**Supporting Insurance Strategies in Agriculture by Remote Sensing: A Possible Approach at Regional Level**

# Supporting Insurance Strategies in Agriculture by Remote Sensing: a Possible Approach at Regional Level

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**Abstract.** Climate variability is one of the greatest risks for farmers. The ongoing increase of natural calamities suggests that insurance strategies have to be more dynamic than previously. In this work a remote sensing based service prototype is presented aimed at supporting insurance companies with the aim of defining an operative tool to objectively calibrate insurance annual fares, tending to cost reduction able to attract more potential customers. Methodology was applied to the whole Piemonte region (NW Italy) that is greatly devoted to agriculture. MODIS MOD13Q1-v6 image time series were used for this purpose. MODIS data were used to figure out the ongoing climate change trends at regional scale, looking at the NDVI time series ranging from 2000 to 2018; the average phenological behaviour of the main agriculture classes in the area (CORINE Land Cover classes Level 3, CLC2012) was considered looking at the yearly average NDVI value trend in the analysed period. This analysis was intended to describe the yearly tuning of the average insurance risk factor and fares in respect of the reference year (2000). A patch level investigation comparing the NDVI average value of a single CLC2012 patch with its reference class was differently used to map local differences of crops performance, aimed at locally tuning insurance risk and fares around the average one as resulting from the previous step. Proposed methodology proved to be able to describe the average temporal evolution of crop classes performances and to locally tune, at single field and crop type level, the agronomic performances of insured areas.

**Keywords:** Crop insurance, MODIS NDVI, remote sensing-based services.

## 1 Introduction

Crops may be classified as “subsistence crops” if they will support producers (personally or their livestock), or “income crops” if they will be sold for profit. The latter, which will be sold immediately after the harvest, have a financial potential that depends on the yearly growing season, when plants are constantly exposed to various types of threats, included the weather conditions. The current agricultural management model is hardly sustainable in the long term because of the climate changes that occurred in the recent years, which determined higher average temperatures, anomalous distributions of rainfall and lower accumulations of water reserves [1]. Ecosystem response to climate change and its impact on plants have been extensively analyzed [2–4]. Only recently, however, evidences of the effects of climate change on crop production have been documented [5–7]. Climate change damages on crops can determine a significant impact on human activities especially in those countries where the Gross Domestic Product (GDP) is largely dependent on agricultural activities [8, 9]. Crop monitoring at national or supranational, level is therefore needed to measure the production exposure to adversity. Insurance companies are currently looking at remote sensing from satellite missions as a promising tool to support their insurance strategies in the agriculture compart. Remote sensing, based on long image time series, has been thought to satisfy two types of requirements: one related to the ex-post estimation of damages from extreme weather events e.g. droughts, floods and hail [10, 11]; another related to the ex-ante quantification and mapping of risk related to a potential reduction of crop production determined by long term climate change trends. Italy has been within the first countries to tackle the issue of risk management in agriculture, introducing since the 1970s with the National Solidarity Fund (FSN), the principle of solidarity for companies suffering damages caused by natural disasters. The goal of the FSN is to promote prevention and measures in the areas affected by natural disasters, with the aim of promoting the economic and productive recovery of the damaged companies. In the insurance sector the remote sensing is expected to map spatial and temporal differences to better and more consciously calibrate the insurance premiums, longing for their reduction and the consequent easier approach from farmers. Presently, insurance companies must operate a ground survey to evaluate each compensation request; in a not too far future, remote sensing systems should explore circumstantially the entire territorial context highlighting anomalies, thus targeting appraisals to quantify possible losses. Economic and management strategies supported by this new type information will increase competitiveness and business income of insurance companies. Satellite-based remote sensing is often used wherever a large-scale mapping of vegetation is needed [12, 13], making possible land cover classification by a wide variety of strategies. Natural disasters related economy, e.g. insurance strategies, greatly long for low cost tools for risk assessment, possibly applicable everywhere over the world [14–16]. Global data sets, like satellite images archives, available for free or at very competitive prices, may be a good starting point to assess large areas, especially if jointly used with ground data able to correctly address deductions [17]. Governments and international donors currently promote 'Climate Insurance', generic term to indicate a series of financial checks for the purpose of making payments following meteorological events. The G7 (Group of Seven)'InsuResilience' initiative is meant to significantly increase the insurance cover of low income people against negative impact of extreme weather events induced by climate change within the next 5 years. These initiative provides funds to governments in order to stabilize and foster the recovery of a large part of the affected population. For instance, *InsuResilience* pledged USD 400 million at the Paris climate conference [18], and the Global Index Insurance Facility has a portfolio of 148 million US dollars [19]. A rough approximation can be made upon the global volume of agricultural insurance premiums, which are estimated at USD 5 billion in emerging markets. The World Bank estimates that 44 percent of agricultural insurance premi-

