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Multi-Scale Remote Sensing to Support Insurance Policies in Agriculture: from Mid-Term to Instantaneous Deductions

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Abstract

Climate change is today one of the biggest issues for farmers. The increasing number of natural disasters and change of seasonal trends is making insurance companies more interested in new technologies that can somehow support them in quantifying and mapping risks. Remotely sensed data, with special focus on free ones, can certainly provide the most of information they need, making possible to better calibrate insurance fees in space and time. In this work, a prototype of service based on free remotely sensed data is proposed with the aim of supporting insurance companies' strategies. The service is thought to calibrate annual insurance rates, longing for their reduction at such level that new customers could be attracted. The study moves from the entire Piemonte region (NW Italy), to specifically focus onto the Cuneo province (Southern Piemonte), that is mainly devoted to agriculture. MODIS MOD13Q1-v6 and Sentinel-2 L2A image time series were jointly used. NDVI maps from MODIS data were useful to describe the midterm phenological trends of main crops at regional level in the period 2000-2018; differently, Sentinel-2 data permitted to map local crop differences at field level in 2016 and 2017 years. With reference to MODIS data, the average phenological behaviour of main crop classes in the area, obtained from the CORINE Land Cover map Level 3, was considered using a time series decomposition approach. Trend analyses showed that the most of crop classes alternated three phases (about 7 years) suggesting that, presently, this is probably the time horizon to be considered to tune mid-term algorithms for risk estimates in the agricultural context. Crop classes trends were consequently split into 3 phases and each of them modelled by a 1st order polynomial function used to update correspondent insurance risk rate. Sentinel-2 data were used to map phenological anomalies at field level for the 2016 and 2017 growing seasons; shifts from class average behaviour were considered to locally and temporarily tune insurance premium around its average trend as described at the previous step. Synthesizing, one can say that this approach, integrating MODIS and Sentnel-2 data, makes possible to locally and temporarily calibrate premiums of indexed insurance policies by describing the average trends of crop performance (NDVI) at regional level by MODIS data and refining it at field and specific crop level by Sentinel-2 data.

Introduction

Climate change is today one of the biggest issues for farmers. Every year natural disasters hit the agricultural business with cost of billions of dollars. Drought is the most significant threat, followed by floods, forest fires, storms, pests, pathogens, and others. The

United Nations Food and Agriculture Organization (FAO) (Conforti, Ahmed, and Markova 2018) claims that between 2005 and 2015, natural disasters brought $ 96 billion of costs in damaged or lost crops to the agricultural sectors of developing countries. Drought, which affected farmers in all over the world, was one of the main culprits. 29 billion dollars are the economic losses documented by FAO caused by drought (Baas, Trujillo, and Lombardi 2015; FAO 2007).

Drought is also one of the most complex climatic phenomena among those affecting the society and the environment (Wilhite 1993; Wilhite 2012). In Europe it is a recurring event that does not hits the Mediterranean region only, but also occur in areas with high rainfall and in any season (Estrela, Peñarrocha, and Millán 2000). The drought has been the most serious climate risk of the twentieth century, responsible for the loss of billions of US dollars (White 1994). It represents an extreme climate event, which varies in severity and duration on all continents, causing critical damage to the natural environment and human lives (Min et al. 2003; Modarres 2007). The future ecosystem changes and impacts on plants have been extensively analyzed (Easterling et al. 2000; Meir and Grace 2006). However, documented evidence of the effects of climate change on crop production has only recently been provided (Lobell and Asner 2003; Chmielewski, Müller, and Bruns 2004, Tao et al. 2006; Zhang et al. 2019; Grillakis 2019).

During the last century large areas of Europe have been affected by this phenomenon. The severe and prolonged periods of drought have highlighted the vulnerability of our continent to this natural risk, evidencing to the public, governments and operating agencies various socio-economic problems that accompany water scarcity and the need for measures to mitigate their effects.

In relation to vegetation activity and crop productivity, Potop (2011) compared several indices to evaluate its impact on maize crops in Moldova. Mavromatis (2007) and Quiring and Papakryiakou (2003) similarly tried to quantify respectively its effects on wheat production in Greece and Canadian prairies. Results from different studies differ each other, depending on the drought index used to detect impacts. Consequently, a high uncertainty still persists among scientists, managers and end users while selecting the proper index for analysis. The amount of proposed indices and indicators for agricultural drought, or other natural disasters, detection makes the decision-making process complicated. This complexity may cause delayed, uncompleted or unwanted answers. These situations determine negative economic consequences and generate loss of confidence in authorities that are responsible for mitigation actions.

Real time drought monitoring based on few field data is a challenge for ecosystem management and conservation. The most of methods require extensive data collection and in-situ calibration and accuracy may be difficult to be quantified. The imbalance between potential evaporation and the amount of precipitation during the growing season usually causes drought conditions that can pose a threat to both the environment and human activities. Thus, it is necessary to collect frequent information about drought severity and its spatial and temporal distribution for mitigating its effects. Many studies have already explained the important role of remote sensing in agriculture (Colwell et al. 1970; Bastiaanssen, Molden and Makin 2000; Steven and Clark 2013; Atzberger 2013; Sahoo, Ray and Manjunath 2015; Shanmugapriya et al. 2019; Weiss, Jacob and Duveiller 2020), others begun the experimentation of monitoring catastrophic events using satellite data (Silleos, Perakis and Petsanis 2002; Sandholt et al. 2003; Sanyal and Lu 2004; Rhee, Im and Carbone 2010; Rojas, Vrieling and Rembold 2011) and, more specifically, spectral indexes such as the EVI (Enhanced Vegetation Index), SAVI (Soil-Adjusted Vegetation Index), NDVI (Normalized Difference Vegetation Index) and others more (Zhang et al. 2005; Beeri and Peled 2006; Chen et al. 2006; Son et al. 2014; Sánchez et al. 2018; Lu, Carbone, and Gao 2019; Nanzad et al. 2019). For this work, NDVI was selected as reference spectral index to base crop performance monitoring on. In spite of some well-known limits (e.g. saturation in highly vegetated areas), NDVI is certainly the most famous and used vegetation index for biomass and crop productivity estimation; moreover, many EO (Earth Observation) data suppliers make available ready-to-use maps of NDVI as free and immediately downloadable products (e.g. MODIS derived MOD13Q1 product from USGS). These can be easily structured within long time series stacks that ensure homogeneity of pre-processing, i.e. a higher comparability of values and reliability of deductions. Standardization, convenience and ease of use of data are extremely important factors for those users, like insurance companies, that are not familiar with this type of technology.

