.

The other type of UAV follow the same rules of the aircraft of less than 25 kg of take-off mass. In addition they must be registered with ENAC and they can fly just with an ad hoc flying permit.

In this guideline, it's also identify a third category: aircraft used for recreational and sport purposes. In this case, in order to avoid asking ENAC for temporary reserved airspace are, they don't have to fly over urban areas and infrastructure, it is necessary that the aircraft weights maximum 25 kg, has a maximum wing surface of 500 dm², maximum wing loading of 250 g/dm², maximum piston engine size of 250 cm³, maximum electric engine power of 15 kW, maximum turbine engine thrust of 25 kg (250 N), maximum turboprop engine power of 15 kW. Moreover, it is not needed any declaration or authorisation.

The pilot needs a particular permit on the base of the aircraft that he wants to drive: a 'Remote Pilot Certificate' is required for manoeuvring a system under 25 Kg; while, a 'Remote Pilot License' is obligatory for operating heavier aircrafts and *BLOS* operations. A special aeronautical certificate for UAVs pilot have been introduced, which is ensued by some authorized centres after a training period and having an exam.

According to EU Regulation 785/2004, the Regulation also imposes to ensure any kind of drone for any type of operation.

3.4 UAVs classification

The UAV systems, generally used as photogrammetric platforms, are classified on the base of the main characteristics of the aircrafts, like their engine/propulsion system (unpowered or powered), or their aerodynamic features (lighter than air or heavier than air) and their physical traits (flexible, fixed and rotary wings) (Table 3.1) (Eisenbeiss, 2009).

Table 3.1 – Photogrammetric UAV systems categorization (source: Eisenbeiss, 2009)

	Lighter than air	Heavier than air		
		Flexible wing	Fixed wing	Rotary wing
Unpowered	Balloon	Hang glider	Gliders	Rotor-kite
		Paraglider		
		Kites		
Powered	Airship	Paraglider	Propeller	Single rotors
			Jet engines	Coaxial
				Quadrotors
				Multi-rotors

As shown in Table 3.1, the rotary wing platforms are catalogued in single rotors, coaxial (also known as double-rotor systems), quadro-rotors, multi-rotors. Single-rotor systems consist of one main rotor and one tail rotor: the first is responsible of lift and thrust; while the tail rotor is used to correct the yaw motion and the torque. Contrary to the single rotor systems, the coaxial platforms use two main rotors. This is reflected in an increase of the complexity of the mechanical structure, of the flight altitude, of the payload that they can lift up and of the stability of the system. In addition, the single and coaxial systems have more power than four- and multi-rotor systems. Consequently, they are able to raise up more payloads, which influences the size, number and weight of the sensors that can be mounted on the drone (Eisenbeiss, 2011). Therefore, quadrotors are usually equipped with light sensors, so that they can be flown indoors as well as outdoors (Hoffmann, et al., 2004). The application of these systems is strongly influenced by the climatic conditions, like the wind. So, its use is limited to really small areas. This problem can be eliminated by applying multi-rotors. Indeed, their size and weight is similar to

quadro-rotors, but the redundancy of multiple rotors allows to improve the stability and security against systems crashes (Niethammer et al., 2009, Vito, 2009). Gliders, included among the unpowered fixed wing systems, utilize the airstream for the forward motion and uplift; on the contrary, the powered fixed wing use propellers and jet engines for the forward motion. Bendea et al., (2007) have shown that rotary wing systems can be adopted to operate closer to objects than fixed wing UAVs, due to larger flexibility in their control, even if they can stay for less time in the air, covering smaller areas. Balloons and gliders are controlled by ropes, which limit the flight altitude and distance from the operator. In addition, they are strongly influenced by wind, more than rotary and fixed wing UAVs. Like these systems, also the airship application is limited by the climatic conditions, but this platform can stay longer in the air than the fixed and rotary wing platforms.

Alternatively, they could be classified according to the size, the weight, the endurance, the range and the flight quote in

- Tactical UAVs: this category includes micro and mini UAV (their mass range is by 1000 kg), with a close-, short-, medium-range in distance (the range is comprised between few km and 500 km) and a flight altitude between few hundred meters to 5 km and the endurance from some minutes to 2-3 days;
- Strategical UAVs: this class comprises by platform able to fly higher than 20000 m and with an endurance of 2-4 days;
- Special UAVs: this group incorporates unmanned autonomous vehicles.

Therefore, joining the two classifications and evaluating the physical traits of UAV platforms, it is possible to quantify the pros and cons of different UAV platforms. In Table 3.2, the numeration is between 0 (low) and 5 (high).

Table 3.2 - Evaluation of UAVs traits

	Kite/ Balloon	Fixed Wing		Rotary Wings	
		electric	ICE engine	electric	ICE engine
Payload	3	3	4	2	4
Weather and wind dependency	4	2	3	2	4
Range distance	2	5	5	3	3
Landing distance	4	3	2	4	4
Minimum speed	4	2	2	4	4
Endurance	3	3	3	4	3
Maneuverability	2	3	3	4	4
Flying autonomy	-	3	5	2	4

Portability	3	2	2	3	3
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Moreover, UAVs can be classified on the base of the flight performance in manual, assisted or autonomous flight, or according the quality of the navigation system in NO GPS, GPS and DGPS. The quality of the navigation system influence the accuracy of the application: the first allow to have a really low accuracy (m), the second has a moderate accuracy (dm) and the third has an high accuracy (cm).

3.5 Aircraft configuration used in the two case study

In the first case study, “UAVs and photogrammetric technique for detecting copper contaminated soils”, a novel prototype UAV, projected and designed by our research group (Figure 3.1), was employed. Although the quadric-rotors is the ‘gold standard’ for this kind of investigations, we preferred using a hexacopter due to the reasons explained in the previous section, it has a greater stability and power to lift heavier loads. As hexacopter frame, we chose the carbon fibre Tarot FY690s. Its interaxis is of 690 mm and if the entire chassis weighs below or equal to 600 g, it can raise up a load of 3 kg. The vehicle configuration was optimized on the base of the frame and loads. So, six FullPower 4006M engines, six APC M 12 x 4,5 propellers, six 30A OPTO regulators and one Lipo 4s 5000 mAh battery were chosen so that the aircraft can fly for about 10 minutes (the time is strongly influenced by loads and weather conditions) and lift a digital camera.



Figure 3.1 - The Tarot 690s UAV

Moreover, it was equipped with all indispensable hardware elements and software tools necessary for its control, programming and planning of the flight according to Italian Regulation. Therefore, a compact multi-rotor autopilot system, DJI NAZA – M V2, was mounted on for providing good self levelling and altitude holding. It is composed by a main controller, an

independent Power Management Unit (PMU), a global positioning system (GPS) unit and a LED able to identify the UAV health status.

For photographic recording, also a small digital camera, a Canon Powershot S100, was mounted on it. It was chosen for its high resolution (12.1 megapixels), having a built-in global positioning system (GPS) unit, the possibility to acquire RAW format images, its small size (98,9 x 59,8 x 26,7 mm) and weight (200 g). In addition, It was equipped with a 7.44 x 5.58 mm sensor with 5.2 mm focal length and consequently, its pixel size is of 0,00186 x 0,00186 mm.

In the second case study, “Estimating biochemical and physical grassland traits From UAV acquired hyperspectral images”, an octocopter UAV, Aerialtronics Altura AT8 v1A, was chosen. Like in the other case, it was equipped with a ground station for planning and control of the flight paths and all essential tools for its programming (Figure 3.2). However, the main difference with the previous platform consists in the sensors mounted on it. Indeed, in this case, it was equipped with a global position system, a photogrammetric camera Panasonic GX1 for acquiring RGB photos suitable for 3D modelling of the study area, a Hyperspectral Mapping System (HYMSY), for acquiring hyperspectral images.

Panasonic GX1 is a camera of small size (116 x 68 x 39 mm) and weight (318 g), even if bigger and heavier of Canon Powershot S100, with a really good resolution (16 Mpx). Its pixel size is of 14.1 μm^2 , while the sensor size is of 17.3 x 13 mm.

HYMSY was projected and developed at Wageningen University and Research Centre, specifically for small air vehicles, able to lift a load of 2 Kg. Indeed, It is a lightweight hyperspectral pushbroom system, consisting in a PhotonFocus SM2-D1312 industrial camera and a Specim ImSpector V10 2/3 spectrograph. Its wavelength range is of 400–950 nm with a spectral resolution of 9 nm.



Figure 3.2 - octocopter UAV, Aerialtronics Altura AT8 v1A equipped with all essential tools

Chapter 4

Workflow for processing UAV data

4.1 Introduction

This chapter is focused on the description of workflow commonly used for processing data acquired from UAVs. First, an overview of the overall processing procedure is shown; subsequently, the different steps are described in details. Indeed, the entire method is divided in different modules. Each of them is organized in several steps, which can be diverse according to the task. For this reason, before starting any kind of operation, it's fundamental to define the subject under investigation and the suitable platform.

4.2 Workflow

Figure 4.1 shows the procedure commonly applied in any kind of task, organized in modules. Firstly, it is essential to plan the project, which means not just to define the subject under investigation, but also to identify the most suitable platform, tools and software for reaching the goal. Therefore, this is the most important step of the entire procedure indeed, even if only a really small detail is not designed in a proper way, the final result can be damaged.

After that, the real processing phases start. They are classified in data acquisition, image analysis, product generation and final applications. The data acquisition step involves both the platform preparation for taking images and the real act of data capture. The image analysis stage is the consecutive step. It includes the pre-processing examination of the pictures, the processing data and the final product generation. Basically, the operations of this step differentiate according to the goals. So, results are generated and applied to solve the initial problem. Each of these steps is been analysed in depth in the following sections.

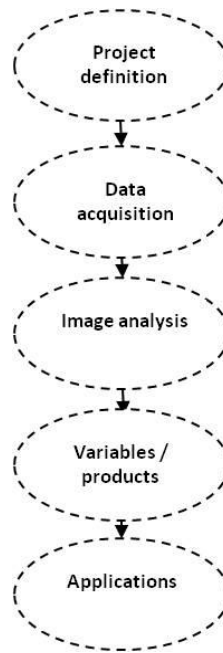


Figure 4.1 - Workflow for UAV data processing

4.3 Data acquisition

After designing the entire project, the data acquisition step starts. As explained in Figure 4.2, It involves several transitions, such as platform and tools preparation; survey planning; flight planning; flight; data acquisition.

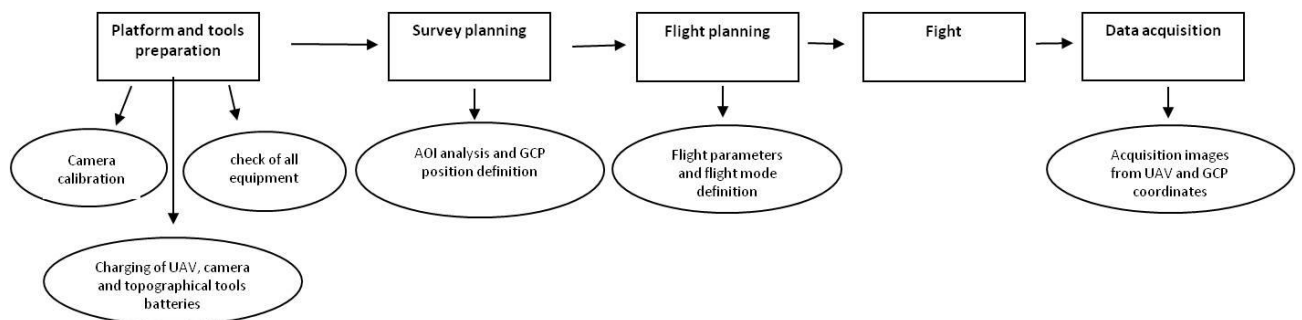


Figure 4.2 - Description of data acquisition procedure

Firstly, it is essential to check the operation mode of all the equipments and in particular of UAV platform, because also a really small malfunctioning of the electronic or mechanical tools could entail a failure and, consequently, damaging people or things. After that, the batteries of UAV platform, camera and topographical devices, sub-sequentially employed for detecting the coordinates of Ground Control Points (GCP), like Global Position System and Total station, have to

be charged. This step doesn't involve just mechanical operations but also a technical action: camera calibration.

Camera calibration is a necessary procedure for obtaining a precise and reliable 3D metric reconstruction from 2D images, since it allows to reconstruct the camera interior parameters, using the collinearity and a multi-image approach (Figure 4.3) (Remondino, 2011). Indeed, the calibration procedure allows to analyse and correct the geometric deviations of the physical reality from an ideal system. The calibration is considered concluded when the interior parameters (focal length, principle point offset and additional parameters (APs)) are known.

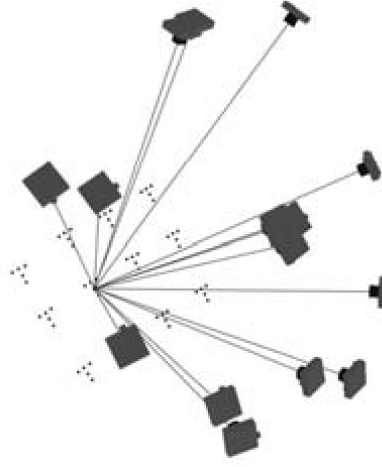


Figure 4.3 - Camera calibration

In order to calibrate a camera system, the physical model (Brown, 1971) is commonly used (Eq. 4.1 – 4.2). In this model all the elements can be related to physical error sources.

$$\Delta x = -\Delta x_0 + \frac{\bar{x}}{f} * \Delta f + \bar{x} * S_x + \bar{y}a + \bar{x}r^2k_1 + \bar{x}r^4k_2 + \bar{x}r^6k_3 + 2P_1\bar{x}\bar{y} + (2\bar{x}^2 + r^2)P_1 + 2\bar{x}\bar{y}P_2$$

(Eq. 4.1)

$$\Delta y = -\Delta y_0 + \frac{\bar{y}}{f} \Delta f + \bar{x}a + \bar{y}r^2k_1 + \bar{y}r^4k_2 + \bar{y}r^6k_3 + 2P_1\bar{x}\bar{y} + (2\bar{y}^2 + r^2)P_2 \quad (\text{Eq. 4.2})$$

where f is the focal length, $\bar{x} = x - x_0$, $\bar{y} = y - y_0$, $r^2 = \bar{x}^2 + \bar{y}^2$, (x_0, y_0) is the principle point offset, K_i is the term for the radial distortion, P_i for the decentering distortion, A for the affinity factor and S_x for correcting the skew in the image plane. The radial distortion (Δr) is usually calculated by applying Eq. 4.3:

$$\Delta r = k_1r^3 + k_2r^5 + k_3r^7 \quad (\text{Eq. 4.3})$$

where r is the radial distance from the image centre. In Figure 4.4 are shown the typical trend of the radial and decentering distortion according to the variation of image radius and focal length. K_i are usually highly correlated. The coefficient K_2 and K_3 are usually included in

application requiring a higher accuracy, like photogrammetry. The decentering distortion is due to a lack of centering of elements along the optical axis. It is usually an order of magnitude bigger than radial distortion and in general it increases with increasing the focal length.

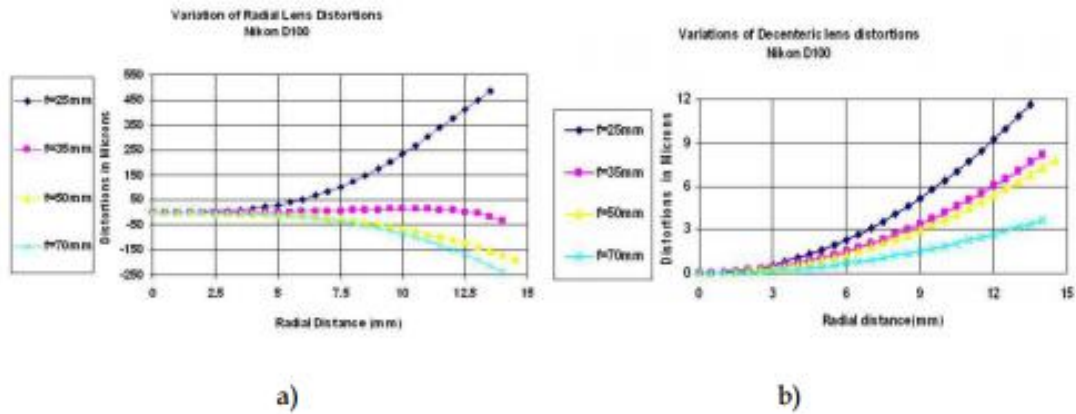


Figure 4.4 - Radial and decentering distortion profile for a digital camera set at different focal length.

Several calibration procedures have been developed over the years, some of them are object based calibration, while others use images taken in a static scene. Zhang (2004) identified three different calibration categories according to the dimension of the object chosen as reference for the calibration procedure:

- 3D reference object based calibration;
- 2D plane based calibration
- 1D line based calibration.

