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Use of geotagged photographs in the frame of Common Agriculture Policy checks

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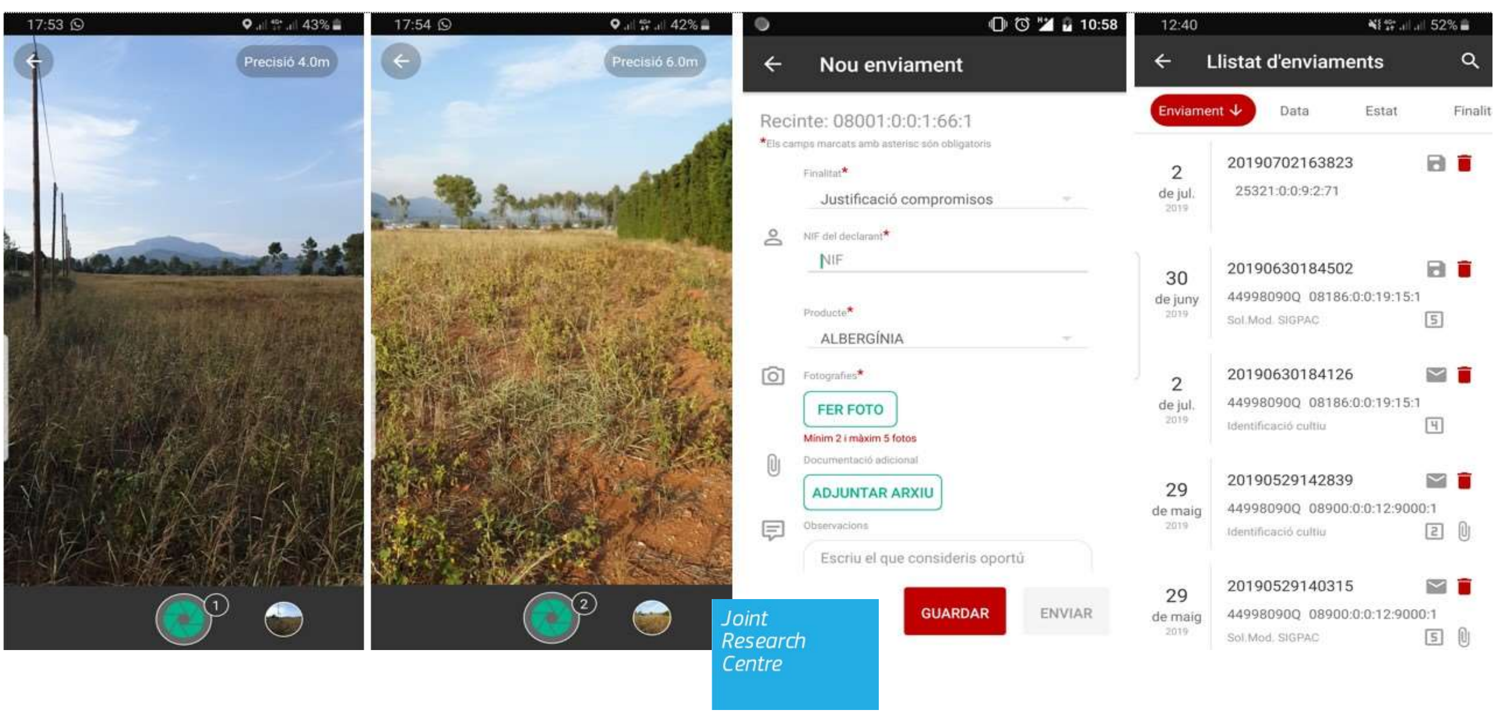

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Foreword

This report intends to provide the necessary technical guidance in order to properly and efficiently use geotagged photos in the frame of CAP checks.

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Abstract

As part of its ongoing move to simplify and modernise the EU's Common Agricultural Policy (CAP), the European Commission has adopted new rules that allow a range of modern technologies to be used in the systems for checks of area-based CAP payments. This includes the possibility to use geotagged photos to support and complement checks methods when the latter do not lead to conclusive results. They can also be used as ground truthing information provided by farmers or other stakeholders. This report intends to provide the necessary technical guidance in order to properly and efficiently use geotagged photos in the frame of CAP checks.

1 Introduction

As part of its ongoing move to simplify and modernise the EU's Common Agricultural Policy (CAP), the European Commission has adopted new rules that allow a range of modern technologies to be used when carrying out checks for area-based CAP payments. This includes the possibility to completely replace physical checks on farms (On-The-Spot Checks, OTSC) with a system of automated checks based on analysis of Earth observation data. The proposed new monitoring approach (Checks by Monitoring CbM) uses the earth observation data extrapolated mainly from the Copernicus Sentinel satellites.

It also includes the possibility to use geotagged photos to support and complement OTSC and CbM methods when they do not lead to conclusive results. They can be used as ground truthing information provided by farmers or other stakeholders for Integrated Administration and Control System (IACS) processes such as update of the Land Parcel Identification System (LPIS).

This report intends to provide the necessary technical guidance in order to properly and efficiently deploy geotagged photos in the frame of CAP checks.

2 Definition - background

Geotagged photos are commonly referred to as digital photographs with spatial information. Geotagging of the photos can be done manually or automatically. In short, a geotag consists in saving at least the latitude and longitude coordinates into the Exchangeable Image File (EXIF) data of each JPEG file.

With the recent fast growing developments, most smartphones and cameras come with a built-in GNSS (Global Navigation and Satellite System) antenna that enables automatic geotagging retrieving time and positioning from the antenna. Often, the tag includes other basic information about the camera model and settings.

EXIF

Make	Apple
Model	iPhone 6
Orientation	Horizontal (normal)
ResolutionUnit	inches
Software	11.3.1
ModifyDate	2018:06:11 09:53:27
ImageDescription	LUCAS 2018, 35303726, Potatoes for LC1, Not relevant for LC2, null for LU1, Not relevant for LU2
Artist	UKSU005
Copyright	(c) European Union, 2015 - Reuse authorised - The reuse policy of European Commission documents is regulated by Decision 2011/833/EU (OJ L 330, 14.12.2011, p. 39) - The reuser has to acknowledge the source of the documents; has the obligation not to distort the original meaning or message of the documents; guarantee the non-liability of the Commission for any consequence stemming from the reuse.
ExposureTime	1/169
FNumber	2.2
ExposureProgram	Program AE
ISO	32

DateTimeOriginal	2018:06:11 09:53:27
CreateDate	2018:06:11 09:53:27
ShutterSpeedValue	1/169
ApertureValue	2.2
BrightnessValue	6.897630332
ExposureCompensation	0
MeteringMode	Multi-segment
Flash	Auto, Did not fire
FocalLength	4.2 mm
SubjectArea	1631 1223 1795 1077
SubSecTimeOriginal	895
SubSecTimeDigitized	895
XPTitle	[illegible]
XPSubject	[illegible]
ColorSpace	sRGB
ExifImageWidth	1600
ExifImageHeight	1200
SensingMethod	One-chip color area
SceneType	Directly photographed
ExposureMode	Auto
WhiteBalance	Auto
FocalLengthIn35mmFormat	29 mm
LensInfo	4.15mm f/2.2
LensMake	Apple

LensModel	iPhone 6 back camera 4.15mm f/2.2
GPSLatitudeRef	North
GPSLatitude	56.004222
GPSLongitudeRef	West
GPSLongitude	2.748719
GPSAltitude	26.94140127 m
GPSTimeStamp	08:53:28
GPSSpeedRef	km/h
GPSSpeed	0
GPSTrackRef	True North
GPSTrack	67.8515625
GPSDateStamp	2018:06:11
GPSHPositioningError	5 m

Figure 1: Example of a geotagged photo of a potato field taken in the frame of the LUCAS survey 2018, together with the detailed information registered in its EXIF file. Note that most of the information is automatically coded from device and GNSS antenna data. Image description and copyright information have been added 'manually'.