Free satellite data from National Aeronautics and Space Administration (NASA) TERRA and European Space Agency (ESA) Sentinel 2 (S2) missions were used to describe agriculture crops growing steps and to protect and facilitate all the parts involved. Optical data proved to be effective in describing vegetation development. In particular, free optical data like Moderate Resolution Imaging Spectroradiometer (MODIS) and S2 ones is extremely important and strategic in a low-income economical sector like the agricultural one since further additive costs deriving from monitoring services could compromise competitiveness of the entire sector (Borgogno and Gajetti 2017). Information obtained from free monitoring services may represent a helpful tool for farmers, making them able to improve ordinary management strategies and move to a higher environmental sustainability of agriculture. As Islam et al., (2017) affirms that the implementation of knowledge about the development and phenology of crops into the classification process introduces further possibilities for improving crop monitoring.

All this said, is worth to remind that Italy was one of the first countries to tackle the issue of risk management in agriculture, introducing, with the National Solidarity Fund

(FSN), the principle of solidarity for those companies suffering from damage caused by natural disasters. FSN involves compensatory interventions when a damage occurs by adverse events. Ground controls and delimitation of affected areas are mandatory. Envisaged measures mainly consist of contribution to agricultural companies that suffered from a yield loss higher than the 35% out of the total (Borriello 2003). Active defense has the purpose of safeguarding crop production, preventing or neutralizing the negative effects of calamitous events through technological devices, such as anti-freeze fans and exploding rockets, to dissolve hailstorms. Differently, facilitated insurance policies focus on risk prevention. The State intervenes with a contribution partially covering insurance fees paid by the farmer. The Minister for Agricultural Policies with the 28405/17 decree extend insurance coverage even further with subsidized policies (indexed insurance policies) against damage from adverse weather conditions to crops, but also for damage to structures or livestock. The decree indicates in Annex 1 the crops, the company structures and the types of insurable cattle. Crops such as corn, wheat and lawn are included in this list. The new policies offer insurance packages that are not available on the market. They are intended to encourage Italian farmers to insure themselves to overcome climate risks.

In France, the policy against new climate risks is the one that has grown most in recent years, reaching a coverage of 30% of the surface area (Chenet 2019). Globally, the agricultural insurance market is concentrated in high-income agricultural countries, with the US alone accounting for 38% of premiums. In Italy, against the atmospheric phenomena that threaten crops, few choose to protect the territory. Climate change is slowly persuading Italian farmers to increase the use of policies against atmospheric risks, albeit with large differences in areas and crops. The first case came two years ago, in the horrible 2017, devastated by frost and drought, which has increased the compensation paid by farms. The presence of extreme weather events has become the norm and, according to Coldiretti (the largest association representing and assisting Italian agriculture), has weighed Italian agriculture more than 14 billion in a decade between production losses and damage to structures and infrastructure in the countryside (Hay 2019; Severini, Biagini, and Finger 2019). In Italy, only 78,000 companies are insured, 9% of the total, representing 8.3% of the national agricultural area and 18.7% of production. There is a deep gap between the areas of Central-Northern Italy and Southern Italy, which still represents, according to the latest Ismea report, only 12% of farms insured at national level (De Ruvo et al. 2019). The farmer is still interested in the small damage, when more and more often an extended catastrophe risks destroy entire farms.

This paper focuses on the so called *indexed* (experimental) insurance policies, trying to calibrate an insurance risk model relaying on time series of spectral indexes map (e.g. NDVI) from remotely sensed data.

Material and methods

Study area

The study area is located in Piemonte, North-West Italy (fig. 1). It sizes about 25388 km^2 and well represents a typical agricultural context of northern Italy. Climate is temperate with a continental character, where North-Western Alps cause a gradual reduction of temperature while altitude increases. Yearly average rainfall gauge is 930 mm and yearly average temperature is 11.9 °C. Thermal inversion phenomena caused by cold air can often affect the area.

[FIGURE 1]

The focus area is located within the Cuneo province including the following municipalities: Cuneo, Fossano, Castelletto Stura, Margarita, Trinità, Sant'Albano Stura, Centallo, Montanera, Rocca de Baldi and Morozzo (fig. 1). The soil is locally characterized by a high permeability and a good availability of oxygen due to the texture, rich in sands (averagely > 50%) and to the skeleton, poor in clay. Soil depth for root development is low due to the high presence of gravel. This work was focused on the following crop classes: wheat, corn, meadow, ryegrass, that represent about 48% of the total area (table 1).

[TABLE 1]

Available data

The following data were used to test the proposed procedure: a) satellite multispectral images from NASA TERRA MODIS and Copernicus S2 Multi Spectral Instrument (MSI) sensors; b) 2012 CORINE Land Cover Map; c) a vector cadaster map; d) a vector administrative boundaries map; e) farmers' applications for EU incentives within CAP.

Satellite data

In this work satellite data were intended to respond to two main tasks in the context of insurance for crops. The first one was to look at mid-term trends of crop performances at regional level, requiring elongated image time series able to describe the average behavior of macro-classes of crop types. For this purpose, low resolution satellite data from MODIS sensor, operating on board of the TERRA satellite mission since 2000, were considered.

To opportunely tune crop performances around their average trend at year level and mapping intra-classes differences at field level, a higher geometric resolution was retained more appropriate to fit the local average size of fields. For this task, data from the Copernicus Sentinel 2 mission were adopted.

With reference to MODIS data, the MOD13Q1-v6 product from Land Processes Distributed Active Archive Center (LPDAAC) collection of NASA (Solano et al., 2010) was used to generate a 432 images time series (hereinafter called TS) of NDVI (Rouse et al. 1974) covering the period 2000 - 2018. Data were obtained from the AppEEARS system (Didan 2015), georeferenced in the WGS84 geographic reference frame and supplied in Tagged Image File (TIF) format. The MOD13Q1-v6 data are 16 days timely-spaced and have a spatial resolution of 250 m. The MOD13Q1-v6 product is composed of all the best available local observations (at pixel level) out of those available in the considered 16 days period. Selection criteria take into account cloud cover (lower), viewing angles (lower) and NDVI local value (maximum in the reference period). A pixel reliability layer (PR) is also available from the MOD13Q1-v6 mapping the following codes: -1 = No Data, 0 = Good Data, 1 = Marginal data, 2 = Snow/Ice, 3 = Cloudy.