3D reference object based calibration involves the knowledge of the geometry in the 3D space of an object, chosen as reference. This object is usually composed by two or three planes orthogonal to each other. This kind of calibration is quite expensive since it needs a costly calibration equipment and a complex setup. Instead, the 2D plane based calibration, requires a planar pattern as reference (Sturm & Maybank, 1999; Zhang, 2000). It has to be oriented in few different directions. It is easier and less expensive than the first one. The third category is characterized by an object, composed by a set of collinear points (Zhang, 2002). It is realized by observing a moving line around a fixed point. Comparing these three methods, the 3D reference object based calibration is the most accurate but also the most expensive (Zhang, 2004). So, the first one is indispensable in all cases in which an high accuracy is required.

Other techniques, without using any calibration object, exist. In this case, just taking three pictures moving the camera in a static scene, it is sufficient to reconstruct both internal and external required for calibration. This technique is based on estimating a large number of parameters.

Moreover, in the case of aerial photos, the calibration procedure is usually performed in laboratory, even if also the in-flight calibration is possible (Colomina et al., 2007). The in flight calibration is performed acquiring pictures at different flight altitude (Nex & Remondino, 2014). Also in the case studies under investigation in this work, it has been preferred the lab calibration because more precise. It is important to underline that the images block taken during the data acquisition phase are not suitable for calibrating the camera and for this reason it is better to separate these two steps.

The calibration method used in the current study is the 1D plane based calibration by applying Agisoft lens software. It involves the printing of a pattern and its attachment to a planar surface or, alternatively, the generation of the patterns made available by software. Subsequently, it has to take few pictures of the model plane under different direction, paying attention to comprise all the scene. After that, the feature points in the images have to be detected and the five intrinsic and external parameters have to be estimated via Agisoft lens. In this way, the lens distortion is minimized. These parameters are consequently employed in the following processing.

Once the preparation tools phase is concluded, the survey planning starts. Analysing the size, configuration and location of the area of interest (AOI), it is possible to identify the proper number and position of Ground Control Points (GCPs) necessary for the topographical reconstruction of the scene, subsequently, surveyed with a GPS or, alternatively, an accurate total station. Moreover, this step allows to have a precise idea of the area and to programme any kind of possible interventions in order to solve any problems that appear.

The trajectory and the different flight parameters are programmed mixing the information acquired during the previous phases, “project definition” and “platform and tools preparation”. Indeed, in order to plan flight parameters (speed, altitude, shooting time), it is indispensable to know data related to the camera sensor traits, type of aircraft, size and configuration of the AOI, applications and flight restrictions, imposed by the Regulation. In general, the camera focal length and the desired image scale and the longitudinal and transversal overlap of the strips are fixed, while the altitude, the speed and the waypoints (distance between two consecutive images) are calculated (Nex & Remondino, 2014). According to Cannerozzo et al. (2012), the flight altitude can be estimated by Eq. 4.4:

$$H = f \cdot N \quad (\text{Eq. 4.4})$$

where, H is the flight altitude, f is the focal length and 1/N the desired scale image.

Each acquired image covers a particular portion of the AOI, the size of which can be calculated by Eq. 4.5:

$$L = \frac{l \cdot H}{f} \quad (\text{Eq. 4.5})$$

l is the length of the image side. Known the side of the image and fixed the overlap is possible to compute the distance between two waypoints by Eq. 4.6:

$$B = l \cdot N \cdot (1 - \mu) \quad (\text{Eq. 4.6})$$

B is the distance between two waypoints and μ is the longitudinal or transversal overlap. It is recommended to use an overlap of about 60-80% in longitudinal side and 40-50% in transversal side. These parameters can be calculated manually or by a dedicated software.

Also the flight mode have to be chosen. It can be manual, assisted or autonomous. This characteristic strongly influences the image quality (Nex & Remondino, 2014). The manual mode gives generally the worst results, since the image overlap and geometry of acquisition is very irregular. On the contrary, using an assisted or autonomous mode allows to improve the acquisition. Indeed, the autopilot, composed by hardware and software elements, is able to fly according to the trajectory and the selected waypoints, communicating with the platform during the flight mission. Platform, auto-pilot and GCS are essential for the results quality. So, when low cost platform and light weight are employed, it is essential to increase the overlap among the images (Remondino, 2011).

In our case, all the parameters have been computed manually while the flights have been performed using the autopilot assistance. Version 4.0.11 of Ground Control Station software has been selected.

Moreover, in order to improve the image quality and to minimize the influence of shadows on the ground, it is required to perform the flights in good weather condition, without clouds, wind and haze and during the brightest hours of the day. Consequently, the flight is performed and the pictures took. During this step it is fundamental to collocate and to acquire the coordinates of the proper made target, subsequently used as GCPs in the following analysis.

In this research activity are designed a properly made target using a cutting board and stoppers for roller shutters, as foot in order to increase the support stability. The different steps needed as shown in Figure 4.5.

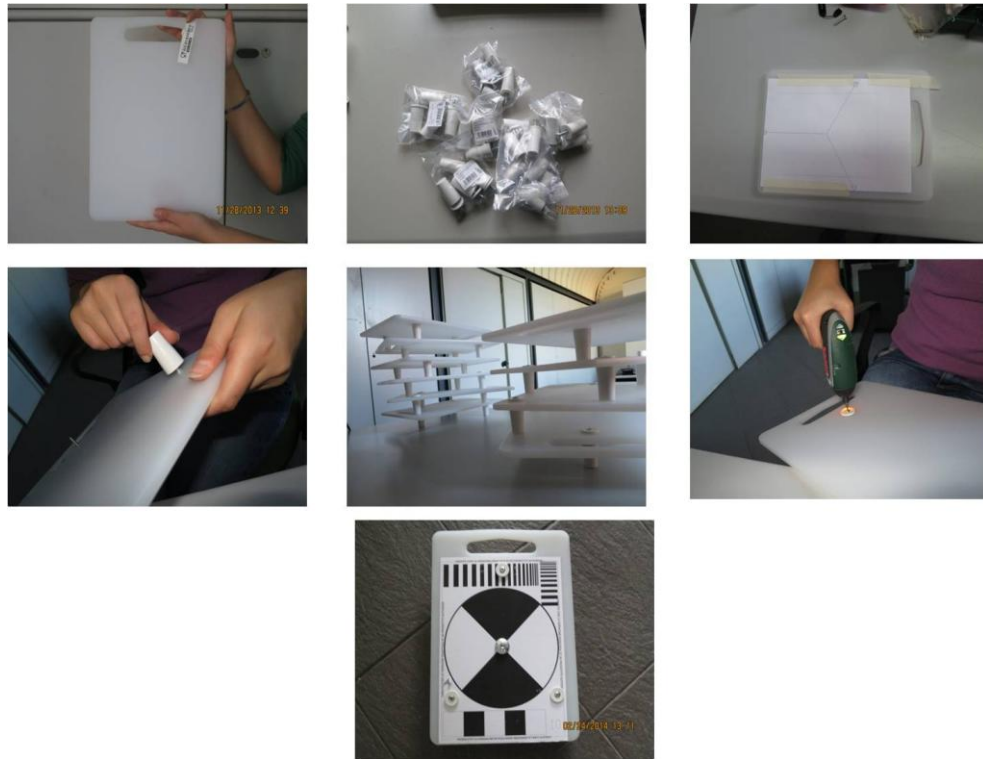


Figure 4.5 - Steps of target preparation and final result

4.4 Image analysis

The images analysis phase is composed by pre-processing and processing steps, each of which is characterized by several stages, as shown in Figure 4.6.

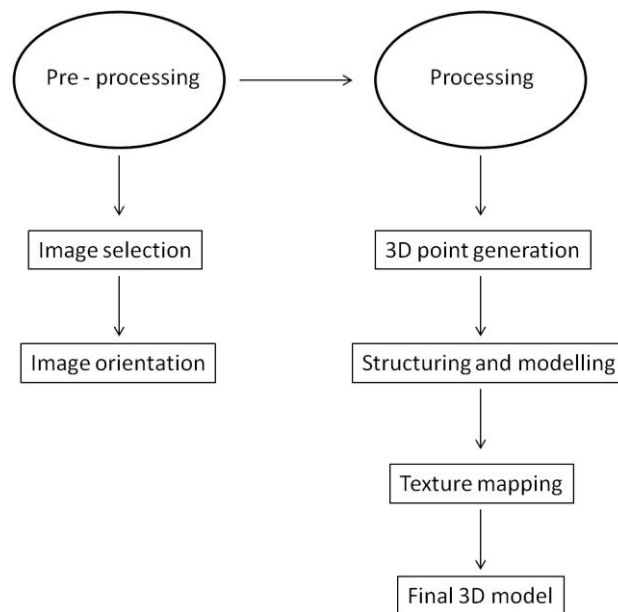


Figure 4.6 - Image analysis workflow

Initially, the image quality check is essential in order not just to verify how many and which of them should be eliminated, because too blurry or not enough clear, but also to confirm that the images have been acquired in the defined positions (Eisenbeiß, 2009). It is absolutely necessary to acquire the images again, when the conditions are not met, like in one of the following situations:

- The image haven't been acquired in the desired positions;
- One or more images have been taken;
- There isn't the correct overlap among the acquired pictures.

Therefore, if the images block has a good quality, the orientation procedure starts. This process is based on determining the position and the angles during pictures acquired. In order to increase the accuracy of this procedure, a set of tie points (GCPs) have to be manually or automatically recognized in the images. To minimize the errors, tie points have to be well distributed in all images and, moreover, in the most of the cases, they have to be presented in three different pictures. These points will be then employed to iteratively solve a system of collinearity equations with the Gauss-Markov model of least squares (Guidi & Remondino, 2007), as explained in Chapter 2. The GCPs coordinates have to be measured with an accurate surveying system, like Global position device or a good total station. GCPs coordinates will be used to calculate the rototranslation matrix for orienting the images from the first reference system to the new one.

Once the image orientation is concluded, the 3D scene measurements can be performed. Applying the basic principles of photogrammetric technique and the knowledge of interior and

exterior camera parameters, a 3D point cloud is generated. The generation of a dense or alternatively sparse 3D point cloud depends on the area of interest and project requirement. The sparse modelling is usually realized by a manual measurements, and it is suitable for architectural or 3D city applications (Gruen & Wang, 1998; El-Hakim, 2002). On the contrary, the automated procedure is preferred when dense surface measurements and reconstruction, like a DEM derivation (Guidi & Remondino, 2007). Several research works, Pierrot-Deseilligny & Paparoditis (2006), Hirshmueller (2008), Remondino et al. (2008), Hiep et al. (2009), Furukawa & Ponce (2010), have demonstrated the great potentiality of this technique for dense 3D point cloud generation. Therefore, in the last years, different commercial, open source and web-based software have been realized to automate this procedure, such as Photomodeler Scanner, used also in the case studies of this research activity, MicMac, PMVS.

After that, a polygon model, generally called mesh, is generated. This step is realized by applying different stages, which order is different according to the available data. A specific process is adopted according to the kind of matrix, which can be regular and structured or unstructured and irregular. The method to apply is easier in the first case than in the second one. In particular, if the point cloud is characterized by a regular and structured matrix, it firstly involves the research of the neighbour potential mesh connections for each 3D point, and later the mesh generation. This can be done by two different approaches according to the software used: zippering and volumetric algorithm. In the first one, the overlapping areas are selected, the redundant triangles are removed and the neighbour potential mesh connections are merged (Turk & Levoy, 1994). Soucy & Laurendeau (1995) evaluate the redundancy of the mesh on the base of the Venn diagrams. The second approach is based on the triangulation union of the point sets (Bernardini et al., 1999). In this method an imaginary ball is rolled on the point sets and a triangle is created for each triplet points. This methodology gets critical when a large number of overlapped areas is presented. Another method, the volumetric algorithm is based on the subdivision of the model space in voxels. This subdivision is done on the computation of the average position of each 3D point (Curless & Levoy, 1996). This method appears more efficient than the previous one.

Therefore, while the mesh generation is immediate for the structured point clouds, on the contrary, the process is quite complex for the unstructured point cloud, since the identification of the neighbour potential mesh connections for each 3D point is not immediate enough, like the previous proceeding. Indeed, in this case, it have to be employed a specific process like Delaunay, which consists in searching the neighbour for each point re-projecting the 3D points on a level surface or, alternatively, another primitive surface and verifying the shorter distance among them.

Consequently, as first thing, it is required to generate an uniform intermediate 3D point cloud, merging the 2.5D point cloud; subsequently, it is needed to complete the 3D generation point clouds using a more sophisticate procedure than a Delaunay algorithm. This latter stage is based on the construction of triangles, interpolating more elements than necessary (Amenta & Bern, 1999), and then, the output is obtained approximating surfaces with the best fit function of raw 3D points (Hoppe et al., 1992; Cazals & Giesen, 2006). The 3D point cloud is later converted in mesh, in order to eliminate and correct all possible topological problems due to the polygonal surface. Sometime the intervention of the operator is needed for removing the spikes or the lack in the meshing part. This operation is really important in particular when the final product have to use to visualize the real-time virtual presentation or to generate accurate copies of the original one. Several approaches are be presented to solve this step, such as radial basis functions (Carr et al., 2001), volumetric diffusion and multilevel partition of unity implicits (Ohtaske et al., 2003). In the reality, this procedure cannot be employed in all cases, like our study cases, since it could introduce not existing data to the measured model (Guidi & Remondino, 2007).

An important and useful step in editing mesh procedure is the optimisation. It allows to obtain a drastic reduction of mesh size, involving the redundancy the triangles surface created in the previous steps without decrease the mesh resolution and geometry. Cignoni et al. (1998) explained algorithms used to simply the mesh.

Before the final product is visualized, there is a last step to apply: textured 3D geometric model construction. Indeed, it allows to obtain a photo realistic representation of the object or area under investigation, extracting the colour from the images and transferring them on the 3D model (Kobbelt et al., 2004). When the camera parameters are known, the textures are automatically extracted and mapped, otherwise homologue points between 3D mesh and 2D images have to be found, colour information extracted and assigned to the surface of the 3D model applying a colour vertex encoding and a mesh parameterization. Some problems in textures reconstruction are due to lighting variations of the images, surface specularities and camera setting. So, in order to eliminate or, alternatively, reduce these kind of problems high dynamic range (HDR) images should be taken (Reinhard et al., 2005; Debevec et al., 2004).

Eventually, the final products, 3D models and ortho-photo, can be visualized. Fortunately, over the years, the power of the computers has strongly increased and consequently, this procedure can be performed in a short period of time.

4.4.1 3D modelling software overview

The main commercial photogrammetry software packages are 3D Builder, Canoma, Photo 3D, PhotoModeler and Australis. Each of them is characterized by specific features and, consequently, by particular advantages and disadvantages, explained in this paragraph.

3D builder is a software developed by 3D company for window environment, able to support different image formats, such as TIFF, JPEG and BMP and recognize several camera types. Moreover, the 3D model obtained can be exported in many formats, like DXF, 3D studio, VRML. It can manage several photos at the same time and it is able to extract the texture directly from the original pictures. The software is described in more details at the following link: <http://www.anything3d.com/product/software/builders.php3>.

Canoma (Meta Creations, 1999) is a Mac/Win software able to generate photorealistic 3D model from one or more scanned or digital photos (<http://www.canoma.com/>). Its operating principle consists into wrapping 17 primitive built-in wireframe templates in order to generate the 3D model. Like the previous software, also in this case the textures can be extracted directly from the original photos.

Photo 3D is a software able to generate 3D model with texture from single and multiples images. This software allows also to correct lens distortion and to calculate automatically the eye position, the axis direction and the coordinates of the model. More information can be found at the following link <http://photo3D.com/eindex.html>.

PhotoModeler (<http://photomodeler.com/>) is a software able to generate an accurate high 3D model and measurement from multiples digitalised and scanned images. After the interior and exterior correction of the camera parameters, it allows to create a dense cloud point, built on homologous points, interactive 3D reconstruction, texture mapping and ortho-photo.

Australis (<http://www.photometrix.com.au/australis/>) is a photogrammetric software realised by Photometrix in 1997 and completely rewritten in 2006. The last version, Australis V8, is able to performance an automatic 3D reconstruction and a photogrammetric camera calibration from multi-station digital image networks.

4.5 Final products and applications

The main final products of this procedure can be classified in the following four groups:

- Digital terrain and surface models (DTM, DSM);

- 3D city models;
- Heritage models;
- Ortho-photo.

Generally, the first and fourth classes are used to describe surface morphology and analyse the processes that characterized the environment, generating topographic maps, analysis of changes, environmental models. On the contrary, the second category is usually employed for city planning, disaster management, transportation analysis. The third class, instead, is applied for conserving, restoring any kind of archaeological element. For that reason, different levels of details are required according to the necessities (Gruen et al., 2005, Guidi et al., 2009, Criminisi et al., 1999).

Therefore, these products are used like base for the successive operations according to the purposes of the research. Indeed, the operation applied in the two case studies presented in this research activity are substantially different. While the DEM is the main character of the first case (Chapter 5), the hyperspectral datacube is the essential element of the second one (Chapter 6).