3 Potential for geotagged photos

Thanks to the ease of use and flexibility of smartphones and digital cameras, the range of objects, situations, actions that can be illustrated and captured through geotagged photos is almost unlimited. From a large rural landscape area up to a zoom on a wheat's head, from a high nature value grassland parcel to a meadow just mowed, vast are the possibilities.

In the CAP checks and management context, geotagged photos can be used in a wide range of situations to serve as input to:

- document Rapid Field Visit (RFV);
- provide parcel information to update the Land Parcel Identification System (LPIS);
- evidence elements not monitorable with satellite imagery;
- provide ground truth for quality assessment or training of machine learning processes;
- follow-up selected inconclusively monitored parcels.

3.1 Provision of images on request

In cases when photos should be provided to evidence the presence of a specific object or activity, the request of such action should be sent to the farmer (or other stakeholder) enough in advance to grant him/her enough time to collect the evidence and to ensure pictures of sufficient quality (e.g. reasonable visibility or light conditions). Thus, the role of timing in the entire IACS process is crucial. In order to minimise efforts on both sides (the administration and the farmer) and to ensure efficient use of geotagged photo, the requests for photos should be sent only if information could not be obtained from satellite imagery use (automatic or semi-automatic processing, visual interpretation (CAPI)).

3.2 Having farmers pro-active in the process

When farmers are requested to capture photos evidencing the presence of an object or activity conditioning the eligibility for a specific subsidy, it is crucial for the processing of the farmer's dossier that farmers act promptly and send the evidencing photo(s) in due time. If not delivered in time, the administration could be forced, as a last resort, to perform a field visit of the doubtful parcel, with a high risk of being too late in the season to still find the relevant evidences. In such situation, the newly introduced possibility of using early warning messages, error prevention system is lost, being back in a system of penalties and costly inefficient field intervention.

It is thus of the upmost importance that farmers endorse these processes and play a pro-active role in providing photos. Nevertheless, it is currently a fact that in many Member States the involvement of farmers in the IACS process is still very limited. Under OTSC process, often, once the aid application has been submitted, very few interactions occur between farmers and the administration especially for farms not having animals. Not only for geotagged imagery, but for the monitoring process as a whole, active role of farmers is needed (acting, reacting to warning messages or request to modify aid application etc.). That means that a change in habits and culture has to be operated. It involves communicating with farmers in a manner that encourages training, learning and their endorsement of processes. It also involves to set information exchange system with farmers easy to use while ensuring safety and security of information transfer. The minimum requirements and functionalities of tools and apps for geotagged photos are described in the following chapters. This information could be used by administrations to produce and provide farmers with a guideline/training on best practices in data collection in a suitable form (video, in app tutorial, short document).

Disclosing the beneficial aspects of using geotagged imagery will certainly involve further actions. For instance, farmers could anticipate parcels/practices that might be challenging and capture photo when they consider it relevant, but would only upload selected photos to the server at a later date, upon request.

4 Technical requirements

According to the recommendations from the Wikicap Common Technical Specifications (CTS), the following metadata should be recorded together with a photo:

- Time and date of the photo capture, preferably obtained directly from the GNSS antenna,
- Geographical location of the camera at the time of photo capture, also preferably obtained directly from the GNSS antenna
- Orientation (heading) of the camera at the time of photo capture,
- The identification of the operator that can be realised by personalised access to the app (login),
- Basic information on the mobile device and inbuilt camera, such as mobile device brand and model number. Such information can help to retrieve e.g. the original image dimensions or focal length of the photo, or to assess the quality of provided measures of camera position and orientation.

The guidelines also recommended to register the elevation and the Dilution Of Precision (DOP) that can qualitatively indicate the positioning precision.
Although most of the above listed metadata can nowadays be automatically recorded by modern photo cameras, a dedicated app for mobile devices should be developed to ensure information integrity and security of transferred geotagged photos. This way, the information content cannot be altered.

5 Functionality of the mobile app and existing solutions

5.1 Usable mobile application

Mobile platforms have become an indispensable part of our daily live and routines, but, to date, no standards exist for design of mobile graphical user interfaces. The principles of desktop software design are not directly applicable not only due to the limited screen size of mobile devices but also due to their non-stationary usage, i.e. while walking or driving (Berkman & Hoober, 2011). The industry providing the major operating systems on mobile devices do publish guidelines for how applications should be designed on, but the opinions on the best practices differ, both in scientific writing and among industry professionals.

A number of studies have searched for features that make the mobile applications usable. According to ISO 9241-11, usability is defined as extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use (ISO, 2018). Usability is a more precise term than the expression “user-friendly”. For users, a usable product should be:

- easy to become familiar with, even during the first contact,
- easy to reach their goal through using it,
- easy to suppress elements of the user interface for their next usage.

The industry recommendations for developing successful mobile applications (Apple, 2019; Google, 2019) advise to keep consistency across all mobile platforms (uniform elements, spacing and spatial organisation), to design an intuitive user interface and to deploy predictable layouts, with legible text regardless of the size of the device screen (Google, 2019). A usable app should behave in a predictable way, i.e. as expected by the users (Apple, 2019). A balance is required between the freedom of user control and the prevention of unwanted outcomes. Ideally, the app should make the users feel they are in control by using familiar and predictable interactive elements, by providing a possibility to confirm destructive actions, or by cancelling operations already in progress (Apple, 2019).

Minimizing actions and screen touches is of major interest for increased usability on mobile platforms. In small handheld devices, without a mouse and a keyboard, it is far more burdensome to select objects and input information than it is on desktop computers. Therefore, scrolling is favoured over clicking and is it advised to optimize a mobile app to keep clicks and field entries to an absolute minimum.

5.2 Offline app functionality

In order to allow for full offline app functionality, support data should be downloaded and stored locally in the mobile device prior to the planned data collection. Such support data could be required to guide the user to the locations where the photos should be taken, to display ancillary data (i.e. corresponding LPIS layers, patches of orthoimagery covering the parcels of interest etc.) and to instruct on how to capture the images (see section 8).

In cases when orthoimagery is provided as one of the layers displayed in the app, information about the image acquisition date should be provided together with a reminder that the current situation in the field might not be reflected in the image.

5.3 User guidance and examples from existing apps

Due to the multitude of farming situations where geotagged images are collected (wide variety of landscapes, areas of interest or type of auxiliary data used), it is very difficult to provide universal rules that are applicable in all cases. Nevertheless, the following information needs to be provided early in the season to the farmer in order to minimise his/her efforts and maximise chances to obtain valuable evidence:

- When should the photos be captured? (e.g. very relevant for automatic crop recognition, when the plant development stage may be linked with the recognition success rate, less relevant for man-made objects that do not evolve dynamically in time)
- What should they depict? (Are multiple objects/subjects of interest allowed in the camera view?)
- How should the frames be taken? (Distance to the object or scale? Camera pointing horizontally? Pointing downwards? From an elevated point? Etc.)
- How many photos should be captured?
- How and when should they be submitted?

Such instructions / guidelines can be conveyed in multitude ways, e.g. using posters, leaflets, written tutorials (step-by-step), in app guidance and tips, tutorial videos etc. What is the most effective methods with the highest acceptance in the farmer community is a choice left to the Member State's administration.

Some smartphone apps dedicated to collection of the geotagged photos by farmers and/or inspectors have been already developed by Administration of some MS and by private companies.