With reference to the Sentinel 2 mission, 31 Sentinel 2 Level-2A data were obtained from the Theia system (theia.cnes.fr). They were obtained as 100 x 100 km^2 tiles orthoprojected into the WGS84 UTM 32N reference frame (Sentinel-2 User Handbook; 2015). Level-2A products were supplied already calibrated in "at-the-Bottom of the Atmosphere" reflectance (BOA), guaranteeing immediate usability for land applications. Table 2 shows the main technical specifications of both MODIS and S2 MSI (Multi Spectral Instrument) sensors.

[TABLE 2]

Auxiliary data

The 2012 CORINE Land Cover dataset level 3 (hereinafter CLC2012) was used to map cultivated areas over Piemonte. CLC2012 was obtained, for free, from the Land Monitoring Service Copernicus. Technical features of CLC2012 are reported in table 3. According to the CLC2012 nomenclature, the level 3 is the most detailed level in the hierarchical classification system adopted by CORINE Land Cover project. This level maps homogeneous landscape patterns having more than 75% of the characteristics of a given class according to the nomenclature rules (Büttner 2014). With reference to agricultural classes, table 4 reports the list of the agricultural classes as coded in CLC2012 Level 3 that were considered for this work.

[TABLE 3]

[TABLE 4]

Farmers' declaration for European incentives of the years 2016 - 2017, was used to find and locate the cultivated crops in the study area. Farmers apply every year to receive EU contributions supporting their activity. A database containing farmers' applications is currently made available by the Piemonte Region institutional website (Sistema Piemonte) and can be downloaded at municipal level (MO Excel format).

A vector format cadastral map (2018 updated, nominal scale 1:2000), mapping parcels in the study area, was used to geolocate farmers' applications. This made possible to generate an official administratively-based map of existing crops in the area. Cadastral map was obtained by the Piemonte Region Geoportal already georeferenced in the WGS84 / UTM zone 32N reference frame.

A vector map of administrative boundaries (2019 updated, scale 1:100000) was also obtained from the Piemonte Region Geoportal.

NDVI Time Series Generation

NDVI is well known to be a spectral index useful for retrieving vegetation canopy biophysical properties (Leprieur, Verstraetel and Pinty 1994; Jonsson and Eklundh 2002). According to some recent studies it could also be used for supporting remotely sensed-based crop insurance models (Jensen et al. 2019; Sarvia, De Petris, and Borgogno 2019) being a good predictor of crop yield (Haghverdi, Washington-Allen, and Leib 2018; Zambrano et al. 2018). Although many other indices from remotely sensed data are suggested in literature for vegetation monitoring, as we have specified in the introduction, we decided to focus on NDVI according the following criteria: a) the study area (Piemonte Region) highly suffers from haze (both natural and anthropic) for many months along the growing season. Consequently, spectral indices able to minimize these effects are mostly desirable. It can be mathematically proved that indices defined in term of ratios (or ratios of differences), with no additive terms (often empirical), are the most promising ones being able to minimize this effect, whose consequence, in data interpretation, is especially high when working with index time series. Consequently, attention was addressed to these types of vegetation indices (slope based like NDVI, NDRE, NDWI, etc.), driving to exclude other ones like EVI, PVI, SAVI, MSAVI, EVI. With these premises and with reference to the TERRA MODIS MOD13Q1 product used in this work (only containing NDVI and EVI grids) to describe vegetation trends in the mid-term period, NDVI was the best candidate. Moreover, NDVI permits an easier integration with data from UAVs (Unmanned Aerial Vehicles) and UGV (Unmanned Ground Vehicles) that, ordinarily, are equipped with low cost multispectral sensors that, minimally, can record red and NIR bands needed to derive the correspondent NDVI map. This issue, presently, cannot be neglected given the ongoing improvement and spreading of remote sensing based precision farming techniques (Borgogno and Gajetti 2017).

With reference to the MOD13Q1-v6 product, a regularly timely spaced MODIS NDVI TS (about 23 images/year, one image every 16 days) can be easily obtained. Consequently, a NDVI TS of 432 maps (hereinafter called MOD_TS) was generated exploring the period 2000–2018.

As far as S2 data are concerned two annual NDVI TS were generated for the 2016 and 2017 agronomic seasons for a total of 31 “good” images (a filter was applied to exclude images showing in the study area a percentage of cloud cover > 20%). S2 band 8 (wide band NIR) and band 4 (Red band) were used for NDVI computation. S2 native NDVI TS was pre-processed removing “bad” observations from the local NDVI temporal profile of each pixel and densifying the TS 5 days regularly spaced one. Both the operations were achieved contemporarily by a self-developed IDL (Interactive Data Language) routine. Filtering was operated by exclusion with reference to the quality layer supplied with the BOA S2 product. S2 TS densification/regularization was obtained by spline interpolation with tensor (value = 10) applied at pixel level. Finally, the new pre-processed S2 TS was made of 146 NDVI maps

5 days regularly spaced (hereinafter called S2_TS). S2_TS was split in two stacks, singularly representing the two considered years (2016 and 2017). Splitting was operated according to the so called "agronomic year", i.e. the period ranging from November to November of two consequent years (starting on 11^{th} November).

Analyzing Crops Performance

Assuming insurance risk associated with the expected performance of crops, a simplified procedure for updating risk estimates based on NDVI TS from both low (MODIS) and high (S2) resolution satellite imagery was developed, with reference to the two above mentioned levels of investigation: trend and tuning.