Chapter 5

Case study 1: UAVs and photogrammetric technique for detecting copper contaminated soils

5.1 Introduction

Campania Region has known for the beauty and the prosperity of its territory. Unfortunately, over the years, it has been the subject of illegal spills or/and accidental activities, that why the accumulation of heavy metals in agricultural soils is verified. This is considered one of the most critical environmental problem since heavy metals in agricultural soils are usually absorbed by crops, affecting the food quality and consequently the safety (Oliver, 1997; Muchuweti et al., 2006). Indeed, European Union (2002) has shown that each heavy metals has a specific effect on the body health. For example, arsenic (As), mercury (Hg), zinc (Zn), copper (Cu) and aluminium (Al) cause gastrointestinal problems, like diarrhoea and vomiting, and systemic effects, such as tremor, ataxia, convulsions, paralysis, depression or pneumonia (McCluggage, 1991); while lead (Pb) and Cadmium (Cd) affect human life expectancy of about 9-10 years (Lăcătușu et al., 1996). So, for these reasons, Campania Region has gained the nickname of “Land of fires” and it is been included in the 44 Italian places with high levels of cancer risk by National Institute of Health.

Therefore, it is important to know the real heavy metals distribution in agricultural soils, even if the Italian situation is strongly heterogeneous and complex since the heavy accumulation is correlated to a combination of geogenic and anthropogenic pollutants (Cicchella et al., 2005). Geogenic pollutants are mainly related to the processes of parent rock genesis, extremely rich of metallic elements, due to volcanic activities and related events, such as hot springs and fumaroles (De Vivo et al., 1995). On the contrary, the anthropogenic pollutants are linked to industrial, agricultural and accidental or voluntary activities. For example, industrial activity results in high concentrations of cadmium (Cd), chromium (Cr), copper (Cu), mercury (Hg), lead (Pb), nickel (Ni), and zinc (Zn) (Filippelli et al., 2012); use of inorganic pesticides and chemical fertilizers produce an high concentration of Cu, Hg, manganese (Mn), Pb and Zn (Swaine, 1962); motor vehicle traffic increases the concentrations of Cd, Cr, Cu, Ni, Pb, selenium (Se) and Zn in the areas near driveways (Albanese and Cicchella, 2012). There are also other causes of soil pollution, like gasoline pumps and illegal spills (Lima et al., 2012). Currently, the geogenic pollutants distribution in Campania

Region is known quite well and, consequently, foreseeable (Albanese et al., 2007). Completely different is the situation about the anthropogenic mapping. Indeed, their patchy distribution complicates the possibility to map and predict their extent and location.

Among the anthropogenic pollutants, it's really important to be able to map and predict copper distribution, because it is one of the essential elements in inorganic pesticides and chemical fertilizers. So, it is commonly used in agronomy and diffused on , although its high concentrations in agricultural soils strongly affect the health of plants and animals with toxic consequences. Thanks to its chemical features, it belongs to group 11 elements of the periodic table, it is a very versatile ion and so it is able to interact chemically with the organic and mineral soil components. For this reason, it is not very mobile in the soil since its mobility depends on the chelation by organic matter and adsorption processes, which is strongly affect by the pH of the soil. Moreover, Stevenson and Ficht (1981) have shown that 1 g of humic acids has the ability to chelate from 48 to 60 mg of copper. Therefore, copper accumulates in the superficial soil layers (Kabata-Pendians and Pendias, 2001).

Nowadays, the procedures employed for pollutants mapping consist in characterizing and sampling soils, typically, using a regular grid of 10 x 10 m, resulting in 100 samples for ha. Then, it is carried out analyzing each unit of homogeneous soil with a large set of organic and inorganic substances. Therefore, it is evident that this procedure is time consuming and expensive, because it involves both field work and laboratory activity. Consequently, it has also another restriction: it is really difficult to characterize a large area with this dense mesh and, for this reason, the development of a new methodology able to go beyond its limits is necessary. The new method could be based on applying some landscape structures able to act like physical or biogeochemical barriers against contaminants, if set between a source of pollution and a receiving water body (Muscott et al., 1993). Wetlands are included in this category due to their ability to absorb pollutants. Indeed, thanks to plants presence, they dilute contaminants concentration in absence of significant nitrogen concentration and denitrification processes. (Montreiul et al., 2008). Over the years, several indices to predict wetland distribution at the catchment scale have been introduced and their efficiency have been analyzed by Infascelli et al. (2013). Among these, Topographic Index (TI) and Ordinate Climate-Topographic Index (OCTI) have given the best outcomes. In particular, Topographic Index (TI) hasn't been employed just for predicting wetland distribution (Merot et al., 2003), but also in different kinds of studies, such as for identifying flow paths (Robson et al., 1992), for monitoring vegetation patterns (Moore et al., 1993) and forest site quality (Holmgren, 1994), for detecting the spatial distribution of soil moisture and runoff source areas (Chirico et al., 2003).

These indices are commonly calculated from digital elevation data (Sørensen et al., 2006). In order to transfer these indices from large to plot scale, it is necessary to compute them on a highly accurate land-form mapping (Chirico et al., 2005; Capolupo et al., 2014).

Since the introduction of fast computers and fifth-generation software for photogrammetry have been realized (Mulder et al., 2010), land-form mapping is generally performed by visually interpreting aerial photos (Dent and Young, 1981). Indeed, these new technologies have lead a significant reduction in photo processing time thanks to their ability to work with hundreds of photos in the mean time and to automatically restitute them (Pierrot-Deseilligny et al., 2011). An accurate landform mapping could be performed using several devices, such as laser scanners (Khorashahi et al., 1987; Huang et al., 1988; Bertuzzi et al., 1990; Romenkens et al., 1986), or photogrammetric technique (Rieke-Zapp et al. 2001). Both techniques have similar results in terms of accuracy and resolution, even if laser scanner needs more amount of time for data collection and processing. Moreover, also the drone introduction in photogrammetric field has significantly improved outputs and permitted further reduction of time and cost of data acquisition, since drones allow to reach difficult-to-access areas and to drastically reduce flight quota (Nex et al., 2013), acquiring high-resolution aerial photos at scales ranging from 0.1 to 10 ha increasing DEM accuracy. For this reason, currently, photogrammetry is considered the best one to generate a DEM of good quality and adapted to the size of object or area under investigation.

The goal of the current study is to attempt a highly innovative methodology for the prediction of copper at small scales mixing approaches commonly used in different context. In particular, it is based on an “inverse” approach to detect the points to be sampled by applying transport modelling, models for predicting the distribution of wetlands transferring topographic index (TI) and the clima-topographic index (CTI) normally used at large catchment to catchments of limited scales. Indeed, the principle at the base of this method is that areas with accumulated contaminants such as wetlands have been assimilated to sedimentation micro-basins.

In order to detect copper and to transfer these indices to more limited scales, it is required to generate an extremely accurate land-form mapping involving the following phases:

- land-form mapping;
- modelling of transport process;
- calculation of indices suited to predict wetlands distribution;
- detection of areas characterized by potential heavy metal accumulation that would reveal the presence of illegal spills; and
- validation method.

5.2 Material and methods

5.2.1 Area of interest

The study area is the municipality of Trentola Ducenta, located in Caserta Province (Southern Italy) at an altitude of 68m above mean sea level. It is one of 77 communes of the NIPS Litorale Domizio Flegreo and Agro Aversano, one of the six more contaminated areas of Campania Region.

The experiment was carried out in an area measuring 4,500 m² (Figure 5.1), suspected of being contaminated with heavy metals and organic pollutants. It was sampled with a regular mesh of 5 × 5 m, acquiring in this way a total of 170 points. Each of them was characterized by analysing the concentration of 15 elements and, in particular, of copper. Analyses were performed by the Mass Spectrometry Laboratory of University of Naples Federico II, employing the method EPA 6010C 2007. This protocol involves firstly the reaction of each sample with nitric acid and, then, the measurement of characteristic emission spectra by inductively coupled plasma-atomic emission spectrometry (ICP-AES) using an optical spectrometry. Indeed, aerosol, resulting from a nebulisation process of the samples, is transported to the plasma, where a radio-frequency inductively coupled plasma produces a specific emission.

Traces of copper have been found in all samples, even if in different concentration.

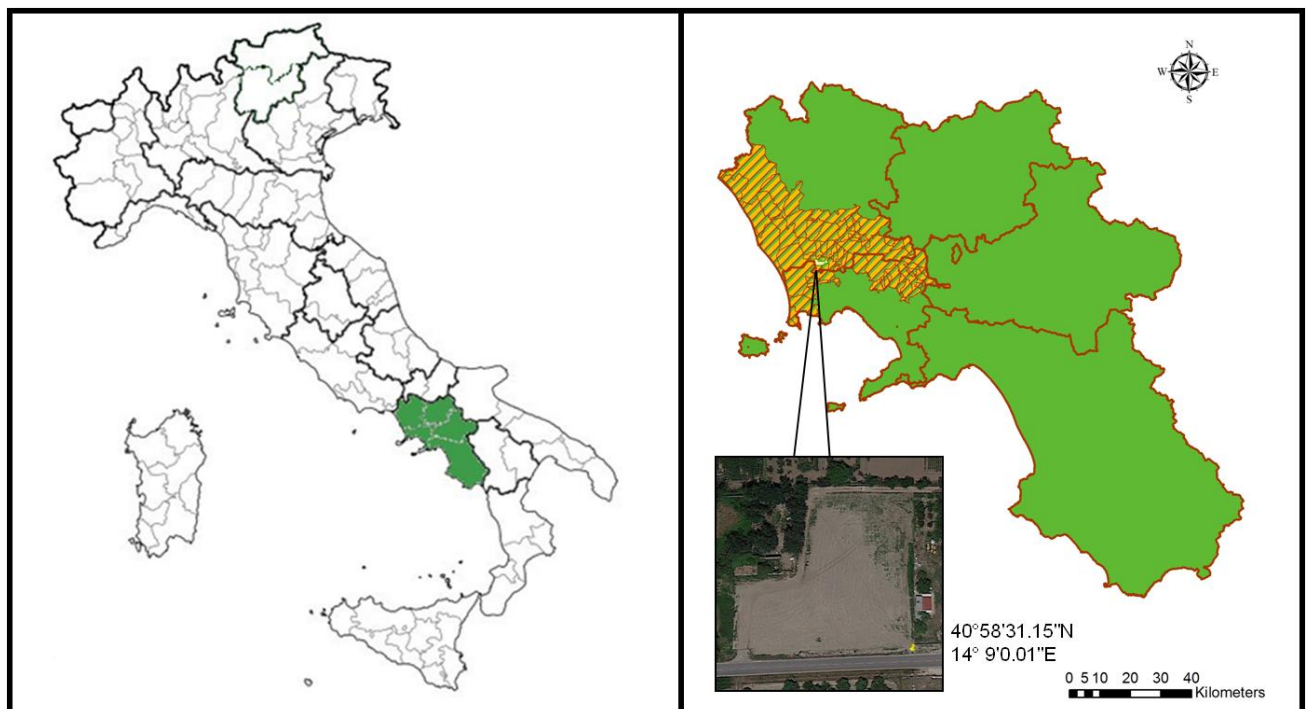


Figure 5.1 - Area of interest

5.2.2 Landform mapping

In order to obtain of a high resolution DEM, the area of interest have been over-flown with the use of a hexacopter (Figure 5.2). Its configuration has been optimized according to the frame and load to be lifted, as explained in section 3.5.



Figure 5.2 - The Tarot FY690s drone equipped with all essential hardware elements and software tools

We chose to adopt a hexacopter although the quadricopter is the ‘gold standard’, in consideration of its greater stability and power to lift heavier loads. Our prototype is composed by Tarot FY690s hexacopter frame, all essential hardware and software elements necessary for its control, programming and planning of the flight and a small digital camera, Canon Powershot S100. The Tarot FY690s frame is particularly suited to photogrammetric technique since it is made of carbon fibre and it can support a shipment weight of 3,000 g.

Also the choice of the camera was done with particular attention. Indeed, it has a lot of interesting features, like the weight (just 200 g), its resolution (12.1 megapixels), the sensor mounted on it (7.44 x 5.58 mm) with 5.2 mm focal length, the built-in GPS unit and eventually, the possibility to acquire raw images. The camera calibration was performed using Agisoft Lens.

Moreover, ten properly made targets with an appropriate support, as described in section 4.3, were used as GCPs (Nex et al., 2013). They were placed along the perimeter of the field and in its central zone position. Their location was got a Total Station Geodimeter 600, which has an angular accuracy of 3" (10 cm3), i.e., 1.0 mgon, and distance measurement accuracy of $\pm(5 \text{ mm} + 3 \text{ ppm})$.

So, a precision of 1.7 mm in height difference (sen $0.010 * 100$) at a distance of 100 m and a precision equal to 5 mm in planimetric is expected. The topographic reconstruction of GCPs was performed using the Meridiana software.

Following the phases regarding the preparation tools and survey planning, the step related to the flight planning was performed as explained in the previous chapter. The flight was planned in way to obtain a ground sample distance (GSD) of 10 mm. So the flight altitude was set at 25 m, also in consideration of a safety factor of 10% and the speed at 4 ms^{-1} . So it was ensured a longitudinal overlap of 70% and a transversal overlap of 30%. The whole area would be covered with 42 photos but, we preferred to collect a total of 84 pictures, two photos for each waypoint, in order to avoid problems during the 3d modelling phase, due to missed data, or can remove blurry images during the alignment. These pictures were acquired in three different flight missions: during the first two missions, the UAV flew for a total of 12 minutes and 16 waypoints were covered; instead, the third flight lasted 8 minutes covering 12 waypoints (Figure 5.3).



Figure 5.3 - Three flight missions

When also this phase is concluded, the flight was performed and the aerial photo acquired and the image analysis step was started. In order to obtain a metric reconstruction of the scene, orientation and georeferencing were carried out as preliminary steps. As suggested by Triggs et al. (2000) and Gruen and Beyer (2001), imagery orientation involves two different stages: photo alignment and tie point extraction. Later, GCPs have been imported in the alignment so to improve image orientation, correct the photo block geometric deformation and georeference the imagery. Subsequently, a polygonal model (mesh), geometrically corrected imaging (orthophotos) and accurate details of the surface (texture mapping) and DEM were generated. Processing of the aerial pictures and 3D model construction were made by applying Agisoft PhotoScan Professional software.

5.2.3 Modelling of the transport process

Firstly, the DEM was interpolated with the Kriging estimator using ESRI ArcGIS Software in order to obtain a GRID format, more light and suitable for following processing. Later, in order to remove the small imperfections and to avoid discontinuities and abnormality drainages in the hydro-graphic scenes, identifying and filling the “pits” with the ArcGIS’ hydrology tool (Infascelli et al., 2013). At this point, the model is ready for the construction of the surface flow direction and flow-direction tool using the mono-directional or eight flow direction (D8) model. This approach was chosen because Wolock et al. (1995) and Beaujouan et al. (2001) have shown to be particularly suitable for modelling the micro-rill network. Subsequently, the flow accumulated in each cell was generated using the ArcGIS flow-accumulation tool made in order to create different micro-basins by applying outlets. For each of them, local and downhill slope, drainage area, mean annual effective rainfall depth and evapotranspiration were estimated in way to calculate TI and the CTI.

5.2.4 Indices for wetlands prediction

In the current study, the accumulation areas, also called sedimentation zones, are assimilated to wetlands. Over the years, several indices have been introduced to predict wetlands extension and location.

First of all, the Soil Topographic Index was presented (Beven et al., 1979):

$$STI = \ln \left(\frac{a}{T \tan \beta} \right) \quad (\text{Eq. 5.1})$$

where α is the drainage area, β the local slope and T the trasmissivity. Later, it was shown that trasmissivity values is usually neglected compared to the drainage area and the local slope. Therefore, the index was modified and a new index, called Topographic index, was introduced as described by eq. 5.2(Beven et al., 1986):

$$TI = \ln \left(\frac{a}{\tan \beta} \right) \quad (\text{Eq. 5.2})$$

For a given amount of rainfall depth, TI values is influenced by the size of the drainage area and the local slope: its values increases with the increment of the size the drainage area and decreases with the reduction of the local slope. This index does not take into account the climatic condition and, for this reason, a more robust index, Clima-topographic Index, was introduced by Merot et al. (2003), (Eq. 5.3):

$$CTI = \ln \left(\frac{Vr}{\tan \beta} \right) \quad (\text{Eq. 5.3})$$

where V_r is the volume of effective annual rainfall and β is the downhill slope. The downhill slope is the slope between the point of interest and the runoff course measured along the hydraulic path. The replacement of the local slope with the downhill slope allows to improve the result both from the technical and the conceptual points of view (Gascuel et al., 1998). Indeed, the local slope is smoothed respect to the downhill slope and, in addition, soil saturation depends on both the up-slope and the down-slope factors, element not considered with TI. V_r is calculated multiplying drainage area with the mean annual effective rainfall, given by eq. 5.4:

$$Reff_{annual} = \sum_{1-12} Reff_i \quad (\text{Eq. 5.4})$$

where $Reff_i$ is the monthly effective rainfall depth, calculated by eq. 5.5:

$$Reff_i = R_i * PET_i \quad (\text{Eq. 5.5})$$

PET_i is the potential evapotranspiration. In the current study, it was calculated by applying Hargreaves equations (Hargreaves et al., 1985), considered the best one to compute the evapotranspiration in the Southern Italy (Pindoizzi et al., 2013), eq. 5.6:

$$PET_i = 0.0023 * R_a * (T_{mean} + 17.8) * \sqrt{T_{max} - T_{min}} \quad (\text{Eq. 5.6})$$

Where R_a is the extraterrestrial radiation, estimated applying the method proposed by Allen et al. (1998), T_{mean} , T_{max} , T_{min} are the average, maximum and minimum value of daily temperature, respectively.