One example is the FotoDUN app (DARP, 2019) developed by the Ministry of Agriculture, Livestock, Fisheries and Food (DARP) Government of Catalonia, Spain. This app was made available to farmers to facilitate submitting photos supporting non-conclusive monitoring cases as well as requests for the LPIS update. The development of the app followed a pilot project in which the farmers could upload photos supporting requests for the LPIS data update via an online web form. In both cases, the Web platform and the app, the farmers were provided with a short manual/presentation (digital version, downloadable in a .pdf format) on:

- the link (URL) to the web form or the app installation,
- which credentials to use,
- the data collection protocol,
- the minimum number of images to be taken,
- how to complete the required fields in the photo submission interface,
- examples of good and bad quality photos,
- examples of when the photo evidence should support the claim or support a change of the LPIS.

The app is limited to solely capturing the photos, providing required metadata and submitting them to the Administration server. Prior to going to the field, background (most recent orthophoto) and the reference data (LPIS and Geo Spatial Aid Application GSAA layers) can be downloaded and saved locally to ensure usage even without internet connection. The user is left free to choose the geographic location and orientation for the photo framing, but recommendations are provided in the user manual. At the time of the photo capture, the user interface indicates the estimated positioning accuracy (photo capture is disabled if the positioning quality is too low) and the number of photos already collected at the location (see Figure 2). The fields providing metadata required for photo submission consist of drop down menus with pre-defined categories, fields to attach photos and other documents and a comment field where free text can be inserted. Photos with the metadata may be send to the Administration right after capturing or saved in the app for delayed delivery (if required).

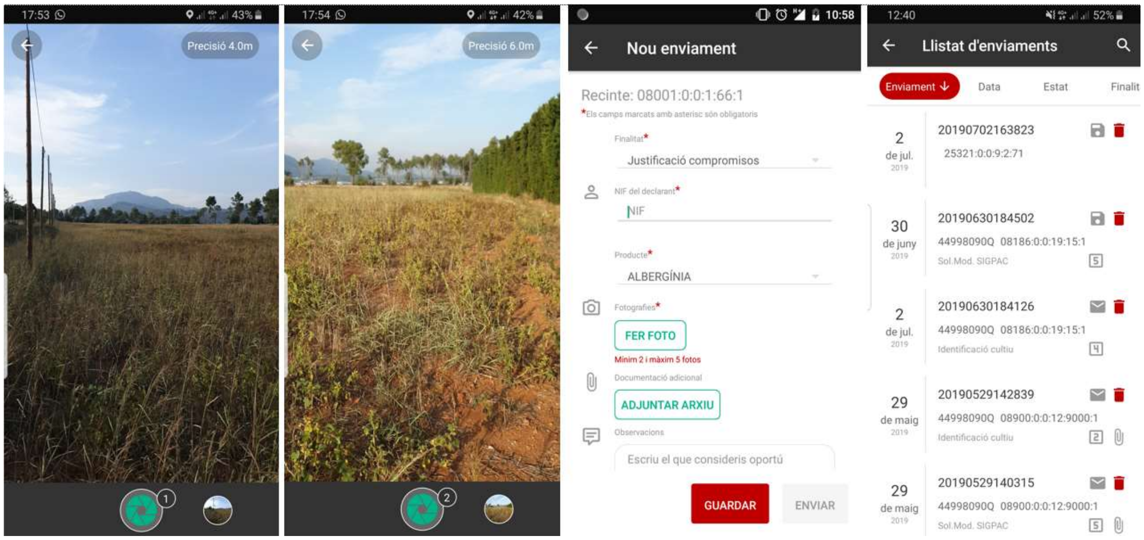

Figure 2. Example user interface screens during photo collection with the FotoDUN app developed by the Ministry of Agriculture, Livestock, Fisheries and Food (DARP) Government of Catalonia. A) and B) the user is informed about the number of photos captured at the location. Shooting photos is enabled only if the estimated positioning precision is below a predefined threshold. C) User interface allowing submission of the photos to the System. D) A list of data submitted to the Administration (marked with an envelope icon) or captured and saved for delivery on request (marked with a diskette icon).

Other, more advanced solutions, already available commercially since a couple of years. For instance the ABACO GEOPHOTO, Abaco, IT has been tested and used by the Maltese Paying Agency (ARPA) and the Public Service of Wallonia (SPW) or the e-Geos GeoTag App tested by different paying agencies (Austria, Belgium, France, Germany and Spain) and used operatively by the Italian paying agency (AGEA) since 2018. They provide more complex functionalities covering, among others:

- two-way communication between the Administration and farmers, including a possibility to send a specific task (action request via push notifications) to the farmer or chat with advisor,
- navigation to the point indicated in the task (action request),
- adapting the information displayed on the screen and the range of allowed actions depending on the proximity to the point (e.g. a photo can only be captured in vicinity of the destination point, or displaying the “horizon line” when photo capture is allowed) or allowing capture only in a range of vertical and horizontal angles,
- interoperability with many open standards databases, e.g. with existing IACS database to visualise the reference parcels and declared crops (GSAA), orthophotos, soil samples, other custom indicators or traffic-lights,
- interoperability with Farm Management Information Systems enables the access to farms proprietary data or data collected by in-field sensors, as well as to the logbook of tracked field activities,
- measurements of dimensions and areas both in the geotagged photos and in the 3D view with Augmented Reality,
- visualising IACS information as augmented reality through the mobile camera

Examples are provided in Figure 3, Figure 5 (ABACO) and Figure 5

Figure 3. ABACO GEOPHOTO: Typical geotagged image acquisition workflow (with augmented reality). After receiving a task, the user is navigated to the point from which the photo should be captured. Current device position and the parcel with the target point are shown on an overview orthophoto map. The number of photos collected for this task is also made visible. Once the geotagged photo is taken a note can be attached.

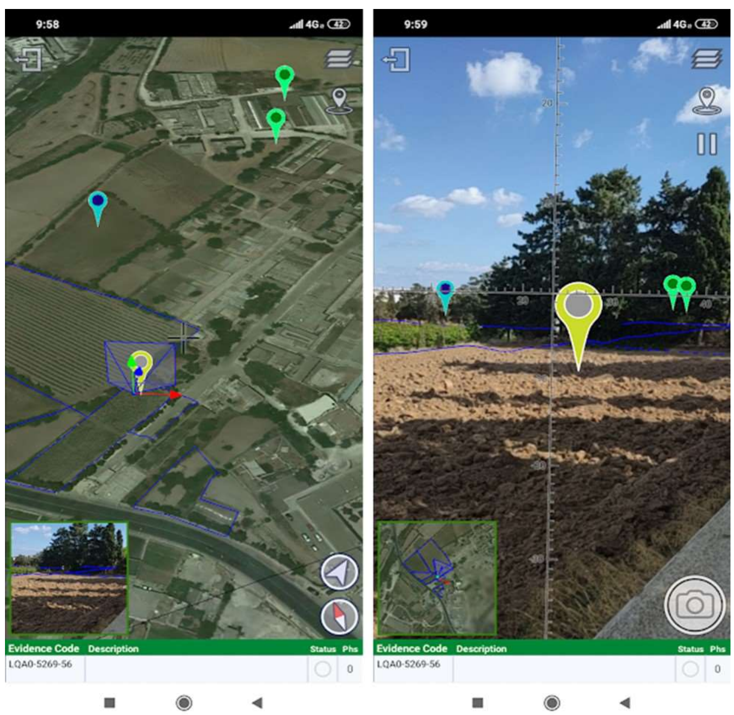

Figure 4. ABACO GEOPHOTO: augmented reality supporting orientation and data collection. Vertical markers indicate parcels and/or features to be captured. The color of markers indicate the nature/scheme of concern (e.g. yellow: BPS, green: EFA …). Parcel zoom or image location are displayed in a small window on screen to support locating and orientating of photos.