Trend analysis was based on MOD_TS and it was operated at crop (macro-) class level, improving the method previously proposed by Borgogno, Sarvia and Gomarasca (2019). Consequently, according to the considered CLC2012 crop classes (table 4) the average NDVI temporal profile was computed for each class by ordinary zonal statistics available in QGIS 3.10. The obtained sixteen days-spaced mean class temporal profiles were then aggregated at year level by computing the yearly 95th percentile. New profiles (hereinafter called PR95Y) containing one value per year (2000-2018) were obtained and analyzed by time decomposition with the aim of extracting the dominant trends (low frequency variations) underlying the entire profile. The adoption of 95th percentile as reference proxy of crop performance was aimed at limiting the effects of outliers, that could wrongly condition deductions if different choices, like mean or maximum values, were considered. PR95Y were analyzed by time series decomposition. Therefore, the main components, i.e. trend, seasonal, residuals were extracted (Verbesselt et al. 2010). In particular, trend component was calculated from PR95Y by LOESS (Locally Estimated Scatterplot Smoothing) filtering with span=0.5 (Cleveland 1979) and a first order polynomial approximation. Seasonal component was modelled by Fast Fourier Transform filtering (FFT)

(Testa et al. 2018) applied to the previously de-trended data. Main (low) frequency components were finally removed from de-trended data to obtain residuals. Trend analyses graphically showed that the most of crop classes (excluded vineyards-221 and mixed natural/cultivated areas-243) alternated three different behaviors (phases) in the considered period, each lasting about 7 years. This time span suggests that, presently and probably, mid-term algorithms for risk estimates in the agricultural context must be tuned with a time horizon of 7 years. With special focus on CLC2012 class 211, corresponding to “not-irrigated arable land”, and including the most important (from an economical point of view) crops in the area, a numerical analysis was done to verify what graphs showed. Analysis was based on a 1st derivative approach, aimed at finding the time of PR95Y maxima and minima occurrences. It confirmed that one minimum took place in 2007 and two maxima in 2000 and 2014, respectively.

PR95Y crop classes were consequently split into 3 phases and each of them modelled by a 1st order polynomial that proved to well fit observations (see table 6 in Result and Discussion section). Each model, has to be interpreted as the basis to operate risk estimation in the considered period, with the hypothesis that higher the NDVI, lower the associated risk for yield reduction.

Significance of changes occurred along the modelled trends was tested by comparing theoretical accuracy of NDVI measures (0.02, Borgogno, Lessio, and Gomarasca 2016) with NDVI differences recorded between the start and the end of the considered phase (table 6 in Results Section).

It was found that exactly class 211, showed the most significant NDVI total variation within all the recognized behavioral phases. Consequently, successive analysis aimed at locally and yearly tuning the model was focused only on class 211.

Modelled trends of PR95Y were translated into the correspondent (possible) insurance meaning by defining the following risk rate correction factor (hereinafter called "discount", *d(t)*):

$$d(t) = \left(\frac{\gamma+\delta}{\gamma \cdot t+\delta}\right) \cdot 100 \qquad (1)$$

where γ (gain) and δ (offset) are the trend line coefficients (estimated by ordinary least square OLS); *t* is the counter of the years passed from the first one (basis year) involved in the considered phase.

If *d(l)* > 100 (NDVI value at the *l* year < NDVI value at the 1st year) the insurance premium should be proportionally increased in respect of the basis year; if instead the value of *d(l)* < 100 the insurance premium should be proportionally decreased in respect of the basis year.

As far as the S2 data are concerned, they were used to spatially and yearly tune average class trends modelled with respect to MODIS data. The obtained (macro-) class discount rate was then refined considering the local conditions where a crop field is located in. Firstly, the 211 CLC2012 class was decomposed, where possible, into the main crops that reasonably could be aggregated in the same CLC codification: wheat, corn, ryegrass and meadow. Class 211 disaggregation was achieved georeferenced farmers' declarations (containing crop type description) for CAP purposes by joining the available cadastral parcels map with the correspondent tabular data. The proposed procedure is based on local NDVI anomaly computation (eq.2), defined as the ratio between the local (averaged at field level) 95th percentile of the NDVI annual profile and the one averaged over the whole considered class (wheat, corn, ryegrass and meadow).

$$z_i(x, y, t) = \frac{\mu_i(x,y,t)}{\mu_{c_j}(t)} \qquad (2)$$

where μ_i(x,y,t) is the 95th percentile of the local NDVI values (averaged over a parcel) of the *i*-th parcel and $\mu_{c_j}(t)$ the 95th percentile of the entire class NDVI values at the *t* year.

It is worth to stress that $\mu_i(x,y,t)$ has to be computed from the same dataset that $\mu_{c_j}(t)$ is computed from, i.e. S2_TS. With this premise, a new correction factor *k(x,y,t)* timely and spatially varying, see eq. 3, can be computed for each cadastral parcel and year to update insurance premium/fee.

$$k(x, y, t) = d(t) \cdot \frac{1}{Z_{pi}(x,y,t)} \tag{3}$$

where *d(t)* is the discount rate for the generic *t* year after the first one of the new modelled trend and $1/Z_{pi}$ is the local and annual tuning coefficient of eq. 2. Parcels with a $Z_{pi}>1$ behave better than the correspondent class average and, consequently, the related annual insurance premium is expected to be lower, being the parcel unlikely to be the object of a disaster. Vice versa if $Z_{pi}<1$. If the applied insurance fee at the starting year of the new trend is known (P_{1st}) the updated one at the generic *t* year after the first one is (eq. 4).

$$P(x, y, t) = P_{1st}(x, y, t) \cdot k(x, y, t) \tag{4}$$

With respect to the above mentioned operational steps, a map of *k(x,y,t)* factor was generated for both 2016 and 2017 years taking care, separately, of the specific statistics of the considered classes. Procedure workflow is reported in the graph of fig. 2.

[FIGURE 2]

Results and discussion

The first analysis was aimed at characterizing main land use classes in the study area with reference to the CLC2012 Level 1 codification. It resulted that the 35% of the Piemonte region is specifically devoted to agriculture, making the area a good benchmark for testing new insurance strategies in the agricultural field (table 5).

[TABLE 5]

In the first part of the work, aimed at testing and modelling mid-term trends of crops, all the CLC2012 Level 3 classes of table 4 were considered. MOD_TS was used to model mid-term trends of vegetation with reference to the annual 95th percentile averaged at class level. Class

NDVI profiles (PR95Y) were analyzed by time decomposition separating trends from seasonality by decomposition approach. It was found that, for the investigated crop classes, PR95Y could be generally split into 3 phases, that were singularly modelled by a 1st order polynomial (figure 3). Obtained values of unitary variation of NDVI (gain of the trend line) and the correspondent coefficients of determination (R^2) are reported in table 6, together with the total NDVI variation within the modelled period.

[FIGURE 3]

[TABLE 6]

Gain values and total NDVI variations were compared with the theoretical NDVI accuracy (0.02) to test "operational" significance of changes. Given the economic impact of class 211 (Not-irrigated arable land) in the area, this solely was selected for the successive modelling steps, disaggregating it into the main included crop types (wheat, corn, meadow, ryegrass). According to table 6 class 211 showed the most significant variation of NDVI trend for all the recognized phases (2000-2007, 2007-2014, 2014-2018).