Therefore, in order to calculate the CTI, the monthly effective rainfall depth was computed by the average of the precipitation of two neighboring meteorological stations, located at S. Andre del Pizzone and Caiazzo, respectively. These data, related to a periodo of about 20 years (1977-1993), are the daily official data included in “Annali Idrologici ed alter pub. del compartimento di Napoli del S.I.M.N.”

So, the two indices, Topographic Index and Clima Topographic Index were computed for each micro-basin identified in the previous step .

5.2.5 Detection of copper contaminated areas and model validation

To identify the copper sedimentation areas, TI and CTI were interpolated with simple kriging interpolator using ArcGis' Geostatistical Analyst tool. The greater the values of interpolated TI and CTI, the higher copper concentration will be.

The simple Kriging is the basic form of kriging interpolation, able to predict the spatial distribution of a variable property. It was calculated using Eq. 5.7 , in which the value to be predicted, $z(x_0)$, is estimated from a linear combination of the observations really close to a point to be estimated:

$$Z_{sk}(x_0) = \sum_{i=1}^N \lambda_i * z(x_i) + [1 - \sum_{i=1}^N \lambda_i] * m \quad (\text{Eq. 5.7})$$

where λ_i are weights and m is a known constant mean of the area of interest.

This estimator is extremely appropriate for the treatment of environmental data because it has the following properties (Castrignanò et al., 2011):

- the estimated value has a great accuracy;
- the error term is calculated together with the estimation, and consequently the kriging values has a degree of confidence;
- It is an exact estimator.

The more complex form of kriging estimator is the Indicator kriging, which allows to verify if an attribute exceeds a fixed threshold value. Indeed, it attributes 0 if the values is under the threshold, otherwise it assigns 1. For this reason, it is considered the best estimator of environmental data (Castrignanò et al., 2000).

Therefore, in order to validate the model and identify the best strategy for detecting copper contaminated soil, the two interpolated maps were compared to the real distribution of copper on the soil surface. In addition, to analyze the relationship between copper concentration and the two indices, the Boolean operation between the layer of two indices and the one related to the copper concentration interpolated with Indicator kriging were performed. The threshold for the copper concentration was chosen according to the Italian legal limit (T.U. Ambientale 156/06). The Boolean And operation was performed using ArcGis' Spatial Analyst tool. It is based on the multiplication of the cells values among two input raster: if the two input values are true, the output is 1, otherwise the final product is 0. The Indicator kriging assigns a true value to the copper concentration when it is greater than 120 mg kg^{-1} ; while, for the indices layer, it attributes 1 only at maximum value of the two indices.

5.3 Results

5.3.1 Copper concentration in soil samples

All soil samples showed traces of copper, even if in different concentrations. Indeed, only seven hotspots (4.1% of total samples) had a greater concentration than legal limit (120 mg kg^{-1}), set according to the T.U. Ambientale 156/06, and twenty-eight hotspots (17.6% of total samples) had a borderline value, involving a value between 100 and 120 mg kg^{-1} (Figure 5.4). Copper concentrations were then interpolated using Indicator Kriging (Figure 5.5).

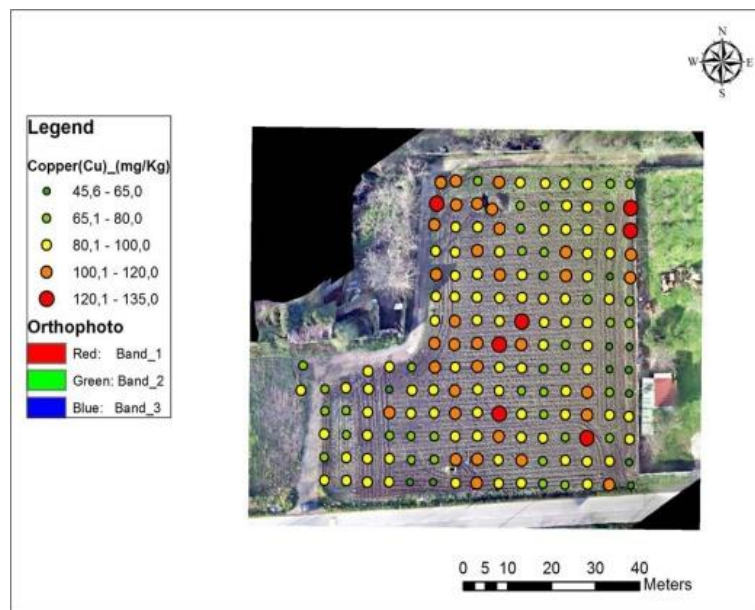


Figure 5.4 - Cu concentrations classified in category (mg/Kg) over the generated orthophoto

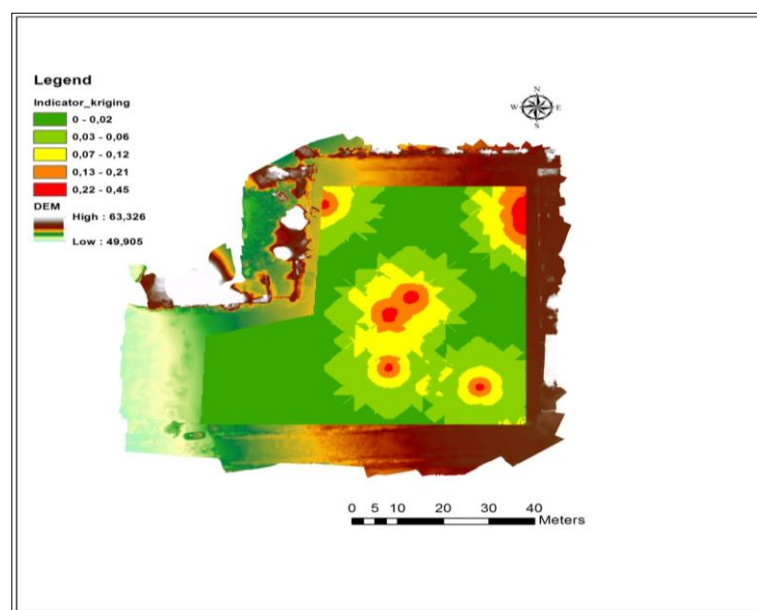


Figure 5.5 - Cu interpolated map using Indicator Kriging

5.3.2 Landform mapping

Eighty-four images were acquired during three flight missions. Each picture covered an area of about 0,00899 Km² with a resolution of 0.00766084 m/pix. Analysing the obtained images, about 2% of them were blurry and consequently, I didn't take into account them during the successive image analysis phase. After their processing, a detailed orthophoto (Figure 5.4) and a high resolution DEM (0.03 m) (Figure 5.6) were generated. Both Figure 5.4 and Figure 5.6 include the neighbouring areas that were subsequently eliminated. So, the generated DEM was interpolated using the Kriging estimator and converted to GRID format.

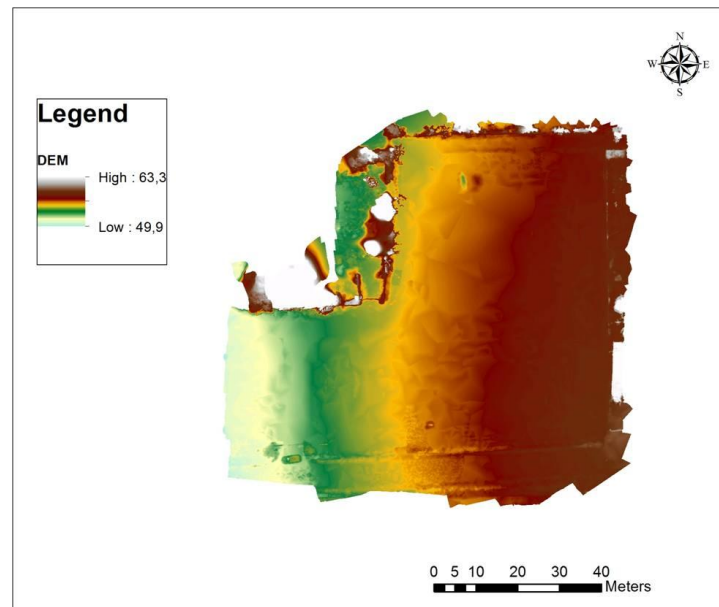


Figure 5.6 - Digital Elevaton Model (DEM)

5.3.3 Modelling of the transport process and wetland prediction indices

The flow direction, flow accumulation (relating to preferential paths of runoff water) and micro-basins raster was generated on the base of the micro-stream network created on the obtained high resolution DEM. After that, three micro basins were identified in the field, one on the upper part (the red watershed), one on the middle fraction (the blue basin) and one on the bottom part (the green area), as shown in Figure 5.7, which covered an area of 1007.30 m², 1050.12 m² and 1001.54 m², respectively.

Before to compute the indices for copper contaminated soil detection, the calculation of climatic condition were required So, the average monthly rainfall amount related to the period between 1977 and 1993 were evaluated. Its average value is equal to 78 mm, with a peak of 137.43 mm. Also the evapotranspiration related to the same time range was computed. Its highest values is

different during the summer months, in which a monthly peak of 157.12 mm was found in July, and the winter months, during which a minimum value of 27.23 mm was recorded in January. Average values of the effective monthly rainfall has a peak value of 77 mm in December and nulls in the warmer months from May to September. Therefore, the effective average annual rainfall is of 27 mm.

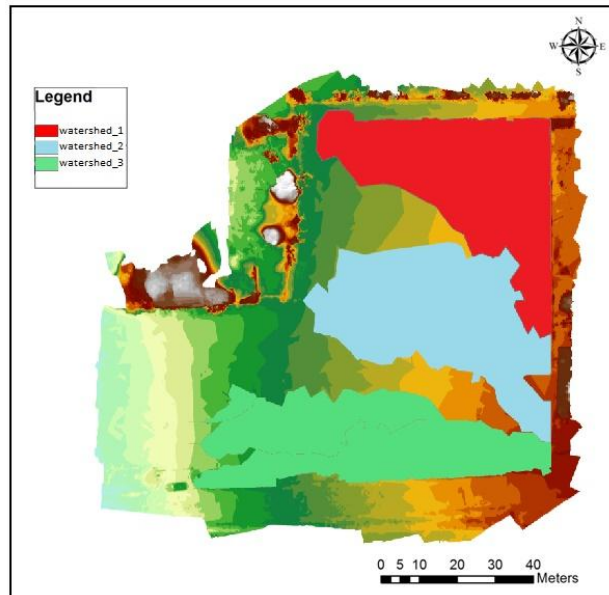


Figure 5.7 - Micro-basins

At this point, TI and CTI were evaluated in each micro-basin of interest. As illustrated in Figure 5.8, range of TI values has a different value in the three micro-basin; indeed It is between - 2.39 and 15.80, -0.99 and 15.84, and -1.88 and 15.79 in the upper, middle and bottom parts, respectively. Also, range of CTI values (Figure 5.9) were substantially different in the three micro-basins. Its values varied between 2.47 and 18.21, 3.50 and 18.25 and 2.46 and 18.20 in the upper, middle and bottom areas, respectively.

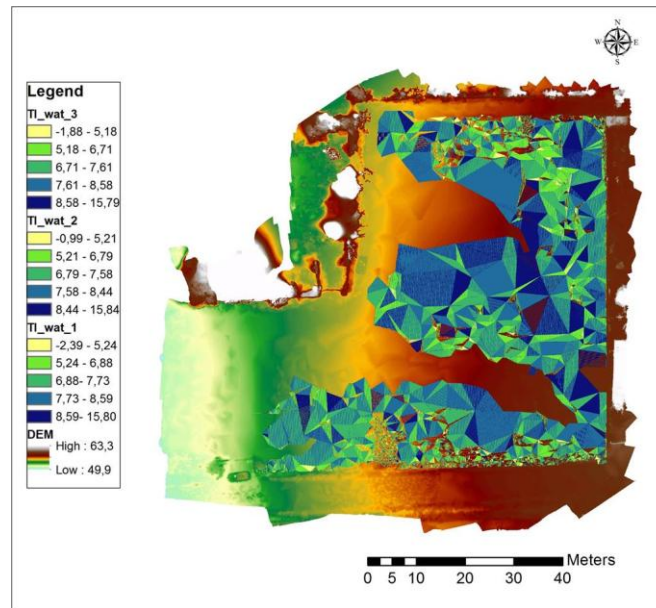


Figure 5.8 - Topographic Index map

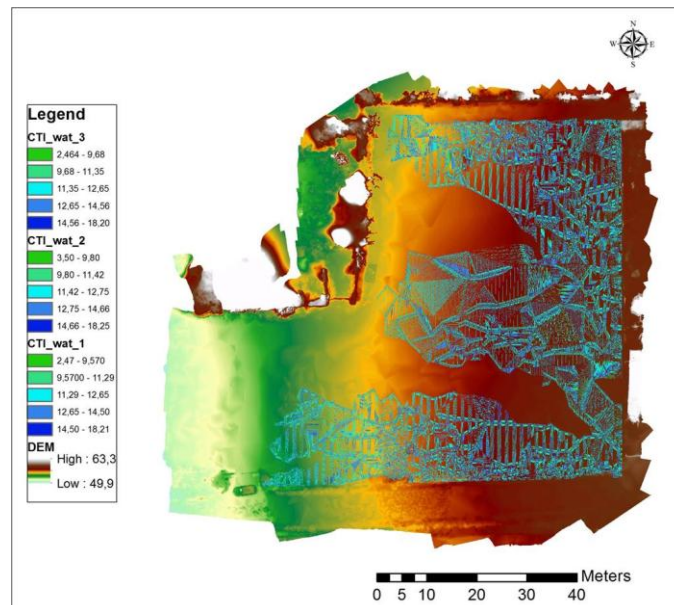


Figure 5.9- Clima Topographic Index map

5.3.4 Detection of copper contaminated areas and model validation

As explained in section 5.2.5, TI and CTI were subsequently interpolated using simple kriging estimator in order to identify areas corresponding to the greatest accumulation of copper, for each micro-basin. Later, these maps were compared with the actual mapping of the copper on the soil surface (Figure 5.10, Figure 5.11). Figure 5.10 shows that, according to Figure 5.8, ranges of values interpolated TI were different in the three sections of the map; indeed, It was between -1,63 and 11,36, 0,72 and 10,22, and -0,75 and 11,94 in the upper, middle and bottom areas, respectively.

The same speech is valid for CTI values (Figure 5.11). Its values were observed between 8,06 and 15,55, 6,47 and 17,50 and 7,75 and 15,98 in the upper, middle and bottom sections, respectively.

Subsequently, the relationship between the interpolated copper concentration and interpolated TI (or CTI) were carried out thanks to “Boolean And” operation (Figure 5.12 and Figure 5.13). Figure 5.121 shows five areas in which the maximum values of both raster coincide; while Figure 5.12 illustrates four point in which the maximum values of both raster coincide.