ums consist of subsidies [20]. Despite the lack of more recent data, these combined figures suggest an annual volume of subsidies to agricultural insurance (not just index insurance) in emerging markets of two billion dollars. This estimate has been verified with personal communications with several experts. The technologically innovative insurance programs, are heralded as promising strategies for decreasing poverty and improving climate risk management and resilience in developing countries that are heavily dependent on smallholder agriculture. These programs may be defined as particularly 'index insurance' linking payouts to environmental proxy variables rather than measured losses [21]. With the growth of interest from governments and donors in these insurance programs , a large number of pilot studies are ongoing worldwide [22–24]. In the Italian agriculture context, the risk prevention insurances policies, are mainly managed collectively at district level, through the so called "*agricultural defense consortia*". Consortia contracts with insurance companies mainly to cover yield losses of their associated. The Italian Government contributes to a part of the premium paid by the farmer. In particular the Ministry of Agriculture decree n. 28405/17 regulates contributions to agricultural insurance premiums defining a yearly plan. The plan aims at extending insurance coverages by means of facilitated policies covering crop, facilities and livestock damages from adverse climatic conditions. Annex 1 of the above mentioned decree defines crops, corporate structures and types of insurable cattle. Crops such as corn, wheat and grass fall into this list. Insurance policies can also cover production losses permitting different insurance choices in respect of both type and quantity of crops. Definition of insurance parameters can be found in Annex 5 of the 28405/17 decree, but can be summarized as it follows.
Revenue policies are contracts that cover the loss of revenue from the insured production. Loss is intended as a combination of yield reduction due to both seasonal adversities and market price reduction with the following definitions: - *yield reduction* is the difference between the actual yield at the time of harvest and the insured yield. The latter can be assumed equal to: a) the average production of the previous three years; b) the average production of the previous five years excluding the years with the lowest and highest production; c) the actual obtainable production of the insurance year, if lower; - *price reduction* is the difference between market reference price, as determined by the Institute of Services for the Agricultural Market (ISMEA), in respect of the third quarter of the year of collection of the insured product, and the price determined by law; - *effective yield* is the one determined with reference to the time of harvest from the period of the insurance company that took charge of the risk.
Indexed policies are insurance contracts that cover the loss of production insured for damage in quantity and quality as a result of adverse weather conditions, identified by a positive or negative variance from a biological and/or meteorological index. The relative damage will be recognized based on the actual difference with respect to the value of the aforesaid index. The following indices can be considered: - *meteorological index* identifies a meteorological event recorded based on a predefined parameter, such as the sum of average daily temperatures and/or cumulated precipitations, referring to a determined period of cultivation development, potentially harmful for agricultural production in a specific production area; - *biological index* identifies a biotic event registered on a predefined parameter, such as for example the lost biomass re-

ferred to a determined period of cultivation development, potentially harmful for the agricultural production in a specific production area; - *adverse climatic trend index* is used to take care about the ongoing climatic trend as described by some selected parameters like rainfall and/or cumulated temperatures (in the cultivation period or in part of it) which deviate significantly from the optimal trend for a certain crop in a given phenological phase generating negative effects on production that can be measured with biological indices. In this work free satellite data from NASA (National Aeronautics and Space Administration) MODIS (Moderate Resolution Imaging Spectro-radiometer) sensor, on board of the TERRA satellite [5, 25, 26], have been used to draw a possible operational tool to calibrate agricultural insurance strategies with revenue policies in the Piemonte region (NW Italy), with special concern about indexed policies. Even if the proposed methodology have been tested in Piemonte, it is thought with a global perspective, that it can be easily adapted to any other part of the world.