The proposed 1st order polynomial model, has consequently to be used to estimate insurance risk trend for those crops belonging to the CLC2012 211 class, with the hypothesis that higher the NDVI, lower the associated risk for yield reduction. Trend defines a general behavior of class 211 in the whole considered region, with no matter about specific site features, yearly meteorological conditions, crop types and crop management practices. Consequently, to refine the risk estimate given by the model, a further analysis is required at field level aimed at qualifying performances of crops (in terms of NDVI value), with reference to their type (as declared by farmers and recorded within PAC declarations). Performance can be evaluated in a relative way by class-specific anomaly computation operated at field level (eq. 2). To exemplify this operation, two maps of NDVI anomaly (2016 and 2017) were generated for the area with respect to the available S2_TS. Anomaly was separately computed and mapped for the four considered crop types and then mosaicked to generate a single map (figure 4) useful for operational purposes.

[FIGURE 4]

Some statistics describing crop type anomalies in 2016 and 2017 were computed and compared trying to emphasize dynamicity of the phenomenon. Three anomaly classes were considered: class 1: $z_i(x,y,t)$< 0.95; class 2: 0.95<$z_i(x,y,t)$<1.05; class 3: $z_i(x,y,t)$ >1.05) Results are reported in Tab.7.

[TABLE 7]

Results show that, in spite of the reduced size of the study area, differences between 2016 and 2017 were not negligible as their differences, reported in table 8, demonstrate.

[TABLE 8]

This fact suggests that agriculture landscape is dynamic and constantly changes in class distribution and performance depending on the considered year. Consequently, robust and reliable ground data would be required to, correctly, locate crops and making possible reasonable interpretations of ongoing processes and anomalies. It is, rarely, possible to, rigorously, compare different years and giving a single interpretation of detected anomalies, since too many variables interact, related to climate/weather, crop rotation, agronomic practices, soil nutrient content, etc. Nevertheless, the proposed procedure permits to map anomalies, i.e the final effect of all the acting agents, supplying a new spatially based support for calibrating and addressing new insurance strategies with the aim of tuning the risk associated with a certain crop in a certain area. This can be obtained translating the anomaly map into the correspondent *k(x,y,t)* factor map. Again, this was done for both the 2016 and 2017 years with reference to the 4 investigated crops (figure 5).

[FIGURE 5]

k(x,y,t) is a map specifically describing the spatial distribution of the updating factor to use for tuning the insurance premium for that type of crop at that position in that year, assuming, as basis, the premium paid in the first year of the ongoing modelled trend.

The proposed methodology tries to face some of the challenges proposed by the review of De Leeuw et al. (De Leeuw et al. 2014) about features that insurance companies require to remote sensing based approaches in the agricultural context. One of them is the need of timely and spatially comparable, crop type specific metrics available with a sufficiently high temporal resolution. NDVI time series from MODIS and S2 dataset well fit these requirements. Additionally, the propsed procedure falls within the general logic of the “index based” crop insurance policies as proposed by different authors (Rao 2010; Bokusheva et al. 2012; Bobojonov, Aw-Hassan, and Sommer 2014). It sounds similar to those reported by many authors (Patankar 2011; Makaudze and Miranda 2010; Turvey and Mclaurin 2012), but the main difference relies in the joint adoption of the following steps. With reference to MODIS-based trend analysis, we preventively synthesized yearly spectral information in a single metric (PR95Y); secondly, a time series decomposition of PR95Y was achieved to extract the average trends (low frequency variations) in the period 2000-2018; finally, a break point investigation was performed to look for trend phases along the explored period.

The adoption of PR95Y as synthetic metric was intended to limit noise effects given by NDVI values related to those annual periods when vegetation is not active. This can somehow limits time series decomposition (Forkel et al. 2013). Conversely, a properly designed metric can drive to a more robust estimate of the inter-annual behavior of vegetation (Zhou et al. 2016; Hird and McDermid 2009). It is worth to remind that common approaches for time series decomposition like BFAST (Breaks For Additive Season and Trend) (Fang et al. 2018) and STL (Seasonal decomposition of Time Series by Loess) (Lu et al. 2003), generally, process the entire multi-annual time series with no a-priori synthesis.

Ordinary long-term trend modelling only show the overall trend along the entire analyzed period, with no interest about possible existing sub-periods. These can be significant and, consequently, important to be recognized to get indications about the average time persistence of a certain trend and to better calibrate models that are expected to have economic impacts. A break point analysis was, therefore, achieved looking for changes in PR95Y trend derivative sign (Schucknecht et al. 2013; de Jong et al. 2012). Three sub-period trends were found, for the most of the analyzed CLC classes. Future developments could be addressed to improve break point detection using algorithms like DBEST (Detecting Breakpoints and Estimating Segments in Trend) proposed by (Jamali et al. 2015; Forkel et al. 2013).

As far as anomaly mapping is concerned a similar approach was found in a recent paper by Shirsath et al. (Shirsath, Sehgal, and Aggarwal 2020), while specific applications in the agricultural insurance sector are reported in Lekakis et al. (2020).

Our expectation is that the proposed procedure, based on freely available dataset and simple data processing, could support insurance companies to monitor crops behavior at the mid and short term, making possible to, somehow, map the probability of finding a favorable or unfavorable trend for a specific crop. This is a basic condition for consciously calibrating insurance fees. In favorable areas, showing an increasing trend in biomass production, a lower annual crop premium could be defined, encouraging farmers to take out insurance. Expectation is that higher the number of insured farmers, lower the insurance fees; consequently, it is our conviction that this approach could drive faster the ongoing process of making farmers closer to insurance. The proposed method can be certainly applied in other regions, but some key concepts must be considered. Firstly, persistent cloud cover can affect results especially in early phenological stages (e.g. emergence, tillering). Secondly, comparison is reliable only if explored fields fall in the same “agronomic region”, where both climate and management system are sufficiently homogeneous.