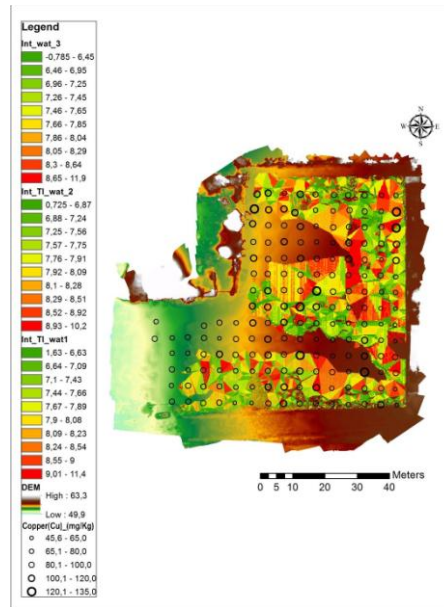


Figure 5.10 - Actual map of copper concentration on interpolated map of TI

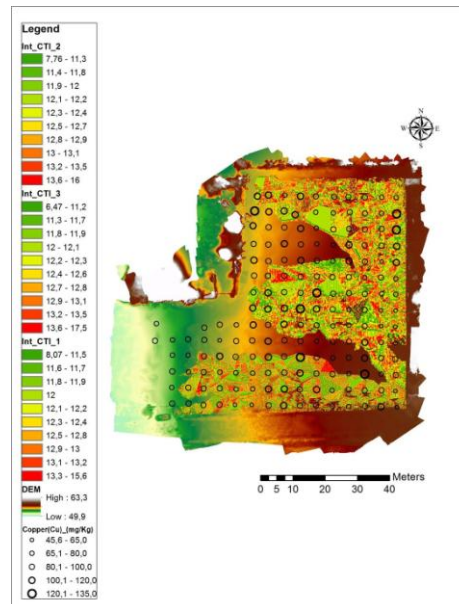


Figure 5.11 - Actual map of copper concentration on interpolated CTI map

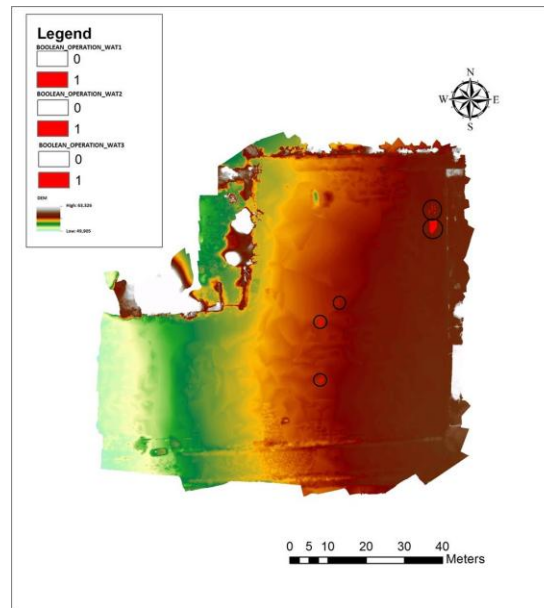


Figure 5.12 - Boolean And operation between interpolated copper concentration and interpolated TI

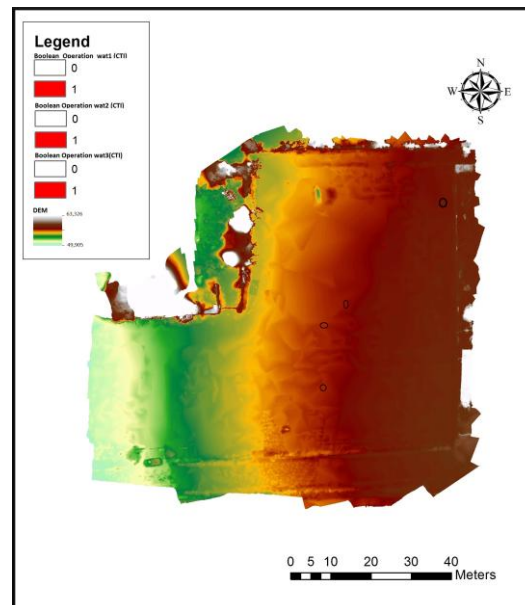


Figure 5.13 - Boolean And operation between interpolated copper concentration and interpolated CTI

5.4 Discussion

According to Nex et al. (2013) and Pierrot-Deseilligny et al. (2011), the introduction of drones and the fifth-generation of software for photogrammetry set up many advantages in the phase of landform mapping. Indeed, the drastically reduction of flight altitude has allowed to increase the resolution of the captured photos; while the sharply decrease of the time required for data acquisition and operating has allowed to speed up the entire procedure. In addition, the fifth-generation of software for photogrammetry has allowed the parallel processing of the 84 frames,

acquired during the three flight missions and able to cover the entire field under investigation. After their processing a DEM with a resolution of 0.03 (Figure 5.6) m and a very detailed orthophoto was obtained (Figure 5.4).

These two products were subsequently used to the successive processing procedure. So, the micro runoff network and three micro-basins (Figure) were identified on the obtained DEM and, in each of them, the TI and CTI were evaluated. These indices were strongly influenced by the various slopes of the basins and the diverse drainage areas, indeed the lower the value of the slope for a given area, the greater the value of TI (CTI). A higher values of TI corresponds to a higher saturation of the soil and consequently to sedimentation points. In contrast of the previous case, CTI is not just influenced by the topographical features, but also by the climatic events, but like TI water accumulates mainly in the flat areas with a consequent increase in the saturation degree. Moreover, the replacement of the local slope with downhill slope allowed considerate both the upslope component and the downslope factor. For these reasons, we agree with Gascuel-Odoux et al. (1998), who shows that CTI is a more robust index than TI. For these reasons, the values of the two indices differ among them. Therefore, Merot et al., 2003 showed that CTI potential decreases due to the highly heterogeneous permeability of soils. In addition, comparing the two indices, maximum TI values covers a larger areas than the CTI, while the minimum values almost coincide. Consequently, observing the two maps, it is clearly evident that CTI is more suitable to identify the areas to be sampled, while TI is more suitable to identify the areas to be sampled. The successive interpolation of TI and CTI allows to create a probably map, in which it is possible to identify zones in which it is more probable found a higher accumulation of copper (red zones) and those in which the concentration is lower (orange, yellow, green). Comparing the two maps, it is clear that the interpolated TI is more suitable to identify areas of accumulation, while the interpolated CTI is able to pinpoint the accumulation points.

The current study shows that all points with a value equal to or higher than the legal limit and the majority of those with a border line value are contained in the micro-basins identified. In addition, it can be observed that the red areas correspond to the areas in which the copper value is higher than the neighbouring ones. Consequently, in that areas is possible to find a concentration value equals or exceeds the normative value. This is confirmed by Figures 5.12 and 5.13. Indeed, the Boolean And Operation between interpolated copper concentration and interpolated TI identifies five areas, in which highest values of TI and copper concentration coincide. The Boolean And Operation between interpolated copper concentration and interpolated CTI, identifies four points, where the highest values of the two raster coincide.

These information could be used by sampling companies. It is convenient to concentrate the sampling only in the red zones of the micro-basins identified. If these samples shows a higher values than legal limit, it is necessary to continue with the sampling procedure, analysing the points including in the orange areas otherwise it could be topped. It is important to decide to stop or continue the sampling according to this information, proceeding to the areas corresponding to values of TI and CTI gradually lower.

5.5 Conclusions

In the current study, a novel approach for detecting copper contaminated soil, involving photogrammetric technique, hydrological models and geostatistics, was developed. It was tested to predict copper accumulation in an experimental field located in Trentola Ducenta, in Caserta province, even if it can be easily transferred to predict trace of elements that can be mobilised adhering to organic matter case. In particular, it allows to identify the areas or alternatively the points to be sampled according to the interpolated index employed. Indeed, like in the previous studies (Castrignanò et al., 2011), geostatistics is confirmed as the best method to spatialize hydrological models.

In conclusion, this approach seems to be robust, rapid and more economic compared to the traditionally techniques applied to characterize the soil. Consequently, it could play a key role in future development of environmental monitoring techniques, since it could be used also in studies for predicting other elements that can be mobilised adhering to organic matter case or, alternatively, for detecting parasites, living in wetlands.

Chapter 6

Case study 2: Estimating biochemical and physical grassland traits from UAV acquired hyperspectral images

6.1 Introduction

Grassland extension is approximately of 52.5 million km², covering roughly 40% of the total world land area (White et al., 2000). Grassland is strongly affected both by environmental conditions, such as topographic location, and by anthropogenic factors, such as (in)organic fertilizer application (Hopkins et al., 2006). So, it is required to organize an efficient management plans of grasslands in order to guarantee their good health status, trying to achieve optimal growth. This becomes even more important if investigated at the field scale, because the farmers need a protocol to apply in order to recognize the optimal time for fertilizing the soil and to identify the ideal time of harvest (Clevers et al., 2007). Currently, the traditional grassland management plans were largely prepared on the base of the qualitative information derived from farmers' experiences. However, the health status of grasslands and the feeding quality of the final harvest could be significantly improved integrating quantitative data and spatial information with the traditional management plans.

Up until now, traditional field-based methods have commonly employed, although they are time-consuming, destructive, and cannot be used to investigate large areas (Clevers et al., 2007; Adjorlolo, et al., 2015). Over the years, several methodologies have been introduced, and, currently, remote sensing is accepted as the best suitable method for characterizing the land surface in a fast and relatively cheap way. Indeed, this approach has been widely employed in study related to the estimation of biophysical and biochemical grassland variables, such as the Leaf Area Index (LAI) or chlorophyll (Clevers & Kooistra, 2012, Cohen et al., 2003, Curran et al., 2001). Further improvements have been added by the introduction of hyperspectral sensors (Clevers et al., 2007; Adjorlolo, et al., 2015; Clevers & Kooistra, 2012). Indeed, they results more sensitive to vegetation variables thanks to presence of narrow contiguous wavebands, which allow to provide a continuous reflectance spectrum of the object under investigation (Adjorlolo et al., 2015; Wang et al., 2012; Darvishzadeh, et al., 2011; Lee et al., 2004; Schlerf et al., 2005; Schaepman et al., 2009). The hundreds spectral bands of this spectrum are strongly correlated and, therefore, it has been required

to select a subset of data in order to reduce the dimensionality of the dataset and eliminate redundant information. Consequently, the selection of the subsets have to be performed considering the sensitivity of the vegetation variables to the spectral bands (Dalponte et al., 2009).

Adapting the spatial resolution to the size of the object investigated is really important because, in this way, the picture is able to capture the spatial detail needed to describe patterns in the field. So, to analyze grasslands traits is required to have the smallest possible resolution. For this reason, the fine spatial scale of grassland biophysical traits, the more suitable tool for acquiring aerial photos is UAV, since it can fly at a very low altitude, consequently incrementing pictures resolution, adapting it on the base of object under investigation (Capolupo et al., 2015; Capolupo et al., 2014; Nex & Remondino, 2014). In addition, UAV can achieve areas with difficult access and plan the flight according to weather condition, eliminating problems due to clouds, and to research purposes. Therefore, it seems to be very utile to mount the hyperspectral cameras on UAVs, as has been explained in just few papers (Zhang & Kovacs, 2012), because, the combination of hyperspectral imaging and of UAVs is still rather limited.

Univariate and multivariate regression models are the two statistical approaches commonly used to investigate the relationship between spectral measurements and vegetation traits. Univariate approach consist in a regression model between a specific subset of combined spectral bands and a vegetation variable. On the contrary, the multivariate method applies a regression model between all observed spectra variables and a vegetation variable (Roelofsen et al., 2014).

The calculation of vegetation indices can be performed on both narrow or broad spectral bands, although, some studies have shown that statistical relationships between biochemical and biophysical traits and narrow-band indices is better (Thenkabail et al., 2002; Schlerf et al., 2005). However, this approach doesn't allow to take into account all the hyperspectral data potential and therefore, several papers have been focused on Stepwise Multiple Linear Regression (SMLR), which allows to fully exploit all of the hyperspectral information available (Curran, 1989; Curran et al., 2001; Huang et al., 2004; Grossman et al., 1996). However, the application of SMLR is limited due to multi-collinearity problems (Kawamura et al., 2013). Partial least squares regression (PLSR) doesn't suffer of this problem, and consequently, it has been recognized as a good alternative technique to SMLR (Cho et al., 2007; Darvishzadeh et al., 2008)

The goal of the current study is to predict vegetation traits in grasslands from hyperspectral images acquired using UAV. In particular, the objects can be summarized in following points:

- Compare vegetation indices and the PLSR approaches so that identify the best strategy for estimating bio-physical and bio-chemical plant traits of grasslands;

- Analyze the influence of the amount and the type of fertilization on grassland traits;
- Investigate the influence of the phenology of grasslands and the timing of spectral data collection on the established regression relations.

6.2 Materials and method

6.2.1 Area of interest

The area of interest is located in the experimental farm Haus Riswick near Kleve in Germany (51°47'12.5"N, 6°10'08.7"E). The grassland field is characterized by 60 grassland plots, each of which covers an area of 12 m² with a length of 8 m and a width of 1.5 (Figure 6.1). Firstly, the plots were fertilized with different levels of organic and inorganic compost and, subsequently, they were split in four groups (Figure 6.2). In particular, some of them were organized with six different levels (0, 85, 115, 170, 230, and 340 kgN/ha) of inorganic fertilization (calcium ammonium nitrate) and the others with three different levels (170, 230, and 340 kgN/ha) of an organic fertilization. The choice of the type and different levels of fertilizers were planned according to the customs of German farmers. In Germany, the value of organic fertilizer normally applied is 170 kg·N·ha⁻¹, even if, under special conditions (no grazing), a maximum value of 230 kg·N·ha⁻¹ can be used. The choice of 340 kg·N·ha⁻¹ was made on the basis of the maximal amount of inorganic nitrogen that can normally be taken up by grassland during a year. Another aspect taken into account was the effect of slurry on a grassland experiment and, therefore, different amounts of slurry were employed for one (2012), two (2012 and 2013), and three (2012, 2013, and 2014) years.



Figure 6.1 - Area of interest

	Rand		Rand		Rand	2014	
repl. 4	4.13		4.02		4.15	Plot number	Treatment 2014
	4.03		4.04		4.07		Total kg N
	4.08		4.06		4.11	1	-
	4.10		4.09		4.05	2	inorganic
	4.14		4.12		4.01	3	inorganic
repl. 3	3.02		3.10		3.15	4	inorganic
	2.06		3.07		3.14	5	inorganic
	3.09		3.01		3.13	6	inorganic
	3.04		3.05		3.12	7	organic
	3.03		3.08		3.11	8	organic
repl. 2	2.11		2.02		2.10	9	organic
	2.13		2.04		2.09	7	inorganic
	2.01		2.03		2.08	8	inorganic
	2.15		2.14		2.07	9	inorganic
	2.05		2.12		2.06	7	inorganic
repl. 1	1.07		1.06		1.05	8	inorganic
	1.08		1.13		1.04	9	inorganic
	1.14		1.09		1.03	7	inorganic
	1.12		1.15		1.02	8	inorganic
	1.10		1.11		1.01	9	inorganic
	Rand		Rand		Rand		

Figure 6.2 - Distribution of the type and amount fertilizer

6.2.2 Hyperspectral and field data collection

An octocopter UAV (Aerialtronics Altura AT8 v1A), equipped with all necessary tool for its planning and control (Figure 3.2), was used to fly over the study area on 15 May 2014 and 14 October 2014. Moreover, the Wageningen UR Hyperspectral Mapping System (HYMSY) was mounted on it (Suomalainen et al., 2015). More information about platform configuration and equipment characteristics are described in section 3.5.

In order to compare the results of the two flight campaigns, they were carried out under the same climatic (clear sky and no wind) and flight conditions, like pattern, altitude, and speed. In particular, in order to obtain a GSD of 200 mm for the hyperspectral data and 20 mm for the aerial photos, the altitude was set at 70 m and the speed at 5 m/s. Moreover, the flight path was adapted on the experimental field features and, consequently, it was organized in three flight lines over the three rows of experimental plots.

During the two flight campaigns, thanks to UAV equipments, a hyperspectral dataset and an aerial images block were acquired, subsequently, radiometrically calibrated, converted to surface reflectance, geometrically corrected, georeferenced. In particular, radiance conversion into reflectance factor included several steps: calibration of scan lines, taking into account the illumination conditions using a 25% Spectralon reference panel acquired before and after the flight. Subsequently, the information were linearly interpolate in order to correct the irradiance changes, caused by the atmospheric conditions. After that, an RGB ortho-mosaic, Digital Surface Model (DSM) was generated using version 1.0.0 PhotoScan Pro software. In order to improve the alignment step, the coordinates of the ground control points (GCPs) were introduced. Moreover, the regions of interest (ROI) were designed according to the plot dimensions and, for each of them, a complete reflectance spectra were extracted and then averaged, integrated, and used in the successive computing steps. The average operation is necessary in order to minimize the noise in the reflectance spectra. Following, the datasets acquired were integrated and organized in three different datasets: the first includes all data related to the plots organized with different levels of inorganic fertilizer both May and October campaigns; the second involves the data related to both May and October campaigns; the third includes all data of May campaign. These classes allow to investigate the influence of the type and amount of fertilizer and the effect of grassland phenology.

After the flights, the grassland height (H), vegetation fresh biomass (FB), dry weight and dry matter (DM), Crude ash (CA), Crude protein (CP), Crude fibre (CF), Sodium (Na), Potassium (K), Metabolic energy (ME) was determined. First of all, the H was evaluated using a grass height meter (Eijkelkamp, The Netherlands). Subsequently, the grassland was completely harvested using the

Haldrup C-65 plot combine (Haldrup, Denmark) in order to obtain grassland traits values. After the determination of vegetation fresh biomass, grassland were dried for 24 h at 105 °C and the dry weight and dry matter (DM) were computed. Subsequently, the chemical analysis were carried out by Landwirtschaftliche Untersuchungs- und Forschungsanstalt Nordrhein-Westfalen (LUFA NRW) using the following methods of the Verband der Landwirtschaftlichen Untersuchungs- und Forschungsanstalten (VDLUFA) (Blasser, 2006). Following are presented the method used to determinate grassland traits:

- Crude ash (CA): VDLUFA method book III, method No. 8.1.1
- Crude protein (CP): VDLUFA method book III, No.4.1.1
- Crude fibre (CF): VDLUFA method book III, No. 6.1.1
- Sodium (Na): VDLUFA method book III/6, No. 10.8.3
- Potassium (K): VDLUFA method book III/6, No. 10.8.3
- Metabolic energy (ME): ME was calculated from CA, CP, and CF as follows (GFE,

1998):

for harvest dates before 1 July:

$$ME(MJ / kg) = 14.06 - 0.0137 * CF + 0.00483 * CP - 0.0098 * CA \quad (\text{Eq. 6.1})$$

for harvest dates after 30 June:

$$ME(MJ / kg) = 12.47 - 0.00686 * CF + 0.00388 * CP - 0.01335 * CA \quad (\text{Eq. 6.2})$$

6.2.3. The Narrow-Band Vegetation Indices

The use of vegetation indices allows to estimate vegetation traits, radically decreasing the dimensionality of the hyperspectral data set. For the current study, the narrow-band vegetation indices computation was preferred than the broad vegetation indices calculation, in consideration that they are more sensitivity to the vegetation traits (Schlerf, et al., 2005, Thenkabail et al., 2002). These indices were computed from the average reflectance spectra of each plot. Even if also other vegetation indices in previous studies (Clevers & Kooistra, 2002; Wang et al., 2015; Darvishzadeh, et al., 2011; Lee et al., 2004; Darvishzadeh et al., 2008) were presented, in this research, only the indices that provided the best results are exposed. The selected indices are: MERIS Terrestrial Chlorophyll Index (MTCI) (Dash & Curran, 2004), ratio of the Modified Chlorophyll Absorption in Reflectance and Optimized Soil-Adjusted Vegetation Index (MCARI/OSAVI) modified by Wu (Wu et al., 2008), Red-edge Chlorophyll Index (CI_{red-edge}) (Gitelson et al., 2003; Gitelson et al.,

2006) and the Normalized Difference Red Edge (NDRE) (Barnes et al., 2000). Their equations and wavelengths are presented in Table 6.1.