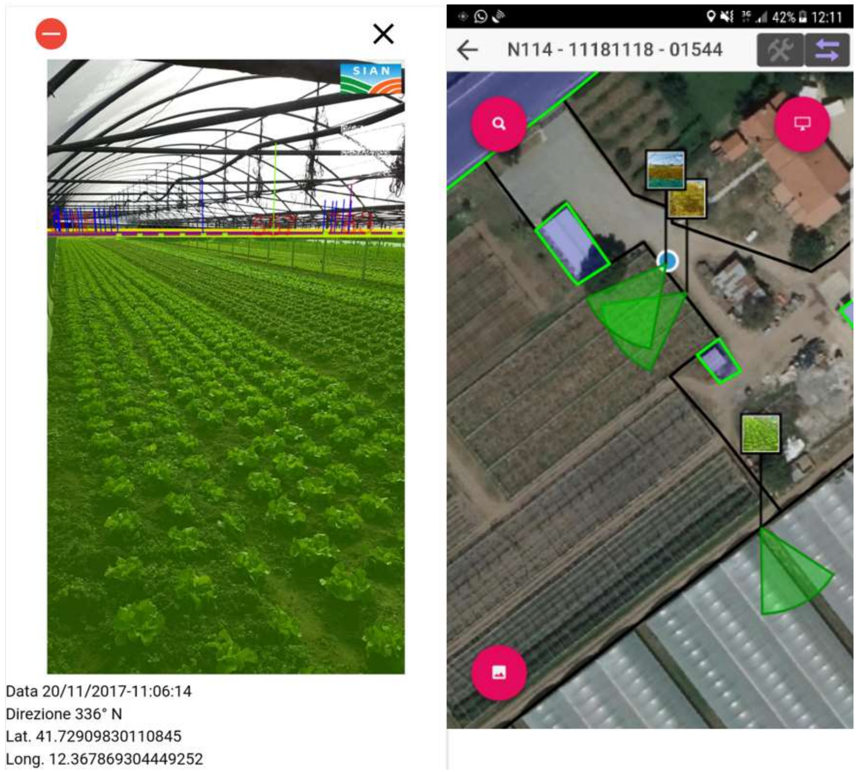

Figure 5. e-Geos Geotag App: augmented reality supporting orientation and data collection. Vertical blue markers indicate vertices of the parcels and the nearby parcels. Image location and orientation as well as image thumbnails are shown in the overview of the collected images.

Augmented reality has proven to be a very effective guidance and learning tool in domains like: tourism and navigation, training and education, entertainment and advertisement as well as assembly and maintenance (Chatzopoulos, Bermejo, Huang, & Hui, 2017; Ramos, Trilles, Torres-Sospedra, & Perales, 2018). In mobile augmented reality (often called MAR) wireless communication, location-based computing and services (LBS) and augmented reality are combined to create an integrated interactive environment (Swan, Kuparinen, Rapson, & Sandor, 2017). Although such a combination is still a challenge for user interface designers (e.g. small display of the mobile devices, potentially low sensor accuracy etc.), MAR is undoubtedly an innovative technology with a huge potential in GIS and geospatial tasks (Knowledge@Wharton, 2018; Werner, 2018). Still, it should be used with caution taking into account the hardware limitations of average and lower-end smartphone devices available on the market. Despite the rapid advances, mobile phones' performance as a computing platform for real time applications is still limited because most mobile phones remain equipped with relatively slow memory access and small cache sizes (Chatzopoulos et al., 2017).

Also, with the incredible speed of developments in the computer vision domain, plant and plant disease recognition in mobile devices became realistic and the number of apps developed is rapidly increasing (e.g. FlowerChecker, PlantSnapp, LeafSnap, PlantNet … see section 11 for references). Their strength and performance rely on live access to huge image collections. In case of application in the IACS domain, image collection should be organised (see also section 9) to build and train algorithms for the purpose of image classification. Thus, a preliminary image classification could be run on the mobile device before a photo is submitted in order to provide the farmer with indicators on the likelihood that the photo is of sufficient quality and that it actually contains and illustrates the information requested.

6 Geotagging

Geolocation is the estimation of the real-world geographic location of an object. In smartphones, geolocation can be based on information about nearby telecommunication towers and WiFi nodes or, more and more frequently, directly from GNSS signals.

6.1.1 Geotag accuracy

The accuracy of a location derived from the telephone service provider's network infrastructure depends on the density of base stations in the area and the development advancement of the timing solutions used by the network. This geolocation technique is based on the network triangulation so that the location of device is estimated based on estimated distances to the nearest base stations. The accuracy of such solutions, relying solely on cellular network, ranges from one to several km (Seyyedhasani, Dvorak, Sama, & Stombaugh, 2016).

The accuracy of the GNSS positioning is influenced by other factors. The satellites broadcast their signals from known positions in space with a certain accuracy, but the signal reaching the receiver is influenced by multiple factors including satellite constellation geometry, signal blockage and multipath reflectance or atmospheric conditions. The quality of the receiver's antenna and the algorithms processing the captured signal are of high importance as well.

Despite the fact that geolocation in smartphones is based on GNSS observations combined with WiFi and cellular tower information, as well as an online database of satellite locations (A-GPS), the positioning accuracy of a smartphone is still considerably worse than that of dedicated GNSS devices designed solely for survey or navigation purposes. This is due to the fact that most of the smartphone GNSS antennas use linear polarization (Zhang, Tao, Zhu, Shi, & Wang, 2018), making it much more prone to multipath effects from GNSS signals reflected by nearby surfaces, than it is in the case of more advanced GNSS receivers (designed to minimize the multipath effect). Performance of the smartphones' GNSS antennas may also be jeopardised by their suboptimal placement inside the device (Roberts et al., 2018). A typical smart device usually includes antennas for GNSS, Wi-Fi, Bluetooth, and two or four for 4G LTE cellular communications that are expected to operate simultaneously without interfering with one another, and the GNSS sensor is not necessarily prioritised in solving such device design puzzle (in opposite to the devices designed solely for navigation or positioning). On the top of that, to save power, the GNSS receiver can be turned off between readings (duty cycle) further deteriorating accuracy of positioning (Roberts et al., 2018).

Based on the above mentioned points, it becomes inevitable that positioning performance of the smartphone varies significantly between brands and models. Nevertheless, ranges of achievable positioning accuracies are reported in literature. A non-exhaustive list of studies exploring potentials of smartphones for point positioning and the resulting 2D root mean square errors 2DRMSE at 95% probability) is presented in Table 1: A non-exhaustive list of positioning accuracies obtained using smartphone devices. Errors reported originally by the authors were in several cases recomputed to derive 2DRMSE reported in this table.

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Type of observation	2DRMSE [m]	Environment	Source
Single frequency GPS	<7	Open horizon	(Robustelli, Baiocchi, & Pugliano, 2019)
Single frequency GPS	<8	Open horizon	(Seyyedhasani et al., 2016)
Single frequency GPS	<10	Open horizon, marine environment	(Specht, Dabrowski, Pawelski, Specht, & Szot, 2019)
Single frequency GPS	<13	Urban canyon	(Robustelli, Baiocchi, & Pugliano, 2019)
Single frequency Galileo	<14 E1 <5 E5a	Open horizon	(Robustelli et al., 2019)
Single frequency GPS+ Glonass	< 12 (except one device: 32)	Open horizon	(Musulin, Kos, & Brčić, 2014)

Single frequency GPS+ Glonass	<7	Open horizon, marine environment	(Specht et al., 2019)
Single frequency GPS+ Glonass + Beidou	<12	Open horizon, marine environment	(Specht et al., 2019)
Single frequency GPS+ Glonass	<5	Open horizon	(Tomaštík, Tomaštík, Saloň, & Piroh, 2016)
Single frequency GPS+ Glonass	<34	Inside forest, leaf-on	(Tomaštík et al., 2016)
Single frequency GPS+ Glonass	<16	Inside forest, leaf-off	(Tomaštík et al., 2016)
Single frequency GPS+ Glonass + Galileo	<5	Open horizon	(Robustelli, Baiocchi, & Pugliano, 2019)
Single frequency GPS+ Glonass + Galileo	<12	Urban canyon	(Robustelli et al., 2019)
dual frequency Galileo (E1,E5) + GPS (with external antenna)	< 2.8	Open horizon	(Roberts et al., 2018)

Table 1: A non-exhaustive list of positioning accuracies obtained using smartphone devices. Errors reported originally by the authors were in several cases recomputed to derive 2DRMSE reported in this table.