Conclusions

This research was stimulated by technicians of the Piemonte Region administration with the aim of finding new ways to monitor crops in such a way to make more attractive (for farmers) insurance policies covering yields loss. Attraction depends on the possibility of convincing farmers of the need of an insurance covering and on the opportunity, for insurance company, of better calibrate (possibly reduce) fees to apply to farmers. Consequently, this work was addressed to develop and propose a methodological approach aimed at supporting agriculture-devoted insurance strategies based on time series of free multispectral satellite data. The basic idea was to relate crop performances at the mid and short term to calibrate insurance fees, taking care about both time trend and spatial distribution of biomass production by crops. A study area was selected within the Piemonte Region (NW Italy) to act as paradigm for testing and presenting the methodology. According to obtained results these considerations can be done: a) MOD13Q1 product, supplying 16 days composite NDVI maps with a geometric resolution of 250 m and ranging from 2000 up to 2018, proved to be effective in describing mid-term trends of crop performance at both regional and agriculture macro-class level; b) NDVI map time series obtained from Copernicus Sentinel 2 data, having a higher geometric resolution (10 m), permitted to detail investigation at field level, making possible to refine insurance risk estimate and linking it to the local specific condition of crops. Refinement was obtained with reference to the local anomaly concept computed around the crop class average value. With respect to the above mentioned criteria, a simple but extremely operational mathematical model was suggested to calibrate insurance fee at year and field level. During the tests an evidence was found concerning duration of growing (or decreasing) trends of crop performances in the area. In fact, a 7 year lasting period was recognized by time series decomposition of NDVI maps time series from MOD13Q1 product, suggesting that a new mathematical model have to be possibly calibrated after 7 years from the starting date of the previously adopted one. Eventual further improvements of the proposed method can be certainly possible especially if a new approach will be applied in ground data supplying. A constant, reliable and spatially distributed flux of information from farmers to the system is desirable to continuously monitoring the numerous varying variables that determine anomaly occurrences. This strategy could drive to propose new insurance indexed policies for protecting the whole agricultural sector in view of the effects of climate change. More appropriate insurance contracts can be proposed to farmers and encourage him to make use of this type of cover for its activity. In other words, insurance company can attract new customers and farmers can protect themselves with reasonable and demonstrable prices.

Aside the main purpose this methodology was developed for, it is expected that it could also represent a valuable tool for investigating vast areas with the aim of recognizing ongoing anomalies in crops behavior: it would offer an efficient, economically competitive and immediate control or service. It is worth to remind that the proposed approach highly relies on accurate field controls that should report type and time of crucial events and crop management activities, that can supply the right interpretation keys of the observed and mapped phenomena.

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Table 1. Spatial size of the main crop types present in the study area.

Crop type	Total Area (ha)	Total Cultivated Area (ha)	Crop Area (ha)	Crop Area (%)
Ryegrass	43720	21063	1769	8.4%
Corn			7403	35.2%
Wheat			3248	15.3%
Meadow			8643	41.1%

Table 2. Technical specifications of TERRA MODIS and S2 MSI sensors as reported in Barnes, Pagano, and Salomonson (1998) and Drush et al. (2012).

	MODIS	S2
Launch date	18/12/1999	23/06/2015
Orbit Altitude	705 km	786 km
Geometric resolution	b1-b3, b7: 250m	b2-b4, b8: 10m b5-b7, b8a, b11, b12: 20m b1, b9, b10: 60m
Radiometric resolution	16 bit	12 bit
Temporal resolution	16 days	10 days (5 days with S2 A/B satellites)

Table 3. Technical features of CLC2012 product as reported in Feranec et al. 2016.

	Value
Satellite data source	IRS P6 LISS III and RapidEye
Time consistency (years)	2011-2012
Geometric Accuracy (satellite data)	≤ 25 m
Geometric Accuracy (CLC)	Better than 100 m
Thematic Accuracy	≥ 85%
Minimum Mapping Unit/width	25 ha/ 100 m
Access to the data	free
Number of countries involved	39

Table 4. Codes used in CLC2012 for qualifying agricultural classes (codes from Feranec et al. 2016).

Level 3 code	Class
2.1.1	Not-irrigated arable land
2.1.3	Rice fields
2.2.1	Vineyards
2.2.2	Fruit trees and berry plantations
2.3.1	Pastures
2.4.2	Complex cultivation patterns
2.4.3	Land principally occupied by agriculture, with significant areas of natural vegetation

Table 5. CLC2012 L1 classes and correspondent size within Piemonte Region.

CLC2012 L1 class	CLC2012 L1 code	Area (ha)	Area (%)
Artificial surfaces	1	109938	4
Agricultural areas	2	1253649	36
Forest and semi natural areas	3	20602216	59
Wetlands	4	-	-
Water bodies	5	30878	1
Total	-	3454681	100

Table 6. Δ_{NDVI} = values of total NDVI variation along the considered period (as resulting from trend line); Gain = average yearly variation of NDVI as resulting from trend line); R^2 = coefficient of determination computed for the 3 trends corresponding to the recognized behavioral phases. In red, values of Δ_{NDVI} that are significant with respect to NDVI measure theoretical accuracy (0.02).

CLC Class	2000-2007			2007-2014			2014-2018		
	Δ_{NDVI} (8 years)	Gain (NDVI/year)	R^2	Δ_{NDVI} (8 years)	Gain (NDVI/year)	R^2	Δ_{NDVI} (5 years)	Gain (NDVI/year)	R^2
211	-0.0512	-0.0064	0.8879	0.0432	0.0054	0.7939	-0.0215	-0.0043	0.8299
213	-0.0040	-0.0005	0.0804	0.0032	0.0004	0.0339	0.0020	0.0004	0.1416
221	0.0240	0.0030	0.6604	0.0152	0.0019	0.3708	0.0185	0.0037	0.8651
222	-0.0096	-0.0012	0.4832	0.0032	0.0004	0.0903	-0.0050	-0.0010	0.2266
231	-0.0232	-0.0029	0.8520	0.0264	0.0033	0.8835	-0.0020	-0.0004	0.0587
242	-0.0152	-0.0019	0.5430	0.0488	0.0061	0.8971	-0.0060	-0.0012	0.5296
243	-0.0128	-0.0016	0.5930	0.0232	0.0029	0.7854	0.0075	0.0015	0.5164

Table 7. Statistics describing anomaly distributions for the considered crops in the study area. Frequencies are given for the following anomaly classes. Class 1: $z_i(x, y, t)$< 0.95; class 2: 0.95<$z_i(x, y, t)$<1.05; class 3: $z_i(x, y, t)$ >1.05)

Year	2016				2017			
Crops	Ryegrass	Corn	Wheat	Meadow	Ryegrass	Corn	Wheat	Meadow
Class 1	12.60%	31.76%	11.64%	8.73%	14.81%	14.51%	19.58%	8.51%
Class 2	43.05%	62.40%	31.61%	32.02%	38.34%	63.98%	39.41%	20.40%
Class 3	44.35%	5.84%	56.75%	59.25%	46.85%	21.51%	41.01%	71.09%

Table 8. Differences of occurrences of the above mentioned anomaly classes between 2016 and 2017 for the considered crops.