Table 6.1 - Selected vegetation indices

Index	Formulation
MTCI	$\frac{R_{754} - R_{709}}{R_{709} - R_{681}}$
MCARI/OSAVI (Wu)	$\frac{[(R_{750} - R_{705}) - 0.2(R_{750} - R_{550})](R_{750} / (1 + 0.16)(R_{750} - R_{705}) / (R_{750} + R_{705} + 1))}{(1 + 0.16)(R_{750} - R_{705}) / (R_{750} + R_{705} + 1)}$
CI _{red edge}	$\frac{R_{780}}{R_{710}} - 1$
NDRE	$\frac{R_{790} - R_{720}}{R_{790} + R_{720}}$

The relationship between grassland traits and vegetation indices was tested using linear regression. The quality assessment of the relationship was carried out by calculating the coefficient of determination (R^2) and the root mean square error (RMSE). On the base of R^2 results and according to classification suggested by (Mutanga et al., 2005), three classes are identified:

- strong correlation: $R^2 > 0.7$;
- moderate correlation: $0.5 < R^2 < 0.7$; and
- weak correlation: $R^2 < 0.5$.

6.2.4. Partial Least Squares Regression (PLSR)

Partial least squares regression (PLSR) is a statistical multivariate regression technique able to predict the dependent variables (Y), corresponding to grassland traits relationship, on the base of the independent variables (X), represented by the hyperspectral data, a restricted number of new orthogonal factors (T) and a set of specific loadings (P). In this way, the high dimensionality of the input dataset is drastically reduced (Roelofsen et al., 2014; Thenkabail et al., 2002; Huang et al., 2004; Cho et al., 2007; Geladi & Kowalski, 1986; Abdi, 2010). So, X is computed by Eq. 6.3:

$$X = T * P^T \quad (\text{Eq. 6.3})$$

T is the “score matrix” and it is constituted by the latent variables (LVs) in order to maximize the covariance between X and, while P is the not orthogonal “loading matrix”. For these reason, T has to respect the following property (Eq. 6.4):

$$T * T^T = I \quad (\text{Eq. 6.4})$$

I is the identify matrix.

Y is evaluated by equation 6.5:

$$\bar{Y} = T * B * C^T \quad (\text{Eq. 6.5})$$

B is a diagonal matrix, which is composed by weights on the diagonal positions, and C is the “weight matrix” of the dependent variables. The goodness of fit of the PLSR model is significantly affected by the number of selected LVs. Generally, its value increases until a certain number of LVs and then it declines again. Consequently, it is essential to select the optimal number of LVs for each model in order to obtain the best quality (Abdi, 2010; Reddersen et al., 2013; Williams & Norris, 2001). The optimal number of LVs for each PLSR model was evaluated on the base of root mean square error (RMSE) for the leave-one-out cross-validation (LOOCV). The RMSE of the LOO (RMSE_{LOO}) was calculated by equation 6.6:

$$RMSE_{LOO} = \sqrt{\frac{\sum (\bar{y}_i - y_i)^2}{n}} \quad (\text{Eq. 6.6})$$

where $\bar{y}_i$ and y_i correspond to the leave-one-out predictions and observed values of the traits object of detection, respectively. The values of these observations were predicted using this model.

Even if recent studies have shown that the best results are obtained by splitting the original dataset into a training dataset and an independent test set (Serbin et al., 2014), unfortunately, in this work, it was preferred to apply LOOCV, because of the shortage of the experimental dataset. The quality assessment of the model was carried out using R^2 between measured and predicted values from the LOO cross validation and RMSE_{LOO}, while the goodness of fitness of the model were carried out applying residual predictive deviation (RPD), computed as the ratio between the standard deviation of the reference dataset and the RMSE. It doesn't exist a particular way for setting a threshold for the RPD. Therefore, it was classified according the categorization commonly adopted in literature:

- RPD < 3, low predictive power;
- RPD > 3 is suitable for screening;

- RPD > 5 is suitable for detecting the accurate analysis (laboratory analysis)

All regression analysis was done using the pls package of R software.

6.3 Results

6.3.1 Grassland traits

First of all, the correlation between the grassland variables was analyzed in order to investigate traits of May and October campaigns. Since the results of both dataset are similar, in this study, only the values for May campaign are shown in Table 6.2. Analyzing the Table, it is clear that the results show that the structural variables (height, fresh and dry biomass) are significantly correlated to each other, since Pearson correlation is higher than 0.89. A separate discussion is reserved to the biochemical features, which have a substantially lower correlation. For instance, Na is characterized by a low correlation with metabolic energy and crude fibre, a reasonable correlation with K and crude ash, and a high correlation with crude protein. Moreover, also the Pearson correlation between structural and biochemical features is reasonable, except for Na and crude protein. In addition, all grassland traits are characterized by a positive correlation. A separate discussion is necessary for metabolic energy, since it has an inverse correlation with the other traits.

On the contrary, Table 6.3 shows the harvest statistics of the structural and biochemical variables related to the May harvest. Although each of the grassland biochemical characteristics show a very low variability, with the exception of Na, the lowest coefficient of variation (CV) is proper of metabolic energy.

On the contrary, the harvest statistics of October harvest is shown in Table 6.4. Like in the previous case, the variability of the biochemical grassland traits is rather small, with the exception of Na, and the metabolic energy has the lowest variability. About the structural traits, the lowest variation is shown by the height. Although some similarities between the two datasets related to the two harvest moments can be traced, the range of the grassland traits is rather different: the range of values of all three structural traits for October is considerably lower compared to May, while the biochemical traits ones are comparable, with the exception Na. This can be seen also by Figure 6.3, in which is illustrated the effect of the different fertilizer treatments on grassland traits. Its influence depends on the applied treatments, the traits under investigation and grassland phonological status. In particular, the dataset of May shows the higher the inorganic fertilization level, until a threshold of 230 kgN/ha, the higher the structural trait values will be; on the contrary, inorganic fertilization level higher than 230 kgN/ha decreases the structural feature values. Among biochemical variables,

only crude fibre shows the same trend of structural traits. All of the other biochemical variables show higher values according with the increment of the inorganic fertilization level. Completely opposite is the pattern of the metabolic energy: its value decreased with the increasing inorganic fertilization until 230 kgN/ha, after which its value increased. Instead, it can be identified less differences between the pattern of structural and biochemical traits, with the exception of metabolic energy, which shows a dip at 230 kgN/ha. A separate discussion is reserved to the pattern of variation of the structural and biochemical traits regarding the October observations. The pattern of all of the structural traits is substantially the same: both under the influence of inorganic fertilization treatments and under the organic manure fertilization, they show an increasing pattern, with the exception of a dip at 230 KgN/ha, under the effect of inorganic fertilization application. In contrast, it is not possible to recognize a common trend for the biochemical characteristics. Indeed, under the inorganic fertilizer application, crude ash and crude protein show a common pattern of variation, characterized by a decrement until a threshold of 115 kgN/ha, and then an increment. However, under influence of the organic manure, crude ash and crude protein shows a completely different pattern of variation: crude protein peaks at 230 kgN/ha while crude ash decreases. The variation of metabolic energy and potassium is more or less constant over all treatments, while sodium pattern is independent of the amount of fertilizer treatment.

Table 6.5 shows the significance levels from applying a Student's t-test between organic and inorganic fertilized plots in May, in October, and between May and October observations. Analyzing the table, it is evident that both grassland structural and biochemical traits are strongly affected by the plant phenology but not by the type of fertilizer. In addition, the Student's t-test based on organic and inorganic fertilizer in May and October is also influenced by the plant-phenology.

Table 6.2 - Pearson coefficient of structural and biochemical traits

Traits	Height	Fresh Biomass	Dry Matter Yield	Crude Ash	Crude Protein	Crude Fibre	Na	K	Metabolic Energy
Height	1	0.92	0.89	0.59	0.32	0.76	0.19	0.68	-0.72
Fresh Matter yield	0.92	1	0.94	0.59	0.34	0.79	0.22	0.66	-0.75
Dry Matter	0.89	0.94	1	0.413	0.15	0.76	0.03	0.52	-0.74
Crude Ash	0.59	0.59	0.41	1	0.81	0.45	0.70	0.89	-0.36

Crude Protein	0.32	0.34	0.15	0.81	1	0.10	0.89	0.74	0.046
Crue Fibre	0.76	0.79	0.76	0.45	0.10	1	-0.017	0.059	-0.98
Na	0.19	0.22	0.03	0.70	0.89	-0.017	1	0.57	0.14
K	0.68	0.66	0.52	0.89	0.74	0.059	0.57	1	-0.50
Metabolic Energy	-0.72	-0.75	-0.74	-0.36	0.04	-0.98	0.14	-0.50	1

Table 6.3 - Summery statistics of the grassland traits for the May harvest

Statistics	Height (cm)	Fresh Biomass (kg/Plot)	Dry Matter Yield (dt/ha)	Crude Ash (g/kg)	Crude Protein (g/kg)	Crude Fibre (g/kg)	Na (g/kg)	K (g/kg)	Metabolic Energy (MJ)
Min	23.9	11.4	24.1	79	88	200	0.2	21.9	10.2
Max	40.9	28.1	50.7	101	164.3	247.5	1.5	28.1	10.9
Mean	33.9	20.9	37.8	89.1	112.4	232.3	0.5	25.5	10.5
SD	4.8	5	7.4	6.5	22.6	14.9	0.4	1.7	0.2
CV	0.1	0.2	0.2	0.07	0.2	0.06	0.6	0.06	0.02

Table 6.4 - Summery statistics of the grassland traits for the October harvest

Statistics	Height (cm)	Fresh Biomass (kg/plot)	Dry Matter Yield (dt/ha)	Crude Ash (g/kg)	Crude Protein (g/kg)	Crude Fibre (g/kg)	Na (g/kg)	K (g/kg)	Metabolic Energy (MJ)
Min	15	6.2	11.3	88	131	270	0.1	22.6	9.7
Max	19.7	15.2	27.1	100	183	298	0.9	26.1	9.9
Mean	18.1	10.6	18.6	93.6	150.4	279.3	0.5	24.6	9.8
DS	1.4	2.6	4.5	3.5	15	8.6	0.3	1.2	0.06
CV	0.08	0.2	0.2	0.03	0.1	0.03	0.6	0.05	0.006

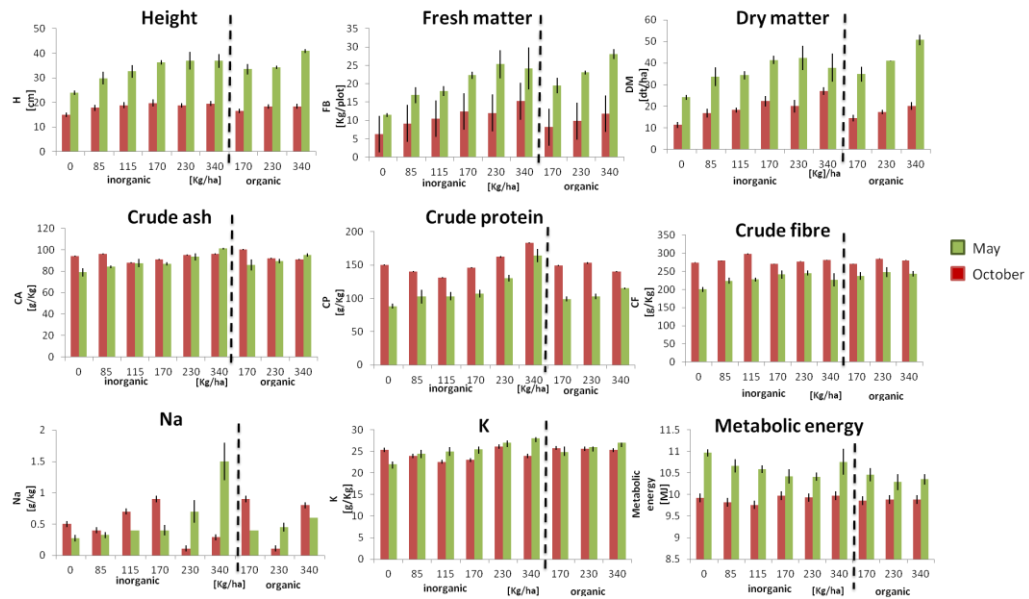


Figure 6.3 - Influence of the type and the amount of fertilizer treatment on grassland traits and their standard deviations

Table 6.5 Significance level obtained by applying the t-test between organic and inorganic treatments in May, October, and between May and October data

Traits	Significance Level between Organic And Inorganic Fertilized (May)	Significance Level between Organic And Inorganic Fertilized (October)	Significance all Treatment Levels between May and October Data
Height	0.35	0.67	<0.001
Dry Matter	0.25	0.57	<0.001
Fresh matter yield	0.31	0.62	<0.001
Crude Ash	0.77	0.72	0.082
Crude Protein	0.56	0.69	<0.001
Crude Fibre	0.17	0.82	<0.001
Na	0.69	0.62	0.82
K	0.65	0.13	0.23
Metabolic Energy	0.08	0.69	<0.001

6.3.2 Hyperspectral data

The spectral variation of the images acquired during the two flight campaigns is rather small in all the spectra and, only in the NIR part, is more noticeable (Figure 6.4). Indeed, although the red edge slopes are relatively similar, the maximum value of May profile is higher than the maximum value of the October outline. In addition, all of the NIR part has the same trend expect for 950 nm, where the pattern is reversed. Regarding the NIR part, also another difference can be noticed: the spectra originated by May images is flat, while its trend increases with an increase in the wavelength for October observations. Moreover, the profiles of minimums of the average reflectance spectra are analogous; even if, in the NIR region, the values of October are slightly bigger than the May ones. Also the spectral profile of the average of the three different organic levels for May and October campaigns shows the same pattern. Moreover, the organic manure level affects the overall spectra, increasing the maximum value between 170 and 230 kgN/ha for the May dataset, and between 230 and 340 kgN/ha for October observations.

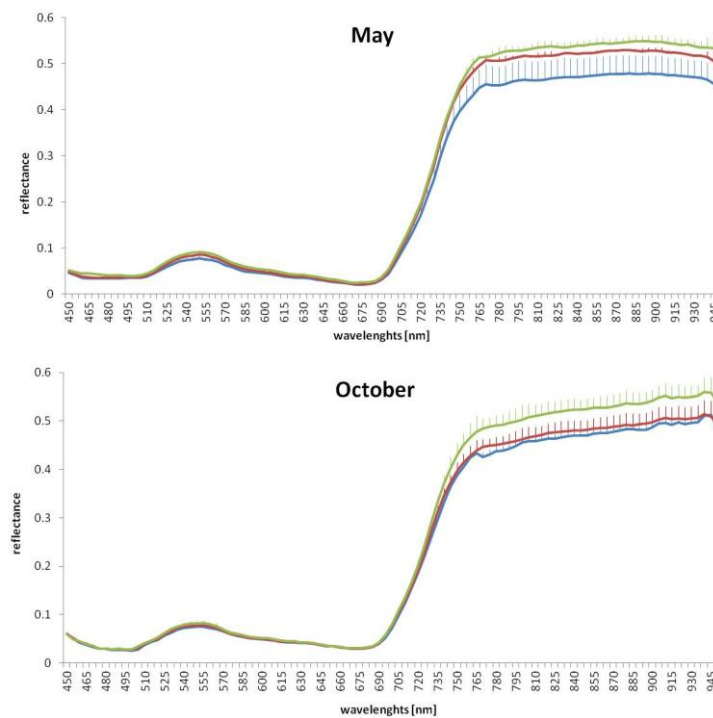


Figure 6.4 Average and standard deviation of the spectra for the three different levels of organic fertilization (170, 230, and 340 kgN/ha) for May and October harvest.

