Assessment and Monitoring of Soil Erosion Risk and Land Degradation in Arable Land Combining Remote Sensing Methodologies and RUSLE Factors

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Abstract. Soil degradation is a phenomenon that describes the degradation of soil quality due to which agricultural land in particular is unproductive as a consequence of the loss of ability to produce crops and biomass. The causes are many but, especially in the inland areas of the Mediterranean regions, some dynamics related to agriculture have particularly influenced the grading process. Specifically, agricultural over exploitation with unsustainable practices and land abandonment are causing ecological alterations that require contextual analysis to assess the medium and long-term effects. The aim of this work is to investigate the role of some factors that make up the RUSLE index have in the detection and monitoring of potentially degraded areas.In particular, the areas cultivated with arable crops were chosen as the area to be analyzed, because the average annual rate of soil erosion (A factor in RUSLE equation) is high despite the presence of vegetation cover and shown evident problems due to the phenomenon of degradation. In order to identify the potential degraded areas, two factor of RUSLE index have been correlated: C factor that describes the vegetation cover of the soil and A factor which represent the amount of potential soil erosion. All methodologies have been applied in a rural area in the northern part of Basilicata Region (Italy) using GIS and remote sensing approaches, as allows the possibility to perform a series of a complex studies and can be efficiently implemented in environmental monitoring plans.

Keywords: Land degradation · Remote sensing · QGIS · RUSLE method · C-factor

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1 Introduction

The issue of environmental protection and sustainable development has been brought to the attention of the scientific community in recent decades with the aim of studying its management dynamics, defining the processes for achieving specific targets to preserve the global ecosystem. Due to a constant and increasing anthropic activity [1], the intensive production and exploitation of natural resources, also linked to the phenomena caused by climate change, we are observing an ever-diminishing capacity of the soil to satisfy the needs of the community [2].

Based on these considerations, we wanted to focus the study on one of the most widespread phenomena globally, land-degradation defined as a reduction or loss, in arid, semi-arid and dry sub humid areas, of biological or economic productivity. and the complexity of rainfed farmland, irrigated farmland or range, pasture, forest and woodland resulting from land uses or a process, or combination, of processes, including processes arising from human activities and housing models [3, 4].

In Italy 10% of the national territory is at risk of land degradation and in particular in Basilicata region the percentage of the territory affected by the phenomenon is 24.4% among the highest at national level preceded only by Sicily. To address the land degradation problem, Italy has defined a "LND Land Degradation Neutral-ty" program which provides for the balancing of the recovered soil with the degraded one [5, 6].

Soil degradation processes consist in the loss of the biophysical properties of the soil determined mainly by factors such as erosion and salinization [7].

The causes are many but, especially in the inland areas of the Mediterranean regions [5], some dynamics related to agriculture have particularly influenced the degradation processes. Specifically, agricultural over exploitation with unsustainable practices, the land abandonment, are causing ecological alterations that need analysis to evaluate the medium- and long-term effects. Indeed, some agricultural practices, which are oriented to an overexploitation of the land, to an excess of mechanized processing and the use of chemistry [8] are leading to a reduction of soil quality and subsequent degradation (erosion caused by water and wind, compaction, decrease of soil organic carbon and soil biodiversity; salinization, sodification and contamination of the soil by heavy metals and pesticides, or by excess of nitrates and phosphates). The other phenomenon, namely the abandonment of agricultural activities and more in general of the territory, is to the attention of the scientific community as it can produce environmental and landscape impacts, as well as socio-economic impacts [9]. The effects can be very variable in relation to territorial contexts and therefore they are dependent on climatic, ecological, biological, pedological and topographical factors.

The present work was developed starting from implementation of RUSLE method [10], using Remote Sensing techniques and Geographic Information Systems (GIS). Once the monthly erosion rate A was calculated, the Getis spatial autocorrelation index [11] was used in order to obtain a persistent/non persistent binary map consisting of 0 and 1, where 0 stands for non-persistent erosion and 1 for persistent erosion persistent/permanent erosion respect the entire observed period. Spatial autocorrelation measures the degree of dependence between events, considering at the same time the similarity and their distant relationships. Self-correlation indicators measure whether and to what extent a data set is autocorrelated across the study region. In the presence

of positive spatial autocorrelation, similar values of the variable are spatially grouped, while in the presence of negative spatial autocorrelation, the dissimilar values of the variable are spatially grouped; the absence of spatial autocorrelation indicates a random distribution of values in space.