Anomaly 2016 - 2017				
Class	Ryegrass	Corn	Wheat	Meadow
1	2.20%	-17.24%	7.93%	-0.22%
2	-4.71%	1.58%	7.80%	-11.62%
3	2.50%	15.67%	-15.73%	11.84%

Figure 1. Study areas: a. Administrative boundaries of Piemonte Region, NW Italy. This area was assumed as the reference one for the mid-term analysis. b. Administrative boundaries of municipalities considered as focus areas for the instantaneous deductions. Their position within Piemonte Region is shown in yellow in a). Reference system is WGS 84 / UTM zone 32N, EPSG: 32632.

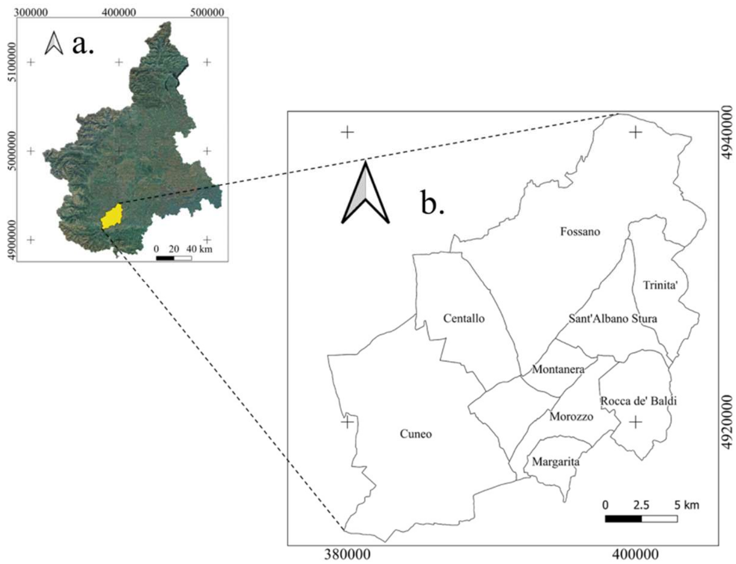

Figure 2. Workflow showing the main conceptual steps of the proposed methodology.

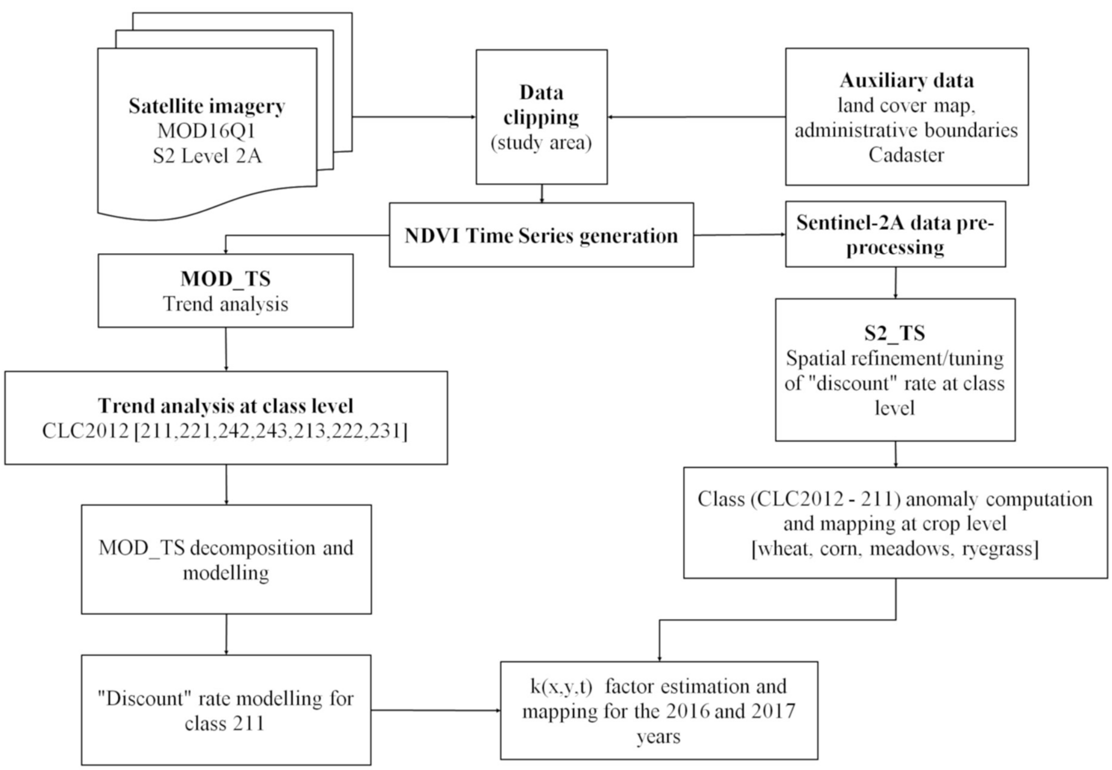

Figure 3. Temporal profiles of NDVI (PR95Y) given for all the considered agricultural classes from CLC2012-Level 3. a. Non-irrigated arable land (CLC 211); b. Rice fields (CLC 213); c. Vineyards (CLC 221); d. Fruit trees and berry plantations (CLC 222); e. Pastures (CLC 231); f. Complex cultivation patterns (CLC 242); g. Land principally occupied by agriculture, with significant areas of natural vegetation (CLC 243). Graphs clearly show that three different phases characterized the period 2000-2018. They were separately modelled by a 1st order polynomial.