# 2 Materials and Methods

## 2.1 Study area

The study area is located in the Piemonte region (NW Italy, fig. 1). It sizes 25388 km2 and well fits size requirements for moderate resolution satellite imagery. It well represents the northern Italian agricultural context with a typically temperate climate having a continental character, where NW Alps gradually determines a temperature reduction while altitude rises.

## 2.2 Available Data

A NDVI (*Normalized Difference Vegetation Index*, [27]) image time series composed of 432 images covering the period 2000 – 2018, was generated from the MOD13Q1-v6 dataset available from the NASA LPDAAC collection [28]. Data were obtained in TIF format, WGS84 geographic reference frame from the AppEEARS system [29].
The MOD13Q1 Version 6 product provides a Vegetation Index (VI) value at a per pixel basis. NDVI is referred to as the continuity index to the existing National Oceanic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) derived NDVI. The grid consists of 4800 rows and 4800 columns of 250 meter pixels. The algorithm chooses the best available pixel value from all the acquisitions from the 16 day period. The criteria used is low clouds, low view angle and the highest NDVI/EVI value. Along with the Vegetation layers and the two QA layers, the HDF file will have MODIS Reflectance bands 1 (Red), 2 (NIR), 3 (Blue), and 7 (MIR), as well as four observation layers (Didan 2015). Pixel reliability (PR) and CDOY layers, supplied with the MOD13Q1-v6, were considered for NDVI TS calibration. Pixel Reliability layer (PR) defines the overall quality of the NDVI value of each pixel, giving information about its status, as explained in Table 1. This information was used in TIMESAT [30, 31] to weigh NDVI values according to their qual-

ity: the lower the weight, the less the NDVI value affects the estimation of the function fitting parameters since a greater uncertainty is assigned to it [31].

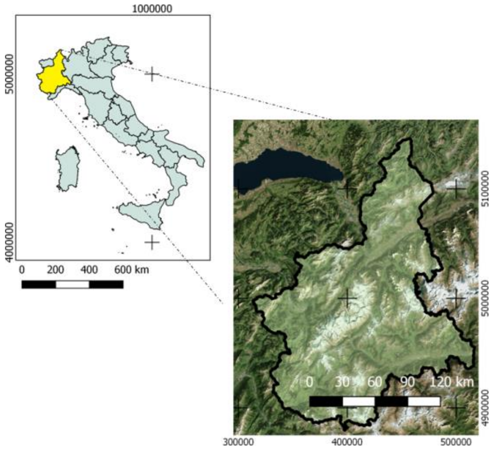


**Fig. 1.** the study area is located in Piemonte, NW Italy (Reference frame: WGS 84 UTM 32N).

Composite day of the year layer (CDOY) contains, for each pixel of the image, the day of the year in which reflectances used in the VIs computation were acquired; this information is needed to properly build NDVI time series (TS) placing NDVI values at the right dates for each pixel.

According to Leprieur [32] NDVI is a vegetation index designed for retrieval of vegetation canopy biophysical properties, and according to Turvey [33] that can be used in Index-Based crop insurance design.

**Tab. 1.** MOD13Q1/A1 Pixel Reliability

| Rant Key | Summary QA | Description |
|---|---|---|
| -1 | Fill/No Data | Not Processed |
| 0 | Good Data | Use with confidence |
| 1 | Marginal data | Useful, but look at other QA information |
| 2 | Snow/Ice | Target covered with snow/ice |
| 3 | Cloudy | Target not visible, cover with cloud |

NDVI is computed according to eq. 1:

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \quad (1)$$

where $\rho_{NIR}$ and $\rho_{RED}$ are the NIR and RED at-the ground reflectance, respectively, at that pixel location. Many studies proved that NDVI appears to be a good predictor of the agricultural production and that can be related to insurance premiums in agriculture [34-35]. The CORINE Land Cover dataset, release 2012, level 3 (hereinafter CLC2012), was used to map cultivated areas over Piemonte. CLC was born at a European level specifically for the detection and monitoring of land cover and use, with particular attention to environmental protection requirements. The CORINE Land Cover (CLC) inventory was initiated in 1985 (reference year 1990). Updates have been produced in 2000, 2006, 2012, and 2018. It consists of an inventory of 44 land cover classes organized in 4 hierarchical levels of meaning. In the following work used the Level 3 2012 CLC classes. Technical features of the CLC2012 dataset are reported in table 2. Agricultural classes from CLC2012 considered for this work are reported in table 3.