In Android 7+ operating devices, developers have been given more flexible access to the raw GNSS data received by the chipset. More complex data filtering and computation techniques, that have been used for years in surveying equipment, are now being deployed in smartphone application to improve the positioning accuracy. One example of such algorithm was presented and implemented recently in the eGNSS4CAP project (GSA, 2019a).

In the future, operational Galileo providing services like OS-NMA (Open Service Navigation Message Authentication) or High Accuracy Service (HAS), in combination with other constellations and dual-frequency GNSS chipsets, will bring increased accuracy to the next generation smartphone devices (triple frequency phones required). At the moment Galileo brings better availability and better performance in challenging environments to all the devices capable of receiving its signals.

Regarding smartphones equipped with dual-frequency GNSS receivers, despite the very promising results (sub-meter accuracy) obtained with similar chipsets in applications for the automotive market, the results obtained in point positioning remain at the level of several meters. This is mainly due to the previously mentioned design limitations of the smartphones that render phase-based and fixed ambiguity solutions inviable. Without an external antenna, at best ~1m accuracy (GSA, 2019c) (the float solution) can be achieved when using Real Time Kinematic (RTK) corrections (usually linked to extra costs and to a need for network coverage). Improvement of the GNSS antenna or using an external one can bring the positioning accuracy with RTK corrections down to sub-decimetre levels (GSA, 2019c).

6.1.2 Camera heading accuracy

Similarly to the GNSS chipsets, the choice of the three-axis magnetometers, commonly used in smartphones to determine the orientation relative to the north is a compromise between design constraints, cost of components, power and accuracy (Blum, Greencorn, & Cooperstock, 2013). Compass headings might be influenced by the user's body position, how the phone is held, the environment around the user or even by the device own magnetic field (e.g. speakers and microphones are made of magnets) that can be also changing with fluctuating processing power. Techniques for filtering the noisy data or for making use of sensor fusion (with a gyroscope or an accelerometer), help to increase the accuracy of camera heading. The estimated average accuracy of the camera heading reported in literature can be summarised as being close to 10º (Deng, Wang, Hu, & Wu, 2015; Michel, 2017).

In order to maximise accuracy of the camera heading measurement, the compass/magnetometer of the phone, should be kept calibrated. The purpose of calibration is to establish compensation for how the components in the phone (such as screws, speaker magnets, etc.) interfere with the measured magnetic field. The compass calibration is usually performed by repetitive 8-shape movement of the phone, or by rotation round all three axis of the device. During such movements the magnetometer records changes in the measured field and uses them to calibrate the x, y, and z magnetic field sensors. Requests for periodical sensor calibration should be considered when defining requirements for the app collecting geotagged photos.

7 Data security

In order to ensure integrity and security of geotagged photos an operating procedure needs to be foreseen for safe data storage in the device and for exchange with the administration. Such procedure should ensure that the information content cannot be falsified at any time, e.g. by geotag manipulation or image content alteration. This task can be addressed in many ways, e.g. by using steganography based techniques (Mazurczyk & Caviglione, 2015), such as encoding data/codes within EXIF metadata (M. Y. Wu, Hsu, & Lee, 2009) or modification of least significant bits of pixels (Mazurczyk & Caviglione, 2015). In such methods a code can be encrypted in the photo at the time of image capture and its integrity cross-checked at database entry upon delivery to the Administration.

Other anti-manipulation measures are also available, such as checking for installed known applications generating fake GNSS positions, watermarking photos with coded (bar code) location, date and time or cross-checking the GNSS position with the location estimated based on the nearby Wi-Fi and Cell Phone Towers (with compromised accuracy).

In the future, use should be made of the Galileo Open Service Navigation Message Authentication, that will guarantee to users that they are utilising non-counterfeit navigation data coming from the Galileo satellites. OS-NMA will be disseminated on the first GALILEO frequency E1b (avoiding the need for dual-frequency GNSS chipsets in smartphone devices) and the service should become operational in 2020 (GSA, 2019c).

Nevertheless the GNSS chipset manufacturers need to properly implement the OS-NMA capability at the chipset level in order to enable correct decoding of the authentication navigation message. To date, very few mobile devices are able to correctly read the simulated OS-NMA (GSA, 2019c). On the mobile application side, an open source library enabling the use of the OS-NMA v.1.0 has been developed within the eGNSS4CAP project (GSA, 2019a) and its documented code is available at the project's github repository (GSA, 2019b).

8 Image capture

The image capture protocol should be fit for purpose. Metadata, such as the trigger for sending the photo (voluntary, required etc.) and the motive, e.g. confirmation of mowing, confirmation of crop type, request for LPIS update, clarification of irregularities in the crop development (i.e. caused by a flood, drought etc.), can be very useful at the stage of image sorting and automated data processing (see also section 9).

Regardless of the intended image content, it is advised to be present on the view where the photo will be taken for several seconds, and hold the camera motionless before releasing the shutter. This is due to the fact that the smartphone providers implement sensor fusion and smoothing algorithms in the determination of the geolocation and the compass readings. Such algorithms introduce a small delay in the provision of the position/orientation and lingering on the position for a short time before the photo is taken is likely to increase the precision of the geotag and camera heading.

It is advised to capture photos in landscape format (horizontally) and point the camera so that the element to evidence is depicted in the image centre. Only relevant objects should be included in the image frame, i.e. fingers, personal belongings, vehicles or other people should not be in the picture. Furthermore, farmer and the MS administration should respect the local privacy rules. Photo anonymization, according to the MS rules, might be required at some point of the data exchange.

Photos should be captured in good light conditions so that the object is illuminated and clearly visible in the image. Rules for using of camera flash should be communicated to the farmer. Photo shooting towards the sun should be avoided.

Considering the image content, photos may be divided into two main framing categories of "overview" and "macro" photos.

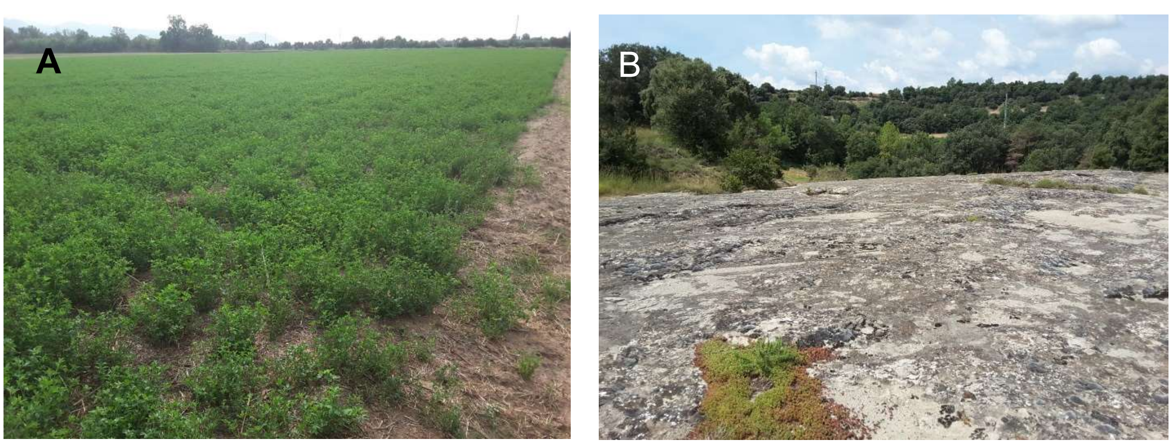
8.1 Types of photos

8.1.1 Overview photos

An overview photo should depict a larger part of the field and include landscape elements other than the main object (crop, activity etc.), if possible. This type of photo aims at reducing the uncertainty linked with the limited accuracy of the geotag and at providing an overview of the field condition. The photo should be captured so that a border/corner of a parcel and the nearby landmarks (trees, ditches etc.) are visible and identifiable in relevant orthophoto data, confirming photo location indicated in the geotag, often with better positioning accuracy. Such photos should be taken with the camera oriented horizontally, with the horizon falling at approximately 5/6 of the image height to limit the image area depicting the sky (following the image collection protocol used in the LUCAS 2018 survey (E4.LUCAS (ESTAT), 2019)). The object should be centred in the photo frame.