The correlogram between the average reflectance spectra and selected grassland features for May dataset is shown in Figure 6.5. Comparing the pattern of the two selected structural traits (height and fresh biomass), it is evident that overall profiles are extremely comparable. The most

important area to analyzed is the NIR part (700–950 nm), since it is particularly sensitive to LAI, grassland structure, and canopy thickness of the vegetation. For this reason, the correlation with these two structural traits is pretty high. For this, NIR region is also essential to investigate and evaluate the metabolic energy, because of its inverse proportionality to the quantity of green vegetation. Indeed, the correlation between this area and metabolic energy is high but negative. On the contrary, the most significant region of the spectra for estimating crude protein is the VIS area (400–700 nm), since it is more sensitive to the absorption of chlorophyll at the leaf level. Moreover, it is necessary to underline that the correlation between grassland traits and wavelengths is appreciably affected by the grassland phenology. The same conclusions can be carried out for the correlogram of October harvest, which is different only for the lower correlation values (<0.6) for all grassland characteristics.

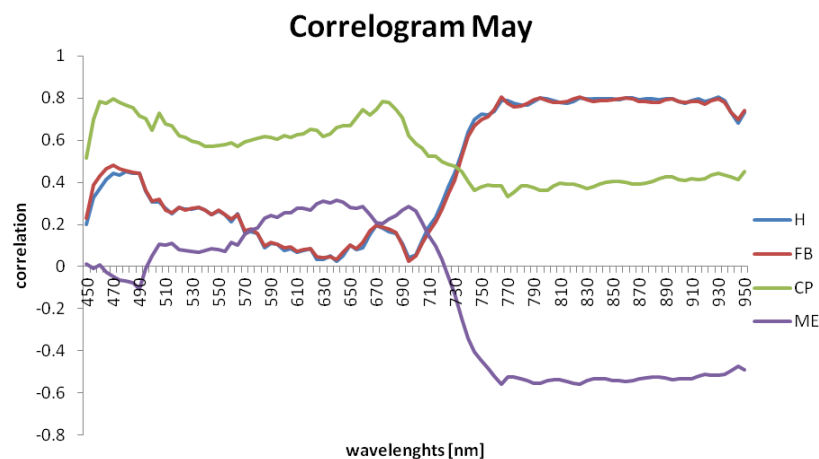


Figure 6.5 - Correlogram between spectral variables of the hyperspectral dataset and grassland traits for the May harvest.

6.3.3 Narrow-Band Vegetation Indices

After extracting and calculating the average reflectance spectra for all the plots, the narrow-band vegetation indices, presented in Table 6.1, were computed. Firstly, the influence of the type and amount of fertilizer was estimated (Figure 6.6). Like the results obtained from the analysis of grassland traits and hyperspectral data, also in this case, the variation of the vegetation indices, under the influence of inorganic fertilization, is more influenced by the growth status of grassland than the different levels of fertilizer. Indeed, the vegetation indices trend is relatively the same within the same dataset while it is different between the May and October surveys. In contrast,

under the effect of organic manure, the variation of the vegetation indices, computed as a function of organic manure, is constant for all indices and for both datasets:

The results of the linear relation between narrow-band vegetation indices and the grassland variables for the integrated dataset of May and October and the sub-dataset of May only is shown in Table 6.6. R^2 and RMSE values obtained from the linear regression models are rather different between the grassland traits. For instance, the R^2 between height and MCARI/OSAVI is equal to 0.599, while between crude fibre and NDRE it is equal to 0.49. Generally, analyzing Table 6.6, it is clear that R^2 values for the biochemical grassland traits are extremely lower and that it is impossible to define the best vegetation indices since their values depend on the traits and dataset under investigation. For example, for the May dataset, NDRE and MCARI/OSAVI show the highest correlation for the structural traits; while, for the integrated dataset of May and October, the highest correlation is shown by MCARI/OSAVI and $CI_{red-edge}$. Moreover, the relations are affected by the growth status of the grassland and not by the type of fertilization applied.

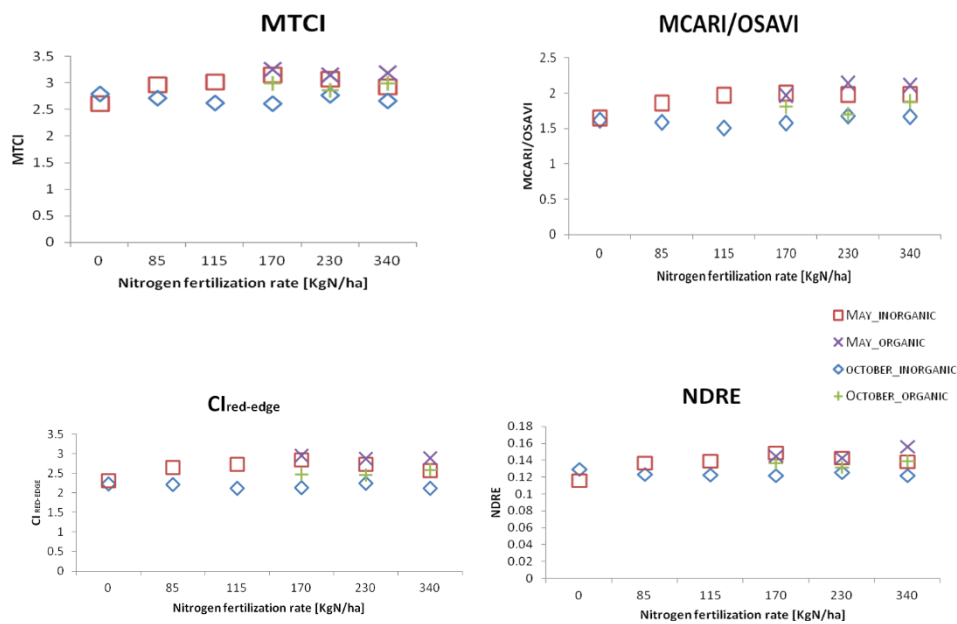


Figure 6.6 - Scatterplot related to the influence of the type and the amount of fertilizer on selected narrow-band vegetation indices

Table 6.6- Results of linear regression models between the selected narrow-band vegetation indices and grassland traits for the integrated sub-datasets of May and October and the sub-dataset of May.

	Plots May								Plots May and October							
	Inorganic–Organic								Inorganic–Organic							
	MTCI		MCARI/O SAVI		CI _{RED-EDGE}		NDRE		MTCI		MCARI/O SAVI		CI _{RED-EDGE}		NDRE	
	R ²	RM SE	R ²	RMS E	R ²	RM SE	R ²	RM SE	R ²	RM SE	R ²	RM SE	R ²	RM SE	R ²	RM SE
Height	0.45	2.62	0.56	3.32	0.39	3.90	0.58	3.25	0.4	6.52	0.599	5.38	0.598	5.40	0.4	6.40
Dry Matter	0.47	2.94	0.51	3.86	0.43	4.35	0.57	3.85	0.36	5.19	0.57	4.29	0.53	4.66	0.38	5.06
Fresh matter yield	0.36	3.82	0.45	5.19	0.30	5.57	0.46	4.85	0.35	8.86	0.55	7.31	0.47	7.62	0.38	8.70
Crude Ash	0.07	4.54	0.25	5.76	0.036	6.53	0.14	6.15	0.006	5.90	E-05	5.90	0.040	5.78	0.0013	5.90
Crude Protein	0.04	15.32	0.05	21.17	0.0019	1.96	0.04	21.27	0.13	24.75	0.14	24.62	0.30	22.22	0.084	25.36
Crude Fibre	0.51	8.29	0.41	12.84	0.46	12.32	0.49	11.95	0.09	26.47	0.20	24.67	0.24	24.04	0.059	26.82
Na	0.001	0.25	0.05	0.35	0.0024	0.36	0.13	0.36	0.001	0.33	0.015	0.32	0.0002	0.33	0.017	0.32
K	0.18	1.18	0.31	1.53	0.12	1.73	0.28	1.56	0.27	1.39	0.32	1.35	0.20	1.46	0.31	1.36
Metabolic Energy	0.51	0.12	0.42	1.18	0.50	0.17	0.46	0.18	0.07	0.37	0.19	0.35	0.22	0.34	0.05	0.38

Nevertheless, classification proposed by Zhao et al. (2007) suggests that relation between the grassland traits and the vegetation indices in both subsets is modest, although the structural

traits show promising results. Thus, in Figure 6.7 the best estimator for the selected grassland traits is shown. Figure 6.8 and 6.9 show the variation of height and metabolic energy, chosen as example, based on the linear regression with the best narrow vegetation index on the dataset of May. The different of shades of green correspond to areas with the lowest values, while the red ones to the red with higher values. Height of grassland is uniform over all plots (>34 cm), even if values smaller than 30 cm are visible for the non-fertilized plots. Low height values can be found also in highly fertilized plots, probably, because the biomass gets too heavy for the stems to support it. A bigger spatial variation is observed for metabolic energy.

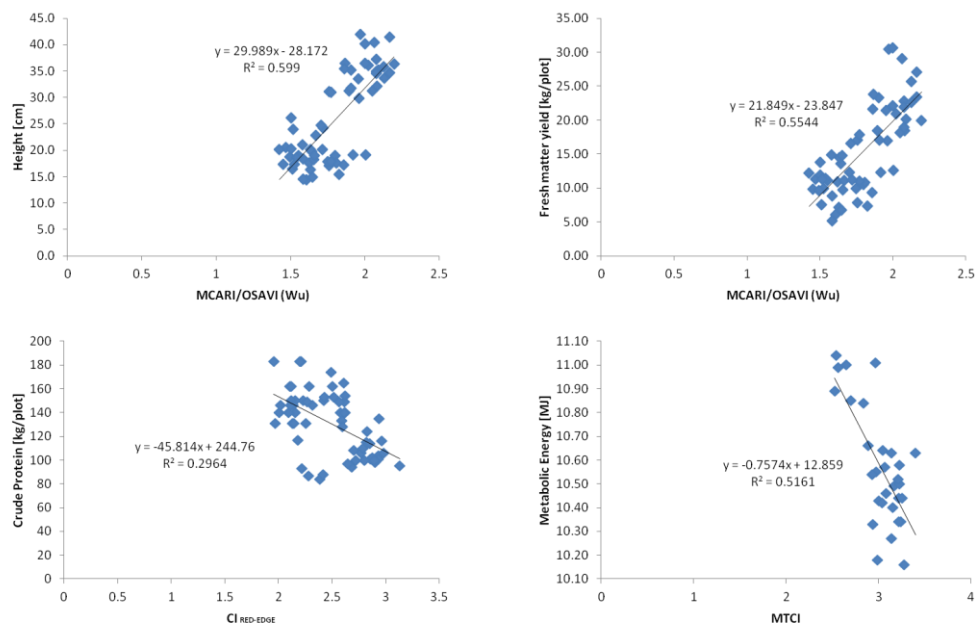


Figure 6.7 - Scatterplot of the best relationships between selected grassland traits and vegetation indices for the integrated dataset of May and October, except the metabolic energy, for which the best result was found instead in the integrated May dataset.

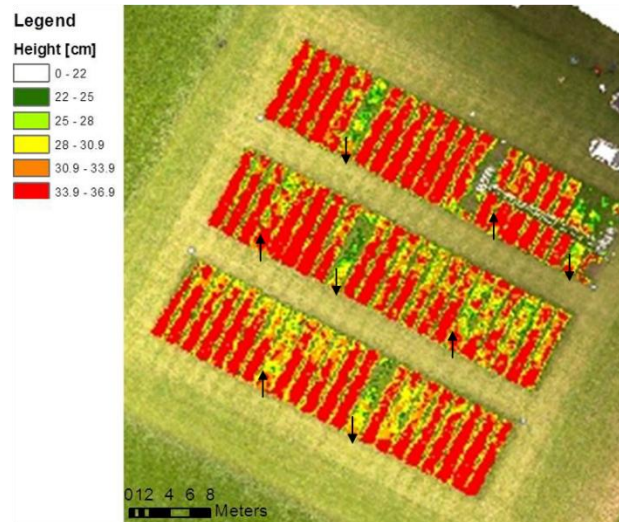


Figure 6.8 - Height variation within plots by applying the NDRE index on the acquired hyperspectral dataset of May.

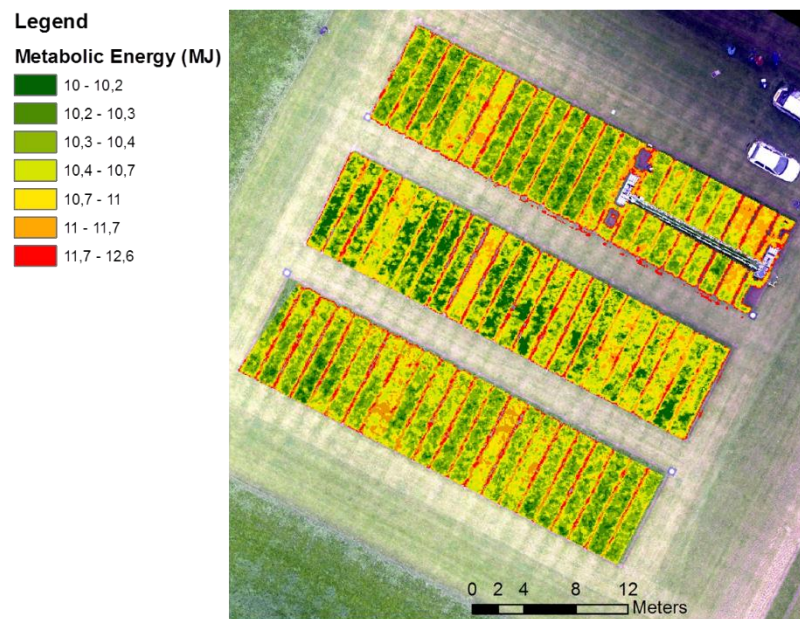


Figure 6.9 – Metabolic energy variation within plots by applying the $CI_{rededge}$ index on the acquired hyperspectral dataset of May.

6.3.4 Partial Least Squares Regression (PLSR)

Like in the previous case, also Partial Least Squares Regression (PLSR) was applied for investigating the relationships between grassland features and the average reflectance spectra of the two integrated datasets (Table 6.7).

Table 6.7 – PLSR results for integrated sub-dataset of May and October and the sub-dataset of May.

Traits	Plots May					Plots May and October				
	Inorganic–Organic					Inorganic–Organic				
	R ²	RPD	RMSE	RMSE _{L00}	LF	R ²	RPD	RMSE	RMSE _{L00}	LF
Height	0.7	2.22	2.29	2.71	3	0.86	4.0	2.13	3.15	6
Dry Matter yield	0.63	1.97	3.81	4.48	3	0.83	3.78	2.95	4.48	6
Fresh Matter yield	0.72	2.29	2.31	2.73	3	0.81	3.86	1.67	2.78	7
Crude Ash	0.62	2.01	3.36	4.04	3	0.47	1.58	3.74	4.26	4
Crude Protein	0.56	1.79	12.28	14.38	3	0.76	2.34	11.73	12.79	4
Crude Fibre	0.46	2.08	6.07	12.16	5	0.78	2.48	11.21	12.75	4
Na	0.39	2.19	0.16	0.28	5	0.21	1.26	0.26	0.28	4
K	0.68	6.08	0.3	1.02	7	0.39	1.46	1.12	1.27	4
Metabolic Energy	0.44	2.73	0.09	0.17	5	0.80	2.59	0.15	0.17	4

Thanks to the classifications proposed by Zhao et al., (2007), it is possible to analyze in which cases and with which grassland features, a strong, moderate, or weak correlation exists. The higher values of R² (R² > 0.7) were achieved on the integrated datasets of May and October, including all type and levels of treatments. For this type of dataset, the most of traits (height, fresh biomass, dry matter, crude protein, crude fibre, and metabolic energy) have a strong correlation, while the others (crude ash, K, Na) show a weak correlation (R² < 0.5). The values are considerable different for the sub-dataset of May, including both organic and inorganic fertilizers. Indeed, this show a high correlation for height and fresh matter yield; a low correlation for crude fibre, Na, and metabolic energy, and a moderate correlation for dry matter, crude ash, crude protein, and K.

RPD shows results in line with R². Indeed, also in this case the best results were obtained in the integrated dataset of May and October, including all treatments of organic and inorganic fertilizations. In it, a RPD suitable for screening is shown by height, dry matter, and fresh matter yield, while, a low prediction value is shown by all the other features. The other sub-dataset presents a RPD value suitable for laboratory analysis only for K prediction. Nevertheless, it is important to underline that for the other characteristics the RPD is not so small, since it is around 2.0 in all sub-datasets. The scatterplot of measurement and predicted values, related to the same variables chosen as example in Figure 6.7, is shown in Figure 6.10.