An administrative boundaries vector map (hereinafter called AB, 1:100000 map scale, 2012 updated), mapping municipalities (1181) over the whole Piemonte Region, was used to compute statistics of cultivated areas at municipality level. It was obtained for free from the Regional Geoportal.

**Tab. 2.** CLC2012 technical features

| Technical feature | Value |
|---|---|
| Satellite data source | IRS P6 LISS III and RapidEye |
| Time consistency | 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 |

**Tab. 3.** Agricultural classes according to CLC 20122.

| Level 2 | Level 3 | Content of the classes |
|---|---|---|
| 2.1 | 2.1.1. | Non-irrigated arable land |
| | 2.1.3. | Rice fields |
| 2.2 | 2.2.1. | Vineyards |
| | 2.2.2. | Fruit trees and berry plantations |
| 2.3 | 2.3.1. | Pastures |
| 2.4 | 2.4.2. | Complex cultivation patterns |
| | 2.4.3. | Land principally occupied by agriculture, with significant areas of natural vegetation |

**MODIS NDVI Time Series Analysis**

The whole Piemonte Region resulted to be imaged by 432 NDVI maps, 16 days regularly distributed. PR layers, supplied in the same number of NDVI maps, were used for a first selection of "good" observations (PR = 0 or 1) along the NDVI temporal profile of each pixel. All other observations were excluded from computation. This determined that native regularly spaced NDVI time series were turned into irregularly spaced one. Remaining observations were therefore interpolated by spline with tension (value = 10) with reference to the correspondent DOY, from the associated DOY layer, obtaining a new 5 days spaced NDVI profile (time series was densified from 23 to 73 image per year). A further refinement was achieved only for vegetated pixels that were found within the image by testing that the yearly NDVI maximum value was over 0.5. The refinement was intended to remove anomalous, but "good", NDVI values along the expected phenological trend of vegetated areas (e.g. late snow, soil flooding, etc.). Consequently, the previously interpolated NDVI image time series was filtered using an FFT (Fast Fourier Transform) approach on year basis. The yearly NDVI temporal profile of each pixel was transformed into the frequency domain. The three most powerful frequency components were retained, while all the other ones were filtered out. Consequently, a reverse FFT was applied to return back to the

NDVI domain determining the final NDVI profile that was analysed. For each of the available years and for each image vegetated pixel, the annual mean NDVI value was computed between the Starting of the Season, SOS, and the End of the Season, EOS ([Testa,testa]). SOS and EOS were placed along the pixel NDVI profile in the moment when the local NDVI value became higher (SOS) and lower (EOS) of 0.4, forcing research within the middle of February and the middle of November. For not-vegetated pixel (yearly NDVI maximum < 0.5) the yearly NDVI mean local value was calculated simply excluding bad observations (PR $\neq$ 0) with no further refinement. A new stack of 19 NDVI maps $NDVI_{\mu}(x,y,t)$ was therefore obtained (t=2000-2018) by averaging at year level, the filtered/interpolated pixel NDVI temporal profile.

### NDVI Statistics at Municipality Level for Cultivated Areas

CLC2012 and AB vector maps were intersected by ordinary Geoprocessing tools available in QGIS 2.18.4 to get crossed information needed to investigate crops yearly performances as detectable by NDVI annual mean value at municipality and agricultural class level. A new regional tessellation scheme was therefore obtained, generating 7017 patches from the original 2997 ones (from CLC2012 Level 3 map). Zonal statistics from the above mentioned $NDVI_{\mu}(x,y,t)$ maps were computed, making possible to yearly qualify each patch in respect of the average vegetative behaviour that its agricultural part expressed. According to the 19 $NDVI_{\mu}(x,y,t)$ maps, the annual mean NDVI value of each agricultural CLC2012 Level 3 class was computed and the time trend approximated with a 1st order polynomial by Ordinary Least Squares (OLS) estimation. Resulting time-dependent lines were assumed as driving rules to derive an insurance risk factor (hereinafter called "discount rate", $k_i(t)$) useful to tune the average insurance premium in respect of the reference year, that, for this work, was decided to be the first one (2000). The discount rate (hereinafter called K) was computed according to eq. 2.