Panoramic photos, being an on-the-fly created mosaic of multiple images, and covering even up to 360 degrees views could be considered as a type of overview photos.

In Figure 6 and Figure 7 are provided good and bad illustrations of 'scene overview' photo capture.



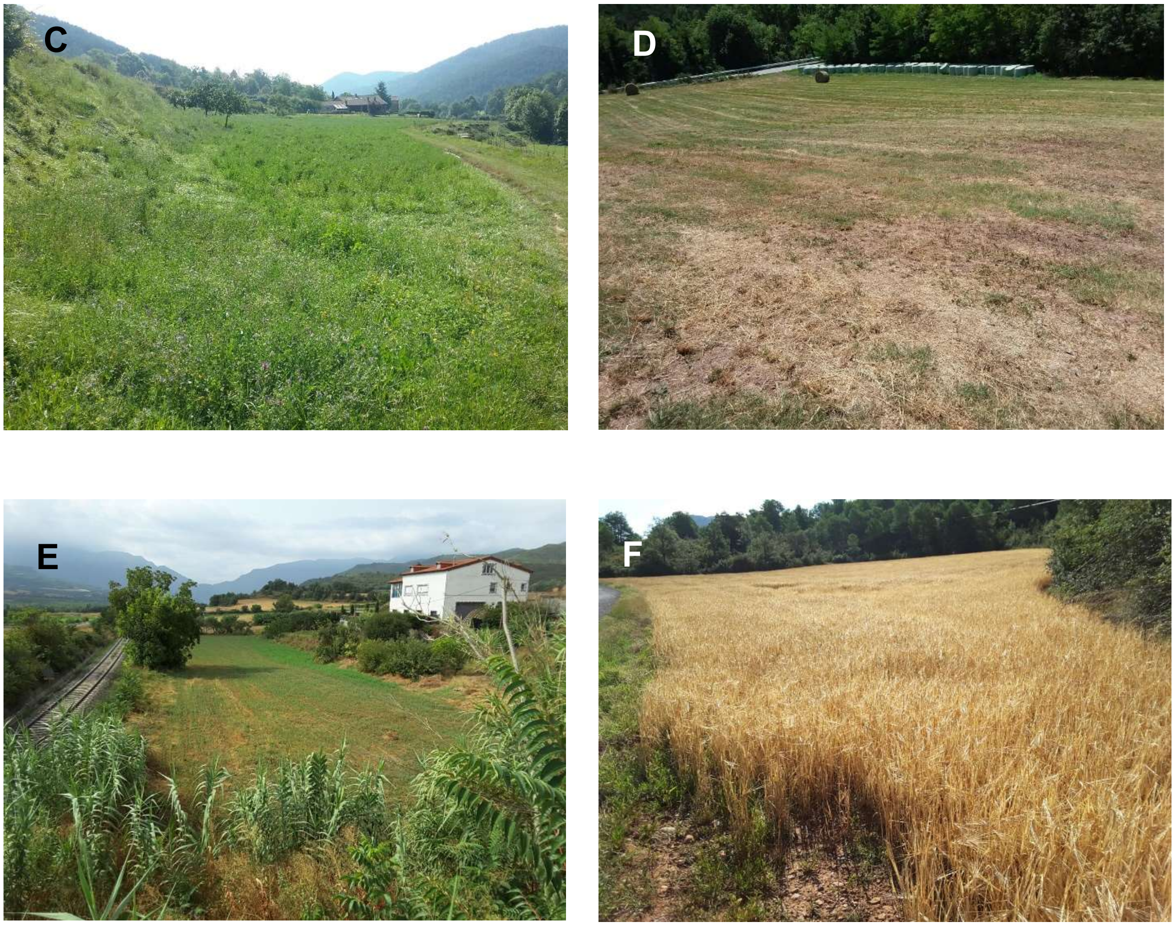


Figure 6. Examples of correctly captured overview photos (photos A to F: Courtesy of the Catalonian Paying Agency, Spain)

Figure 7. Examples of overview photos not following the guidelines: A) irrelevant objects in the picture frame, no landscape features visible; B) irrelevant objects (dashboard) in the picture frame, object not centred, camera pointing too high; C) camera pointing too high; D) obstructed view, dirty/wet lens, camera pointing too high; E) camera pointing too low, no landscape features in the photo frame; F) poor visibility, no landscape features in the photo frame. (Photos A, E, F: Courtesy of the Catalonian Paying agency, Spain; Photos B, C, D: Courtesy of the Belgian-Flemish Paying Agency)

8.1.2 “Macro” photos

Due to the fact that overview photos should by nature include a lot of information (mixed landscape), it will be rather challenging to handle them in an automatic way. Therefore capturing a “macro” photo is advised shortly after (and thus from a nearby position of) each overview image, and with an approximately similar camera heading. Such photo must serve to enable the robust identification of the element to evidence. This subject could be a mixture of crop as Ecological focus area (EFA) cover, presence of rare crops that cannot be reliably discriminated in the Sentinel data etc. Depending on the characteristics of the plants/objects or/and their development stage it might be advised to take a photo with camera pointing downwards or horizontally. Depending on the type and robustness of the foreseen automatic image analysis method (see also section 9), further recommendations could be provided, such as to ban different crops and other objects within the frame or as to take a photo at a certain scale. The latter recommendation is not a straightforward one, considering the variety of smartphone models in use with different sensors and lenses. Rather than expressing the scale as a number or a distance to the crop/object, indications on how to fill in the photo frame with the photographed object could be given, e.g. that the entire plant/object height need to fit into a photo (e.g. in the landscape orientation), the object should be centred in the photo etc.

The **Figure 8** and **Figure 9** provide illustrations of good and bad “macro pictures”.

Figure 8. Examples of correctly captured macro photos (Photos A, C, E: Courtesy of the Catalonian Paying Agency, Spain; Photos: B, D, F: Courtesy of the Bulgarian Paying Agency).