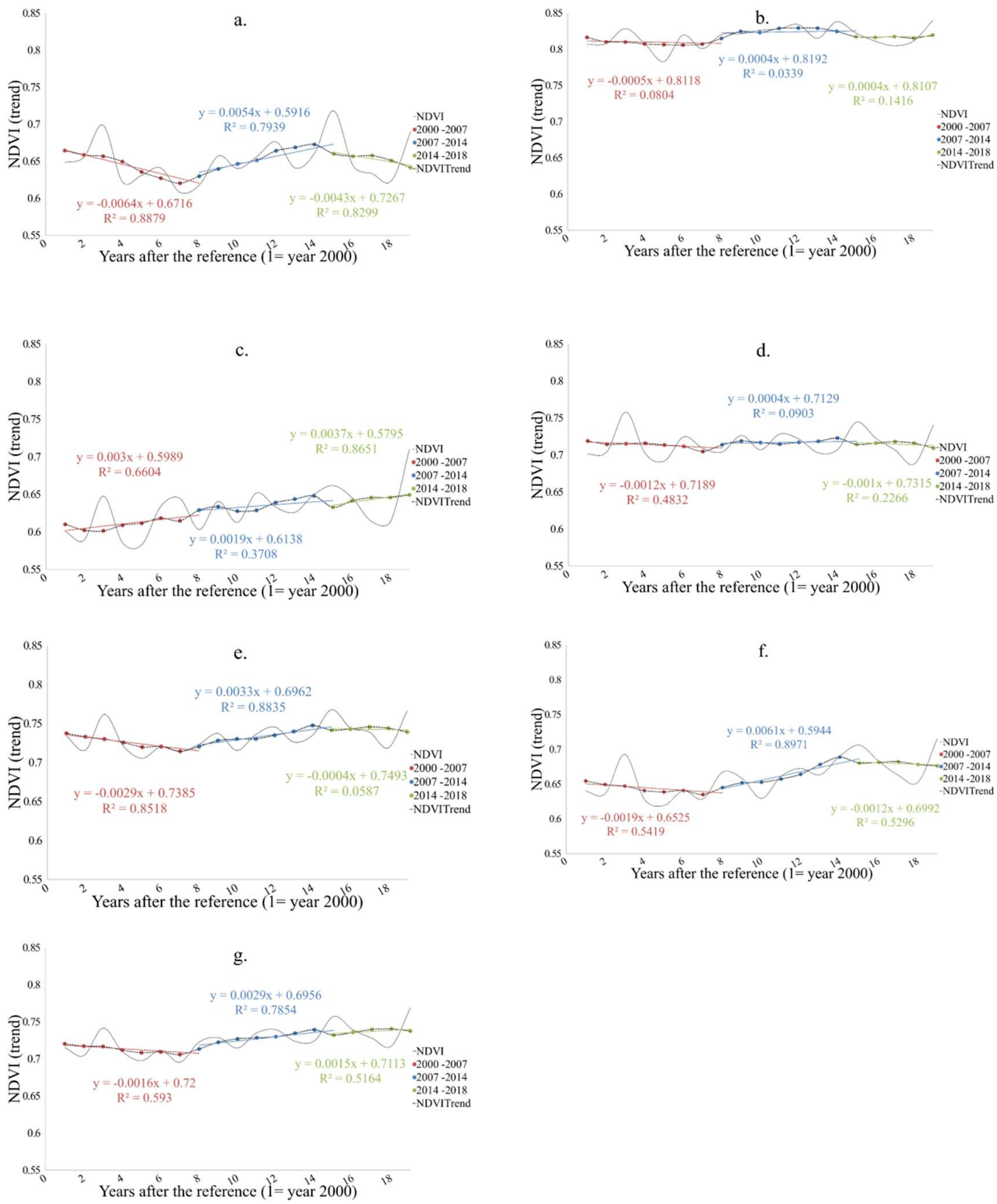

Figure 4. Map of NDVI anomaly in the area: a. Anomaly map for the year 2016; b. Anomaly map for the year 2017. Anomaly was computed at crop class level and then mosaicked to generate the map shown in figure. (Reference system is WGS 84 / UTM zone 32N, EPSG: 32632).

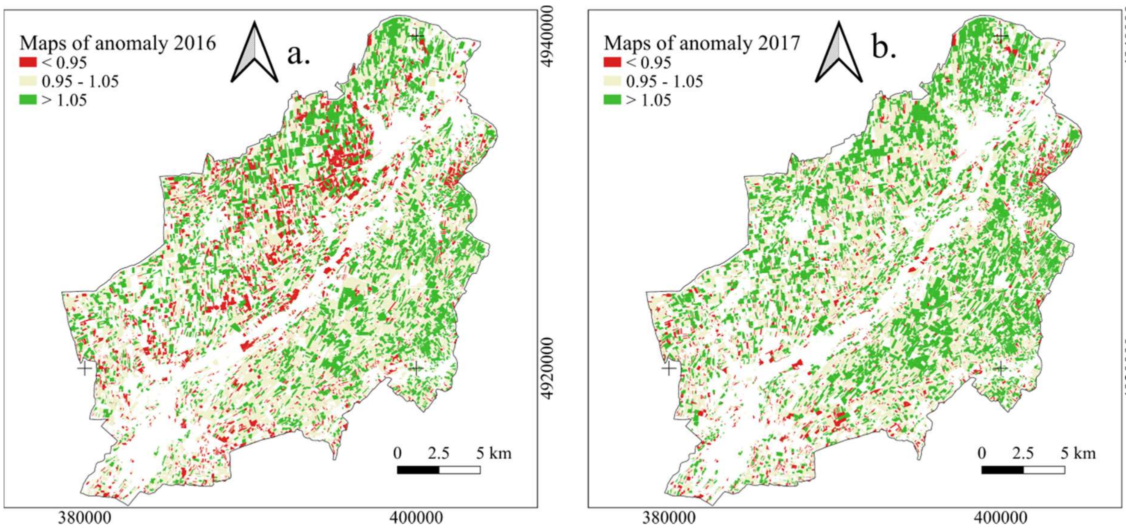

Figure 5. Map of *k(x,y,t)* factor (x 100) given for the 4 investigated crops (wheat, corn, ryegrass and meadows). a. *k(x,y,t)* maps for the year 2016; b. *k(x,y,t)* maps for the year 2017; c. frequency distribution of *k(x,y,t)* in the year 2016 in the area of interest; d. frequency distribution of *k(x,y,t)* in the year 2017 in the area of interest. *k(x,y,t)* was computed at crop class level and then mosaicked. (Reference system is WGS 84 / UTM zone 32N, EPSG: 32632).