$$k_i(t) = \left(\frac{\alpha_i+\beta_i}{\alpha_i \cdot t+\beta_i}\right) \cdot 100 \qquad (2)$$

where $\alpha_i$ and $\beta_i$ are the trend line coefficients estimated by OLS according to the NDVI annual mean values of the CLC2012-Level 3 for the *i-th* class; *t* is the progressive year count from the starting one (2000 is t=1). A k value higher than 100 means that the insurance premium has to be augmented in respect of the reference one (at the year 2000); on the contrary, a k value lower than 100 mean that the premium must be reduced accordingly. The underlying criterion is that an increase of the annual average NDVI value of a certain agricultural class determines a reduction of the risk related to crop production, making possible a refinement of premiums required to farmers. A further step was done trying to relate premiums not only to the average annual NDVI value of the agricultural CLC2012 Level3 classes where a certain insured crop can be included, but also in respect of the local conditions. For this purpose authors computed annual NDVI patches' anomalies ($PA_i$) according to eq. 3.

$$PA_i(t) = \frac{\mu_i(t)}{\mu_{c_j}(t)} \qquad (3)$$

where $\mu_{i(t)}$ is the average NDVI of the *i-th* patch and $\mu_{c_j}(t)$ the NDVI average value of the $c_j$ class that the patch *i-th* belongs to, at the *t* year. For each of the investigated years a map of PA(t) was therefore generated to make possible to locally tune (at patch level) the average class premium in the considered year. Patches having PA > 1 indicates that the insurance premium for fields falling in that patch can be somehow reduced in respect of the average one for that class in that year; PA < 1 means that the insurance premium for fields falling in that patch has to be somehow increased in respect of the average one for that class in that year, since expected yield could be lower the class average one.

## 3 Results and discussion

A first investigation concerned the qualification of the area in terms of main land use classes (according to CLC2012 Level2 classification). Results of this analysis are reported in table 4 showing that about the 35% of Piemonte region is specifically devoted to agriculture, making the area a good benchmark to test new insurance strategies.

**Tab. 4.** Distribution of Land Cover Classes in Piemonte (CLC2012 L3 dataset).

| Coverage class | Number class | Area (ha) | Area (%) |
|---|---|---|---|
| Permanent crops | 2.2 | 77313 | 2 |
| Inland waters | 5.1 | 30878 | 1 |
| Pastures | 2.3 | 37451 | 1 |
| Arable land | 2.1 | 697702 | 20 |
| Heterogeneous agricultural areas | 2.4 | 441183 | 13 |
| Open areas with little or no vegetation | 3.3 | 218068 | 6 |
| Scrub and/or herbaceous vegetation associations | 3.2 | 424397 | 12 |
| Forest | 3.1 | 1417750 | 41 |
| Industrial, commercial and transport units | 1.2 | 25631 | 1 |
| Urban fabric | 1.1 | 84307 | 2 |
| Other | - | 8358 | 1 |
| Total | - | 3463038 | 100 |

Concerning MOD13Q1 NDVI time series processing, to perceptively demonstrate the effectiveness of the adopted data filtering strategy based on the selective application of the FFT, a profile of a sample vegetated pixel is reported in figure 2 with reference to the 2000 year.
Concerning time trend of class annual average NDVI values, according to the CLC2012 Level 3 classification, results of table 5 were obtained. After removal of evident outliers related to the 2007 and 2013 years, NDVI trends were modelled by a

class specific 1st order polynomial, whose coefficients are reported in table 6 together with the correspondent coefficient of determination ($R^2$).

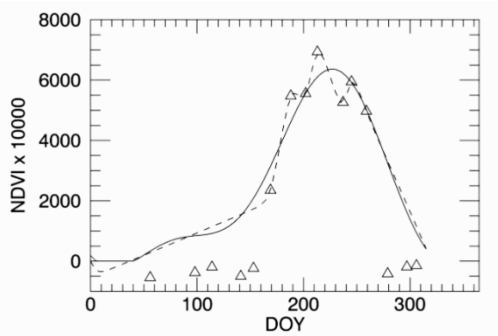


**Fig. 2.** Black line represents the FFT filtered NDVI profile of a sample pixel (year 2000). Dotted line represents the spline function interpolating “good” observations (Pixel Reliability = 0 or 1). Triangles represent raw data before filtering. DOY is the Day of the Year ranging between 0 and 365.