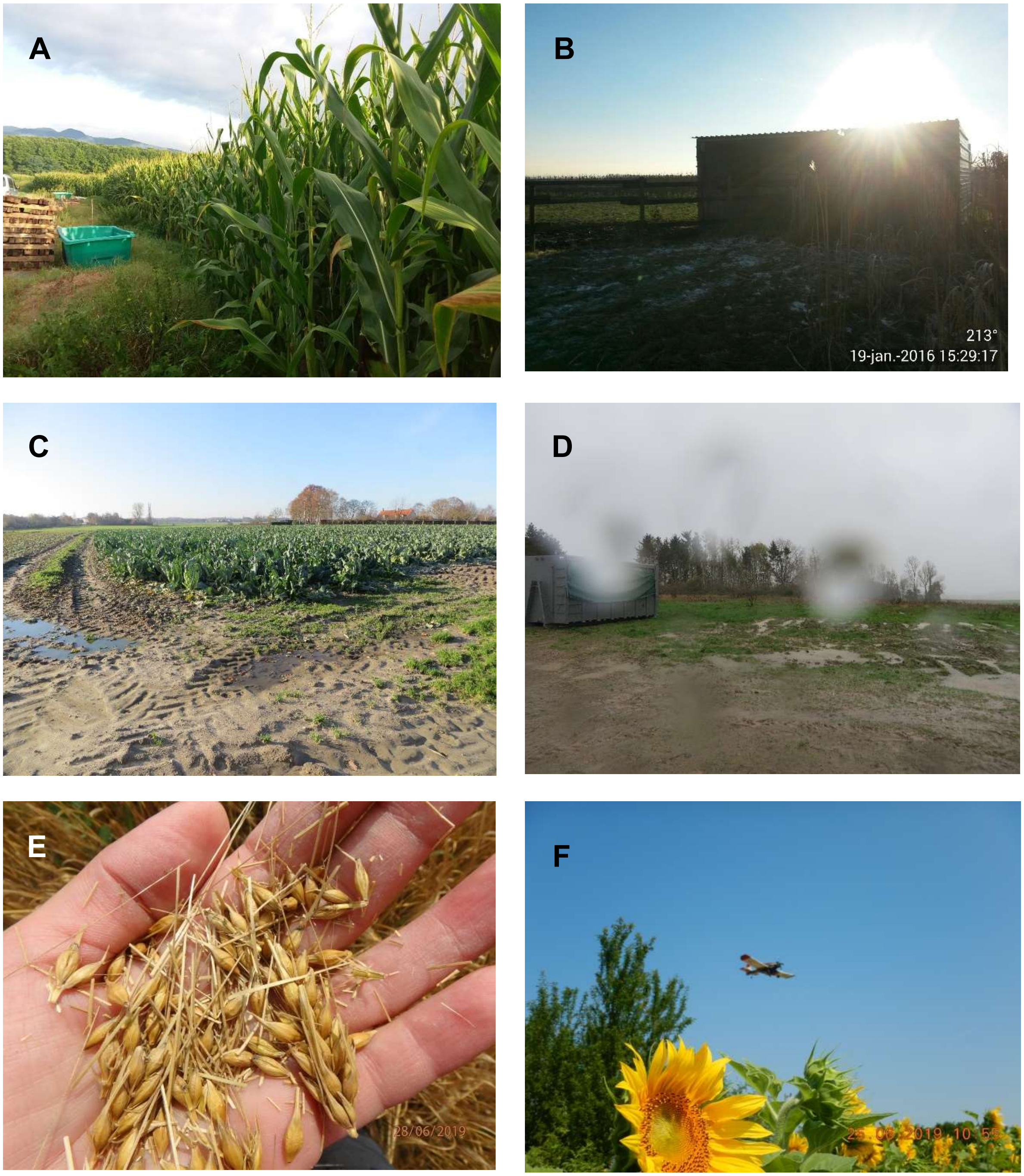


Figure 9. Examples of macro photos not following the guidelines: A) object not centred; B) photo taken towards the Sun resulting in low contrast; C) Photo taken from too long distance; D) wet lens decreases the image quality, too long distance to the object; E) irrelevant objects in the image frame (hand); F) irrelevant objects in the image frame, camera pointing too high. (Photo A: Courtesy of the Catalonian Paying Agency; Photos B, C, D: Courtesy the Belgian-Flemish Paying Agency; Photos E, F: Courtesy of the Bulgarian Paying Agency).

8.2 Choice of the viewpoint and the number of images

When requesting geotagged photos from the farmer, the intension is to obtain sufficient information in order to avoid any physical field visit. Therefore, the collected images should provide an overview of the parcel, but not necessarily cover its entirety and all details. The total number of photos should depend on the land cover/ activity or object type that need to be depicted. Nevertheless, in order to assure comprehensive view on the element and to limit the possibility of image manipulation, for the overview photos it is recommended to provide at least 2 photos of the element captured from different viewpoints or camera heading.

Depending on the purpose of the photo, more or less strict specifications of the photo viewpoint can be provided. In cases when there is an inconsistency in the farmer's declaration in the GSAA and the corresponding analyses of the Sentinel data, the farmer may be directed to the exact viewpoint and be requested to take a photo with a specific camera heading to ensure that the problematic area is depicted in the photos. With the viewpoint and the camera heading pre-set, advices on the optimal time of the day can be provided in order to avoid photos taken towards the sun and thus most probably of insufficient quality.

When leaving the choice of the photo viewpoint to the farmer, general instructions should be provided to optimise the result, e.g. to ensure good visibility into the parcel, landscape features on the horizon, adjust the height of the viewpoint to the land cover height etc.

9 Automated image processing

When provision of geotagged photos will start to be implemented habitually by farmers, administrations will rapidly have to handle and process a very substantial amount of photos. It will thus not be possible to visually check all of them. Automatic screening of photos will then become essential.

With the recent advances in computer vision and machine learning techniques, image content recognition has become a realistic solution, not only to confirm/contradict alleged crop types/activities depicted in the photo but also to filter out of photographs objects that are not of interest for the requested element(s) to evidence.

Over the last few years computer vision domain has been dominated by deep learning (Rawat & Wang, 2017) which seems to be the most successful method for image content recognition (Kamilaris & Prenafeta-Boldú, 2018). Image recognition is the process of identifying what an image depicts. That usually is a straight forward task to humans, but for computers that “see” photos as a matrix of numbers, such task is challenging. Deep learning involves complex data processing and modelling, with the feature extraction performed automatically and represented in a hierarchical way to mimic a human’s brain. It processes data hierarchically in separate neuron layers. Deep learning algorithms involve components such as e.g. convolutions, pooling layers, fully connected layers, encoders/decoders or activation functions. Numerous convolutions are performed at selected layers of the network, altering the representations of the learning dataset and thus serving as feature extractors while the pooling layers reduce the data size. They could be seen as filters transforming the input data into another image, highlighting specific image patterns (Kamilaris & Prenafeta-Boldú, 2018), similarly to how the human brain layers perceive visual information, the first convolutional layers extract low-level features, such as edges and blobs, and the later transformations assess the semantic part to the image.

Compared to other classification methods, such approach to learning features makes the convolutional neural network more robust against changes in illumination, shadows or occluded objects. Because the deep convolutional neural networks find characteristic image features autonomously, less effort is required to process new objects (no need to design feature descriptors). On the other hand, a large amount of training data is required to make the learning process efficient (Ferentinos, 2018).

The learning process for a specific classification task can be facilitated and the required training set size minimized by using transfer learning (Hussain, Bird, & Faria, 2018), a method originating in machine learning, in which a model is trained and developed for one task and is later re-used on a different task. In practice a pre-trained (trained on a large dataset (millions of images)) model can be used, to solve a problem similar to the one that that should be addressed.

Another interesting method for automated processing of photos is visual object detection that aims to find objects of target classes with precise localization in a given image and assign each object instance a corresponding class label (X. Wu, Sahoo, & Hoi, 2019). Following the remarkable successes of deep learning based image classification, object detection techniques have been advancing very quickly in recent years, but still are more complex and demanding in requirements of the input data and parameters tuning. A comprehensive review of the recent methods can be found in (X. Wu et al., 2019).

9.1 Tools, libraries, platforms

Numerous commercial solutions for automated photo classification exist, comprising online platforms for customable/trainable machine learning image content recognition and cloud storage or APIs offering pre-trained machine learning models that can be re-trained and integrated with the in-house development framework.