One of the most important factors of the RUSLE and of greatest scientific interest is represented by C Cover-management factor [12] which measures the type of management of the agricultural activity that is carried out on that soil and can take values ranging from 0 to 1 where 0 indicates good cover and agricultural management practice while 1 indicates a condition of poor management and a condition of non-vegetated soil. It is in fact the vegetation cover that plays a fundamental role in determining the degree of vulnerability of a particular area. Through the C factor compared with the persistent/n erosion rate, it is therefore possible to determine which agricultural areas are potentially degrading. In these areas there are phenomena of altered photosynthetic activity due to organic loss or climate change or incorrect management of arable land [13]. The aim of this work is to provide a tool for analyzing the phenomenon of land degradation on a large scale with a good accuracy.

2 Study Area

The analyzes and calculations were carried out in an area of approximately 1554 km^2 within the Basilicata Region (Fig. 1) including the municipalities of Tricarico, Ginestra, Irsina, Acerenza, Cancellara, Albano di Lucania, Forenza, Maschito, Oppido Lucano, San Chirico Nuovo, Grassano, Palazzo San Gervasio, Tolve, Genzano di Lucania, Venosa and Banzi. The area is characterized by a typically Mediterranean climate, with a pronounced bi-seasonal regime with hot and dry summers and humid and cold winters. Natural risks and anthropogenic activities make this area an interesting study context because the combination of human activities and natural risks contribute to the establishment of degradation phenomena.

For a more complete and detailed analysis of the characteristics of the biotypes of the study area, the Natural Habitats Map of Italy (CNAT 2013) was used because, compared to the Corine Land Cover map [14], it presents more detail in the description of land use [15]. Given the greater level of detail and accuracy, CNAT was chosen as a reference for spatial and statistical analysis (Fig. 2).

As CNAT indicates, agricultural land use classes are prevalent in the study area. In particular, just over 65% is represented by arable land including the classes “Extensive and intensive arable land” (in a higher percentage) and “Extensive crops and complex agricultural systems”. The difference between the two classes refers to the structural and ecological characteristics. In fact, in continuity with what is expressed previously, the extensive crops class refers to highly fragmented cereal systems with small edges of hedges, thickets, stable meadows, etc., typical of the most morphologically heterogeneous areas. In fact, it is possible to identify them in the eastern and southern part of the study area. In particular, the southern area has less coverage of arable land and a considerable variability in terms of land cover.