According to table 6 all classes proved to suffer from a positive trend of NDVI values in the considered period, suggesting that climate conditions are moving towards a more favourable conditions for agriculture in the area (i.e. a decreasing of the risk associated to yield reduction). The strongest correlation between time and NDVI average class value was found for class 243, the only one containing a natural vegetation component, that, since not managed, mostly emphasizes the effects of medium term climate effects. This suggests that, probably, when testing such features, natural vegetation can represent a better witness of ongoing phenomena. Vineyards (class 221) showed the most significant positive trend with a good correlation, too. Pastures (class 231) scored the second highest $R^2$ value confirming that, natural and semi-natural vegetation are better indicators of climate changes.

**Tab. 5:** NDVI annual mean values for the agricultural CLC2012-Level 3 classes in the area.

| Year | CLC2012 – Level 3 classes | | | | | | |
|---|---|---|---|---|---|---|---|
| | 211 | 213 | 221 | 222 | 231 | 242 | 243 |
| 2000 | 0.54 | 0.46 | 0.58 | 0.64 | 0.68 | 0.59 | 0.65 |
| 2001 | 0.54 | 0.45 | 0.58 | 0.63 | 0.67 | 0.59 | 0.65 |
| 2002 | 0.57 | 0.47 | 0.62 | 0.67 | 0.7 | 0.62 | 0.67 |
| 2003 | 0.5 | 0.42 | 0.54 | 0.61 | 0.65 | 0.56 | 0.63 |
| 2004 | 0.53 | 0.46 | 0.57 | 0.63 | 0.66 | 0.57 | 0.64 |
| 2005 | 0.56 | 0.47 | 0.6 | 0.65 | 0.68 | 0.61 | 0.66 |
| 2006 | 0.55 | 0.45 | 0.59 | 0.64 | 0.67 | 0.59 | 0.65 |
| 2007 | - | - | - | - | - | - | - |
| 2008 | 0.56 | 0.47 | 0.6 | 0.66 | 0.68 | 0.61 | 0.66 |
| 2009 | 0.53 | 0.45 | 0.6 | 0.64 | 0.68 | 0.59 | 0.66 |
| 2010 | 0.56 | 0.46 | 0.62 | 0.66 | 0.7 | 0.61 | 0.67 |
| 2011 | 0.53 | 0.45 | 0.58 | 0.59 | 0.67 | 0.57 | 0.65 |
| 2012 | 0.55 | 0.45 | 0.61 | 0.66 | 0.68 | 0.6 | 0.66 |
| 2013 | - | - | - | - | - | - | - |
| 2014 | 0.59 | 0.49 | 0.64 | 0.67 | 0.72 | 0.64 | 0.69 |
| 2015 | 0.57 | 0.47 | 0.63 | 0.67 | 0.71 | 0.62 | 0.69 |
| 2016 | 0.57 | 0.46 | 0.61 | 0.65 | 0.7 | 0.61 | 0.68 |
| 2017 | 0.54 | 0.45 | 0.57 | 0.62 | 0.67 | 0.58 | 0.65 |
| 2018 | 0.58 | 0.5 | 0.64 | 0.68 | 0.71 | 0.63 | 0.69 |

It is worth to remind that not all the variations in NDVI values can be assumed as significant, since: a) in literature, it was proved that averagely the accuracy in NDVI computation from remotely sensed data is about 0.02 NDVI points (ref Borgogno); b) NDVI class mean value assumed as index of yearly crop performance variations should have to be compared with the correspondent NDVI class standard deviation. Authors are working to improve these remaining weaknesses in the proposed methodology.