As an alternative, various successful and popular pre-trained network architectures exist that could be reused in any in-house developments (Canziani, Paszke, & Culurciello, 2016), e.g. Mobilenet (Howard et al., 2017) AlexNet (Krizhevsky, Sutskever, & Hinton, 2017), VGG (Simonyan & Zisserman, 2015) or Inception-ResNet (Szegedy, Vanhoucke, Ioffe, Shlens, & Wojna, 2016) and other.

Among the most popular frameworks enabling usage of deep learning are: Keras, PyTorch, TensorFlow, Theano, Caffe, TFLearn, Pylearn2 and the Deep Learning Matlab Toolbox (see section 11 for information).

Regardless of the choice of tools or platforms, careful and considered planning for collection of the training images is always required.

9.2 Training images

The effectiveness and reliability of a trained model is depending on the quality of its training dataset (Boulent, Foucher, Théau, & St-Charles, 2019). To ensure high model performance (and thus generalization) training data of sufficient diversity needs to be provided. The training dataset has to reflect the reality of the operational environment of the tool (Jayme G.A. Barbedo, 2018), e.g. training images for an automatic crop type classification should depict the entire plant (if possible) rather than just a single leaf or fruit, although that could be sufficient for other applications like disease recognition. The difficulty level of distinguishing between different crop types is linked with their phenological development stage. Plants do not only change their leaf shape and proportions but also the entire plant appearance and colour is changing throughout the season. Therefore two species looking alike at certain point in time and challenging to distinguish for non-experts, might develop features at a later point in their development cycle that allow for eased separation. This fact should be taken into account not only when planning the collection of photos for the training sample, but also when requesting photos from farmers or providing guidelines on how to collect images.

In order to increase robustness of the classification algorithms, training data collection should be carried out at different times of the season (to cover all development stages of the plant, if necessary), of the day (changing illumination), in varying meteorological conditions and with different cameras (lenses) (Boulent et al., 2019). The variety of maintenance practices should also be covered, if these influence the appearance of the plants in images. It is, for instance strongly advised to collect photos of abandoned crops or plants in bad conditions (e.g. after a drought or flooding). As a matter of fact, often geotagged photos will be asked when automatic processing of satellite data will not be conclusive (the so-called yellow cases). Like in the current OTSC method, most of doubtful parcels in CAPI (Computer Assisted Photo Interpretation) leading to need for RFV, correspond to ‘anomalous’ field conditions (due to bad maintenance, problem of crop development …).

Machine learning methods may be affected by the image “background”, especially in complex environments, containing, in addition to the main object/crop, other plants or bare soil (Jayme Garcia Arnal Barbedo, 2016). Nevertheless, the background elements may be linked with the characteristics of certain crops. The models achieve better performance when trained with field images and asked to identify images captured in laboratory conditions (success rates up to almost 68% in Ferentinos, 2018). By contrast, models trained solely with laboratory conditions images performed with a success rate of only 33% in classification of field images. This proves that also for the machine learning classification of images depicting actual cultivation conditions is a challenging and complex task. It requires a large number of training images to ensure the variety of conditions expected in the images provided by the farmers.

The number of images in all classification classes should be balanced. The number of required images depends on the tools and models used as well on the classification class complexity and separability. For the purpose of crop/activity recognition it is advised to use at least several hundreds of photos per class. In order to increase the number of training images artificially and to avoid model overfitting, data augmentation techniques can be applied such as: rotations, image cropping, scaling, mirroring or perspective transformation (Kamilaris & Prenafeta-Boldú, 2018).

On the top of the large image database, machine learning algorithms require also correct image labelling. Although neural networks are robust enough to absorb small number of annotation errors without losing reliability (Bekker & Goldberger, 2016), if many image labels are unreliable, the training process will not be adequate (Boulent, Foucher, Théau, & St-Charles, 2019). Thus it is advised to have experts like agronomists involved at some point of the training dataset collection. This involvement could be considered at the time of the data collection in the field, or at a later stage, in the final screening of already labelled photos.

On the top of the images collected by the inspectors during the on-the-spot-checks to support findings in the inspection report or other purposes and images provided by the farmers, other databases of images might be found useful as training sets, e.g. the images collected during the numerous LUCAS surveys (ESTAT, 2019).

9.3 Achievable results

The overall accuracy achieved in the validation of the deep learning process reported in the literature for tests performed on photos of crops or plants are usually at the level of 70% - 99% (Dyrmann, Karstoft, & Midtiby, 2016; Iordanov et al., 2019; Kamilaris & Prenafeta-Boldú, 2018; Yalcin & Razavi, 2016) and thus very encouraging. Nonetheless, results obtained for certain classes can be as low as 30% (Dyrmann et al., 2016) so the results should be analysed carefully and in-depth, taking into account the objective of the automated data processing. The range of results reported in the literature is so wide in part due to the fact that it is very challenging to assess the generalising ability of the trained model. Results reported for training/validation either on the same dataset (e.g. by dividing the dataset into training and testing/validation sets) or with different datasets may differ significantly. This aspect is especially relevant for the classification of images provided by farmers, using a tool trained on images collected by the inspectors (for purposes other than the one of the farmers).

The result of the automatic photo classification is usually a list of probabilities of an image belonging to several different classes. The result can be further improved by cross-checks with the metadata provided together with the photo. For example: an image submitted as evidence for cultivation of crop A for which the automatic classification tool assigned the class A only as second highest probability score (so classified as another crop type) could still be accepted as evidence for A if the probability rate of class A for this photo is high enough. Such probability threshold is to be decided through tests performed on the final classification models, trained with the final training sets.

The performance of classification can be also improved if the image captured is pre channelled in the classification tool. For instance, in the PlantNet app, when a photo is uploaded, the operator indicates if the picture corresponds to either a flower, a leaf, a fruit, the bark or the entire plant. Classifications are thus ‘eased’ by comparing the considered picture with targeted photo banks.

The performance of the automated method should be quality checked implementing a system of false positive and false negative classification errors.

10 Conclusions

The European Commission has adopted new rules that allow a range of modern technologies to be used when carrying out checks for area-based CAP payments. This includes the possibility to use geotagged photos to support and complement checks methods. There is no doubt that this move would be very beneficial. Geotagged imagery offers possibilities to evidence an unlimited range of situations of land use and land cover. It also spans from scenery view up to detailed macro image.

An arsenal of beneficial background technologies is already available (camera/smartphone with GNSS antenna, apps capturing geotagged photos, plant recognition apps, automatic image recognition …).

The next step is the development of tools adapted to the CAP checks situations, starting from an intuitive app available to farmers to the compilation of dedicated photo collections. Some MS administrations have started to do one or both. The sharing of experience and good practices is an asset to facilitate these developments. Such sharing is the main purpose of this report.

As described in the report many, of the underpinned technologies and tools, are developing very fast and any guidance will have to be updated accordingly.

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Tensorflow https://www.tensorflow.org/

Tflearn: http://tflearn.org/

Theano: https://en.wikipedia.org/wiki/Theano_(software)

List of abbreviations and definitions

CAP: Common Agriculture Policy

CAPI: Computer Assisted Photo Interpretation

CbM: Checks by Monitoring

CTS: Common Technical Specifications

EFA: Ecological Focus Area

GSA: European GNSS Agency

GSAA: Geo Spatial Aid Application

GNSS: Global Navigation Satellite System (This term includes the GPS, GLONASS, Galileo, Beidou and other regional systems)

HAS: High Accuracy Service

IACS: Integrated Administration and Control System

LBS: Location-Based computing and Services

LPIS: Land Parcel Identification System

MAR: Mobile Augmented Reality

MS: Member State

OS-NMA: Open Service Navigation Message Authentication

OTSC: On The Spot Checks

RFV: Rapid Field Visit

RTK: Real Time Kinematic

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