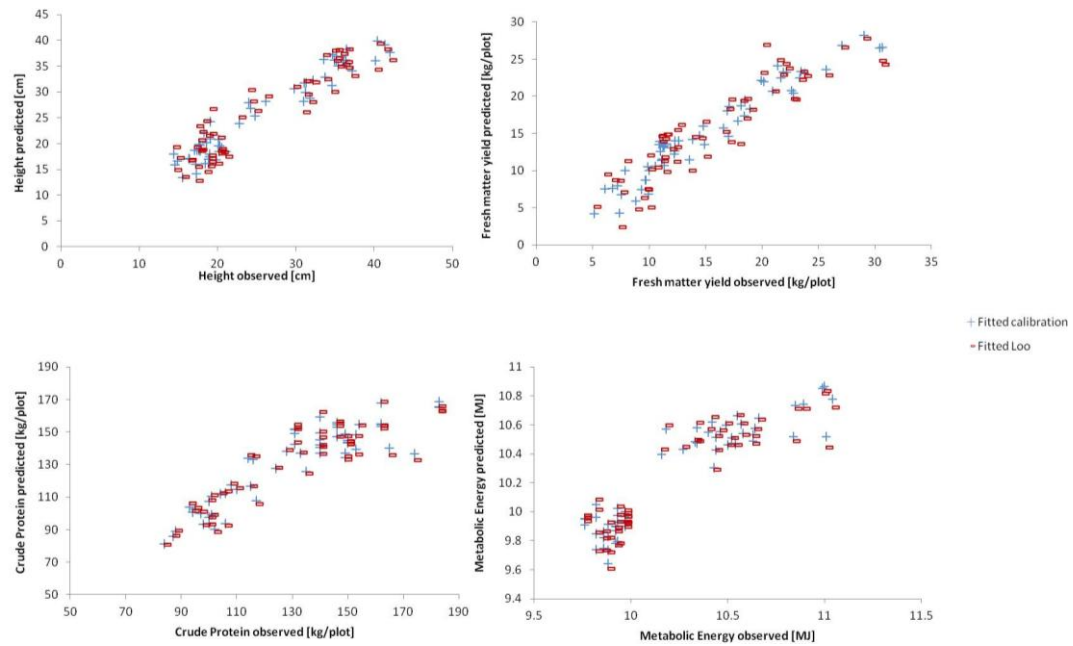


Figure 6.10 - Scatterplot of the measured vs. predicted values for the best PLSR models presented for the integrated dataset of May and October

In addition, the PLSR model is able to select the most significant wavelengths for the traits under detection, as illustrated in Figure 6.11. It shows that the most interesting region is positioned in the visible part of the spectrum (450–545 nm) for each trait investigated, except for metabolic energy, where is located around 545 nm. For crude protein, there is also another region of interest around 645 nm (545 nm–765 nm).

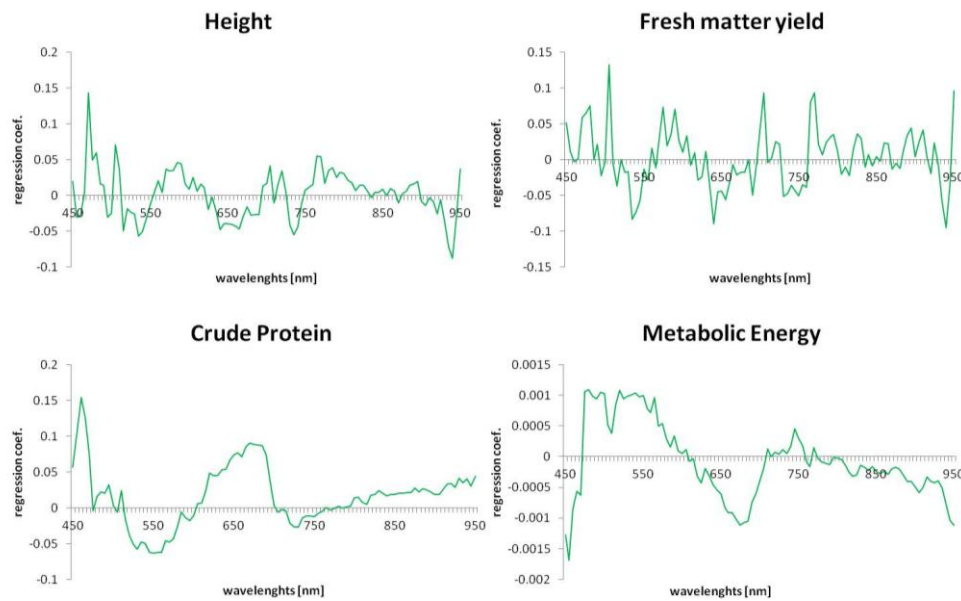


Figure 6.11 - PLSR coefficients for height, fresh matter yield, crude protein, and metabolic energy for the PLSR model of the integrated dataset of May and October

6.4 Discussion

Goals of this paper are to investigate and identify the best statistical strategy for estimating structural and biochemical traits of grasslands from hyperspectral images acquired by UAV and to analyze the influence of the type and amount of fertilization on their prediction capacity. Thus, an experimental field at the farm Haus Riswick, near Kleve in Germany, was selected as study area. It was classified in plots and, for each of them, different levels of fertilizer, chosen on the base of customs of German farmers, were applied. Thus, the area of interest was overflown using an octocopter UAV, equipped with the Wageningen UR Hyperspectral Mapping System (HYMSY) (Suomalainen et al., 2014), in two different flight campaigns, carried out on 15 May 2014 and on 14 October 2014, respectively. After the two flight surveys, the structural and biochemical grassland variables analysis was performed.

These analysis showed different results for all of the traits under investigation, but comparable statistical relationships (Tables 6.2–6.4). In particular, the Pearson correlation for the structural traits (height, fresh and dry matter yield) is appreciably high (>0.89). Unfortunately, it is not possible to draw the same conclusion for the biochemical traits, for which the correlation is substantially depending on the feature considered (Table 6.2). For instance, metabolic energy and crude fibre are highly correlated, even if negatively, (-0.98), while metabolic energy show a very low correlation with crude protein (0.04). Correlation value was influenced by the way used to estimate metabolic energy. It was not directly measured but calculated by applying Equations 6.1 and 6.2. In contrast, the correlation between crude protein and crude fibre is quite low (0.10), even

if, normally, they are negatively correlated (Donath et al., 2004). This because the analysis were carried out at one harvest date and not on a growing plant at subsequent dates. Probably, also the presence of different fertilizer treatments influence this result.

The use of a UAV allows to adapt the spatial resolution to the size of object under investigation. Thus, reducing altitude (70 m) and speed (5 m/s), it is possible to obtain a GSD of 200 mm (Capolupo et al., 2014; Capolupo et al., 2015; Nex & Remondino, 2012; Zhang & Kovacs, 2012). In addition, UAV has also another advantage: it permits to take images in flexible dates, considering the weather conditions, in such a way that the aerial images of two different periods can be compared. Moreover, the use of a hyperspectral sensor, characterized by hundreds of narrow contiguous spectral bands, allows to investigate the small reflectance variations in grassland vegetation traits, that otherwise couldn't be detected, and the small reflectance variation caused by the influence of the type and the amount of fertilization (Figure 6.4 - 6.5). For the same reasons and according to previous studies (Lee et al., 2004; Schlerf et al., 2005; Zhao et al., 2007), it was chosen to calculate the narrow-band vegetation indices instead of broad vegetation indices.

To analyze the influence of the type and the amount of fertilizer and the grassland phenology, the selected narrow-band vegetation indices, presented in Table 6.1, were calculated on each of the three sub-datasets in which the original dataset was split. Nevertheless, although narrow vegetation indices are able to detect the small variation due to the different fertilizer treatments, their prediction ability is moderate. Indeed, comparing the two integrated dataset of May and October surveys, one including both organic and inorganic treatments and the other characterized only by inorganic fertilization, it is possible to see that the results are comparable. In contrast, grassland growth influences the estimation ability of this technique (Table 6.5), confirmed also by the results of Table 6.5. Indeed, higher correlation values were resulted on May dataset. This depends also by the distribution of the two datasets, since they don't follow a specific linear relation, but they constitute two separate clusters. Thus, it is possible to define the best narrow vegetation index. In general, a good estimator ($R^2 > 0.5$) for grassland structural traits is MCARI/OSAVI (Wu et al., 2008), while, for the most biochemical features, is CIred-edge (Gitelson et al., 2003; Gitelson et al., 2006) (Figure 6.7). In conclusion, this method has promising results for evaluating grassland structural features, but not biochemical variables, with the exception of metabolic energy. The spatial variation maps of two features, chosen as examples, are shown in the Figures 6.8 – 6.9.

Also PLSR method was implemented on the same three sub-datasets and, like in the previous case, the results showed that the estimation ability is not influenced by the fertilization

treatments since the results of the first two integrated dataset are comparable. In contrast, it is affected by the grassland growing season. In addition, it is also possible to see that this approach performs better with the integrated sub-dataset of May and October, with the exception of crude ash, Na, and K. Indeed, Table 6.7 shows also that the R^2 values are good (>0.7) for all characteristics, except for crude ash (0.4), Na (0.2), and K (0.3) for the integrated sub-dataset of May and October, including both inorganic and organic fertilization. For the same dataset, also the value of the RPD is good (Table 6.7). On contrary, for the sub-dataset of May including both inorganic and organic fertilization, the R^2 and values are quite high for all traits, while the RPD, shows a value higher than 3 only K. Maybe, the higher coefficient of determination of the May-October group is caused by a higher number of LVs, which could be a sign for overfitting.

Thus, the combination of hyperspectral images and PLSR seems to be the best strategy for detecting structural and biochemical features. In addition, the result of this study is completely in line with the results of previous research studies (Clevers et al., 2007; Darvishzadeh et al., 2011; Darvishzadeh et al., 2008).

In order to validate the results of this research and define a specific grassland management plans, the methodology introduced in this study should be tested on other fields of different size and geographic position. In addition, further points need to be examined, like to take into account more observations over the growing season.

6.5 Conclusions

This study has demonstrated the great utility of hyperspectral images acquired from an UAV for detecting both structural and biochemical features of grasslands, since they are characterized by a continuous reflectance spectrum able to take into account the small grassland variations in reflectance properties due to the canopy or the type and the amount fertilizer. Thus, the information extracted by these pictures can be integrated in grassland management plans in order to conserve and improve the health status of grassland ecosystems.

In addition, both statistical methods applied in the current study show promising results for evaluating the structural traits, but not for estimating biochemical features, even if the best results are obtained by the PLSR model. Moreover, the amount and the type of fertilization do not influence both statistical approaches.

Thus, it can be concluded that the best strategy for estimating grassland traits is obtained mixing PLSR model and airborne hyperspectral imageries.

Chapter 7

Discussion and conclusions

The current thesis presents an overview of exiting UAV systems and their applications on detection and estimating environmental problems. The term environmental problems is used to define any kind of problem, causing changes in the habitat, greatly damaging the human health and the balance of our ecosystem. For these reasons, activities aimed to assess and monitor the features of environmental problems are essential in order to improve the safety and the security. In this case, two different aspects of environmental problems have been selected and analyzed. The first is related to the development of a highly innovative methodology for detecting copper hotspots in agricultural soils in order to identify the points to sample (Capolupo et al., 2014; Capolupo et al., 2015). The second, instead, is focused on the estimation of grassland structural and biochemical traits, in order to implement quantitative data to already existing grassland management plans (Capolupo et al., 2015). Thus, in both cases, the UAV ability is explored.

Indeed, like previously shown by Nex et al. (2013) and Pierrot-Deseilligny et al. (2011), the application of UAVs has introduced many advantages, such as the increment of image resolution caused by the drastic reduction of flight altitude, and the speeding up the acquisition data procedure, due to the decreasing of the time required for data acquisition and operating. In contrast, the employment of fifth-generation of software for photogrammetry has allowed to speeding up the entire data processing, since it has allows to process all the acquired frames in parallel. After their processing, in the first case study, a DEM with a resolution of 0.03 m (Figure 5.6) and a very detailed orthophoto (Figure 5.4) were obtained, while in the second work, a really accurate orthophoto (Figure 6.1) and high resolution hyperspectral dataset were generated.

These products, realized during the pre - processing phase, were then used to the successive procedures of elaboration, which were different according to the research purposes and consequently, in the two case studies analyzed in this thesis. Following, the two case studies are presented.

Therefore, regarding the example related to development of a new technology for detecting copper contaminated soils, as first thing, the micro runoff network and three micro-basins (Figure 5.8) were recognized on the obtained DEM. Subsequently, in each of them, the TI and CTI were computed. Their value depends on the slopes of the basins and drainage areas. So, the value of TI (CTI) increases with the reduction of the value of the slope for a given area. However, while TI

depends only on the topographical features, CTI depends also on climatic conditions. In both cases, their higher values correspond to the points of water accumulation and consequently to sedimentation zones. For these reasons and according with Gascuel-Oudou et al. (1998) and Merot et al., (2003) CTI looks more robust than TI since its potential decreases with the increment of soils heterogeneity. Comparing the maps of the two indices, it is clear that maximum TI values covers a larger areas than the CTI, and therefore CTI allows to define the points to be sampled, while TI allows to identify the areas to be sampled. In order to identify the areas, in which is more probable to find an accumulation of copper, a probably map was generated. The colours of the probably map were related to the different levels of probability, so the red zones corresponds to the areas with a higher probability to find higher accumulation of copper, orange, yellow, green are those in which the concentration is lower. At this point, the validation of the method was obtained firstly with a visual interpretation, comparing the probability maps with the actual distribution of copper, and later, applying the Boolean And operation between interpolated copper concentration and interpolated TI (CTI) (Figures 5.12 – 5.13). Indeed, the result of Boolean operation with TI allows to identify five areas, corresponding to the five hotspots of copper; while CTI identifies only four areas. Therefore, this methodology looks promising, since these information could be used by companies to organize sampling. Indeed, It should be convenient to concentrate the sampling only in the red areas and to extend the sampling procedure to the others areas only when these samples show a higher values than legal limit. It is important to decide to stop or continue the sampling according to this information, proceeding to the areas corresponding to values of TI and CTI gradually lower. In conclusion, the new methodology reaches the research goals and, therefore, in the future, it could play a key role in organising sampling activity.

The processing phase of the second case study is completely different, since, as mentioned earlier, its research goals are totally dissimilar. So, after having obtained the final products of data acquisition phase, the hyperspectral dataset was analyzed in order to reach the aims. Firstly, the structural and biochemical grassland features analysis was carried out in order to know their real values and, so, calibrate the model and choose the best statistical method for their estimation. Examining the results of these analysis, it is possible to notice that their statistical relationships are comparable (Tables 6.2–6.4), even if the Pearson correlation for the structural traits (height, fresh and dry matter yield) is appreciably high (>0.89), while it is substantially depending on the trait considered for the biochemical traits (Table 6.2). Observing this Table is important to underline that the method used to estimate metabolic energy (Eq. 6.1 and 6.2) influenced the Pearson correlation between metabolic energy and the other traits and that, while the correlation between crude protein and crude fibre is commonly negative (Donath et al., 2004), in this case it is positive, even if low

(0.10). Probably, the presence of different fertilizer treatments and the date of the analysis (they were performed at one harvest date and not on a growing plant at subsequent dates) influenced these results.

The two statistical methods applied for estimating grassland traits were computed on the hyperspectral dataset, characterized by hundreds of narrow contiguous spectral bands. The presence of these bands allows to explore the small reflectance variations caused by plant composition and the influence of the type and the amount of fertilization (Figures 6.4 - 6.5). Therefore, in order to take into account these variations and according to previous studies (Lee et al., 2004; Schlerf et al., 2005; Zhao et al., 2007), the narrow-band vegetation indices (Table 6.1) on the place of broad vegetation indices were calculated on each of the three sub-datasets in which the original dataset was split. Observing the results of narrow vegetation indices on the three sub-datasets (Table 6.5), it is clear that the results are influenced by grassland phenology but not by different fertilizer treatments. Moreover, it is not possible to define a good estimator valid for all the traits because their performance is strongly affected by the variable under investigation. In general, MCARI/OSAVI (Wu et al., 2008) can be elected a good estimator ($R^2 > 0.5$) for grassland structural traits, while, $CI_{red-edge}$ (Gitelson et al., 2003; Gitelson et al., 2006) can be considered the best for the most biochemical features (Figure 6.7). Consequently, this method is good prospect for estimating grassland structural features, but not for biochemical variables, with the exception of metabolic energy.

Like the previous approach, PLSR method was computed on the three sub-datasets. Also in this case, its estimation ability is not affected by the fertilization treatments, while is influenced by grassland growing season. Moreover, it is possible to notice that the performance of this approach is better than the previous method, even if, also in this case, the results is strongly depending on the traits under investigation and the growing season considered (Table 6.7).

Thus, the combination of hyperspectral images acquired by drones and PLSR seems to be the best strategy for detecting structural and biochemical features. Indeed, the resolution of this dataset is adapted to size of the object under investigation, while hundreds of narrow contiguous spectral bands allows to investigate the small reflectance variations. In addition, PLSR shows the best results both structural and biochemical traits.

In conclusion, the current research work shows that the combination of the images acquired from UAVs with approaches of other fields is good prospect both for monitoring environmental problems and supporting precision agriculture.

Publications

- Cervelli, E., Pindozzi, S., Capolupo, A., Collins, O., Rigillo, M., & Boccia, L. (2016). Ecosystem services and bioremediation of polluted areas. *Ecological Engineering*, 87, 139-149.
- Capolupo, A., Kooistra, L., Berendonk, C., Boccia, L., & Suomalainen, J. (2015). Estimating Plant Traits of Grasslands from UAV-Acquired Hyperspectral Images: A Comparison of Statistical Approaches. *ISPRS International Journal of Geo-Information*, 4(4), 2792-2820.
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