**Tab. 6:** gain (α), offset (β) and coefficient of determination ($R^2$) values of the 1st order polynomial approximating the time trend of the annual average class NDVI values. Underlined values are discussed in the text.

| CLC2012 Class Code | α | β | $R^2$ |
|---|---|---|---|
| 211 | 0.0016 | 0.5360 | 0.2 |
| 213 | 0.0009 | 0.4522 | 0.1 |
| 221 | <u>0.0023</u> | 0.5762 | 0.26 |
| 222 | 0.0011 | 0.6352 | 0.07 |
| 231 | 0.0017 | 0.6675 | 0.27 |
| 242 | 0.0017 | 0.5830 | 0.2 |
| 243 | 0.0019 | 0.6425 | <u>0.39</u> |

To translate the modelled trends into computation of insurance premiums, the annual discount rate values were calculated for all the CLC2012 Level 3 classes with reference to the 2000 year. Results are reported in table 7 and graphically represented in figure 3. It can be noticed that expectation is that insurance premium average costs, in 19 years, would have had to be reduced from the 3% up to the 7% of the 2000 average cost. Maximum expected reduction was related to vineyards (221), minimum to fruit trees and berry plantations (222).
According to eq. 3, for each of the analyzed years, a map of PA(t) was generated at patch level (figure 4), permitting to locate, in the whole region, where cultivated areas were supposed to perform over, or under, the expected average class NDVI (i.e. expected yield). This further information, translated to the insurance operational compart, could permit to better calibrate, around the class average premium, the one specifically designed for the field for which a farmer is paying its fee. The difference 1.0-PA(t) determines values lower than 0 for those areas that tend to behave better than their own class mean.

**Tab. 7:** Discount rate values computed for the agricultural CLC2012 Level3 classes along the time series.

| Year | CLC2012 Level 3 Discount rate (%, reference = year2000) 211 | 213 | 221 | 222 | 231 | 242 | 243 |
|---|---|---|---|---|---|---|---|
| 2000 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| 2001 | 99.7 | 99.8 | 99.6 | 99.8 | 99.7 | 99.7 | 99.7 |
| 2002 | 99.4 | 99.6 | 99.2 | 99.7 | 99.5 | 99.4 | 99.4 |
| 2003 | 99.1 | 99.4 | 98.8 | 99.5 | 99.2 | 99.1 | 99.1 |
| 2004 | 98.8 | 99.2 | 98.4 | 99.3 | 99 | 98.8 | 98.8 |
| 2005 | 98.5 | 99 | 98 | 99.2 | 98.7 | 98.5 | 98.5 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 2006 | 98.2 | 98.8 | 97.6 | 99 | 98.5 | 98.2 | 98.2 |
| 2007 | 97.9 | 98.6 | 97.3 | 98.8 | 98.3 | 98 | 97.9 |
| 2008 | 97.6 | 98.4 | 96.9 | 98.7 | 98 | 97.7 | 97.7 |
| 2009 | 97.4 | 98.2 | 96.5 | 98.5 | 97.8 | 97.4 | 97.4 |
| 2010 | 97.1 | 98 | 96.1 | 98.3 | 97.5 | 97.1 | 97.1 |
| 2011 | 96.8 | 97.8 | 95.8 | 98.2 | 97.3 | 96.8 | 96.8 |
| 2012 | 96.5 | 97.6 | 95.4 | 98 | 97 | 96.6 | 96.5 |
| 2013 | 96.2 | 97.4 | 95 | 97.8 | 96.8 | 96.3 | 96.2 |
| 2014 | 96 | 97.2 | 94.7 | 97.7 | 96.6 | 96 | 96 |
| 2015 | 95.7 | 97 | 94.3 | 97.5 | 96.3 | 95.7 | 95.7 |
| 2016 | 95.4 | 96.8 | 94 | 97.3 | 96.1 | 95.5 | 95.4 |
| 2017 | 95.1 | 96.6 | 93.6 | 97.2 | 95.9 | 95.2 | 95.1 |
| 2018 | 94.9 | 96.4 | 93.3 | 97 | 95.6 | 94.9 | 94.9 |

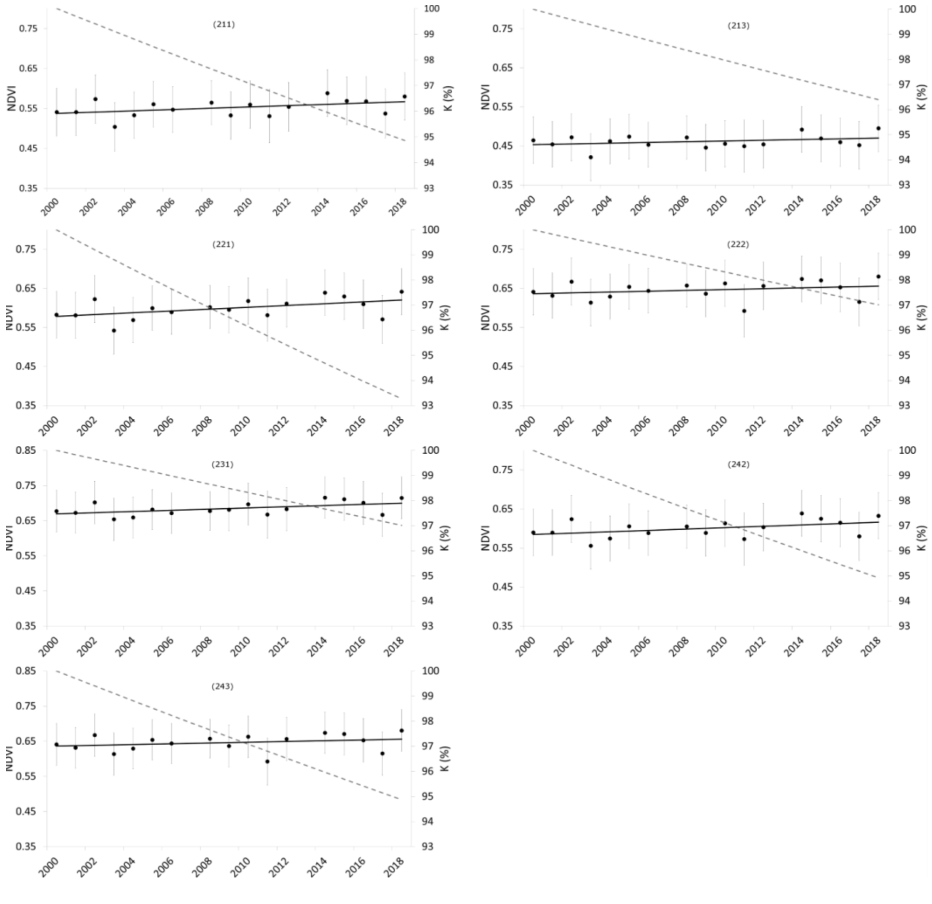


**Fig. 3.** Time trends of NDVI annual mean values (continuous line) and of the discount rate (dotted line) averaged over the agricultural CLC2012 Level 3 classes (reported in each graph).

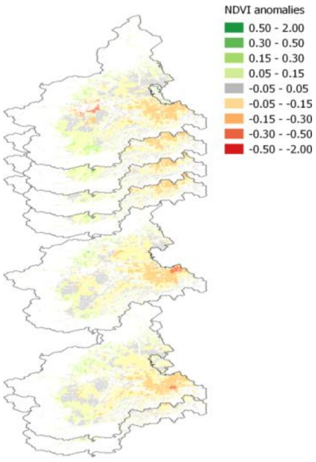


**Fig. 4:** Map of NDVI anomalies computed according to the CLC2012 level 3 classes for the period 2000 – 2018 (Geographic Reference system is WGS-84, EPSG: 4326).

# 4 Conclusion

In the crop insurance sector remote sensing is expected to support premiums definition, longing for such a reduction that could attract more farmers. Presently, insurance companies must operate a ground survey to evaluate each compensation request; in a not too far future, remote sensing systems should circumstantially explore the entire territorial context locating those anomalies useful to better target appraisals to quantify losses. Economical and management strategies, supported by this new type of information, is expected to increase competitiveness and business income of insurance companies. Optical images from MODIS sensor, obtainable for free, in spite of their reduced geometric resolution, proved to effectively support investigation of climate change effects onto crops in the medium period. NDVI time series showed that crop performances, supposed to be directly related to the average annual vigour, could be reasonably described through a linear increasing trend, whose strength depends on the investigated crop type. In general it was observed that low managed crops (from the water supplying point of view), like vineyards and orchards, are more conditioned by changing climate conditions.

It is surprising that even in highly fragmented agricultural areas like the Italian ones, derivable information from a long NDVI time series can operationally support interpretation of crops dynamics useful to address insurance policies. It should be remembered that remote sensing approaches do not exclude accurate ground surveys, that, oppositely, are needed to precisely interpret signals in respect of occurring events and crop management operations making agronomic practices simplest, fastest and most effective, in a precision farming general context.

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