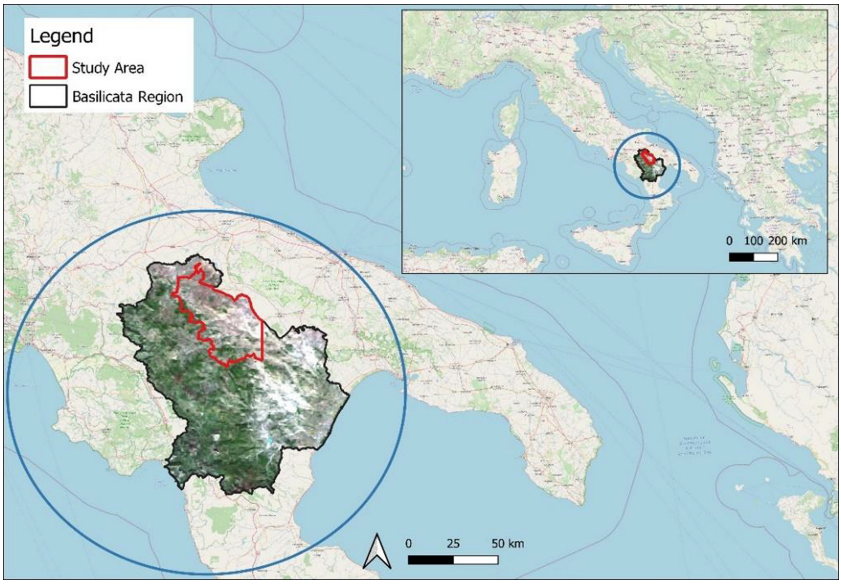

Fig. 1. Study Area

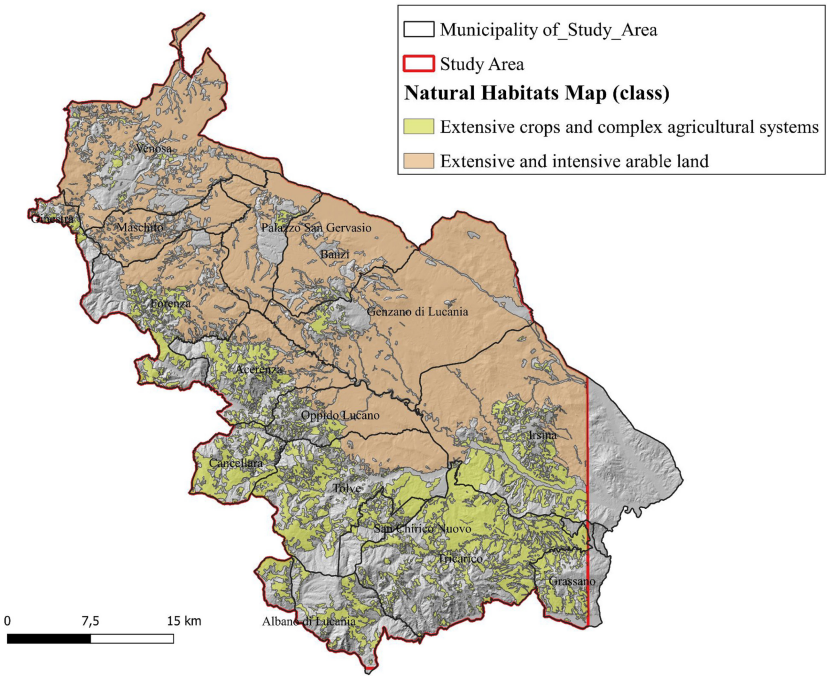

Fig. 2. Natural Habitats Map 2013 of Study Area (only arable land classes)

3 Dataset

The work was based on the integration of remote sensing techniques and Geographic Information Systems (GIS) with open-free source technologies and open data sets. The use of new technologies and the integration of the different datasets of territorial data, offer the possibility of studying and monitoring the evolution of the territory on a high temporal and spatial scale. The increasing efficiency of the analysis techniques, the interoperability of the various data represents a valid tool for the planner in terms of defining plans and strategies consistent with the real needs and environmental problems.

The entire procedure was carried out with QGIS [16] open source software and related plugins. QGIS is a GIS (Geographic Information System) software that allows you to analyze and edit spatial data, it supports both vector and raster data; moreover, it integrates processing algorithms such as GRASS GIS and SAGA GIS.

The starting dataset is represented by the Sentinel 2 medium-high resolution images provided by the Copernicus Mission [17] reworked by the THEIA data center [15]. The purpose of this scientific and technical structure is to facilitate the use of images resulting from spatial observation through more performing correction algorithms.

The observation period of this work runs from September 2019 to October 2020.

4 Methodology

Soil erosion was estimated using the RUSLE model (Revised Universal Soil Loss Equation) [10] developed from the previous USLE model [19].

The estimate of annual soil loss according to the RUSLE model (Eq. 1) is a function of five variables relating to the rainfall regime, soil characteristics, topography, crop coverage and management and conservation cultivation practices, according to the following formula:

$$A = R * K * LS * C * P \tag{1}$$

where,

A [Mg * ha-1* y − 1] is the annual average soil loss, R [MJ mm h − 1ha − 1yr − 1] is the rainfall intensity factor, K [Mg h MJ − 1mm − 1] is the soil erodibility factor, L (dimension-less) is the slope length factor, S [dimensionless] the slope steepness are calculated from [20]. Factor, C (dimensionless) is the land cover factor, and P (dimensionless) is the soil conservation or prevention practice factors [21]. Once the annual erosion rate was calculated, the problem of studying degrade phenomena was tackled through the correlation between the factor C and the eorsion rate A.

Analyzing the trend of the R factor (Fig. 3) it is highlighted that during the whole time period the average values on the study area were recorded in November 2019 and in March 2020.

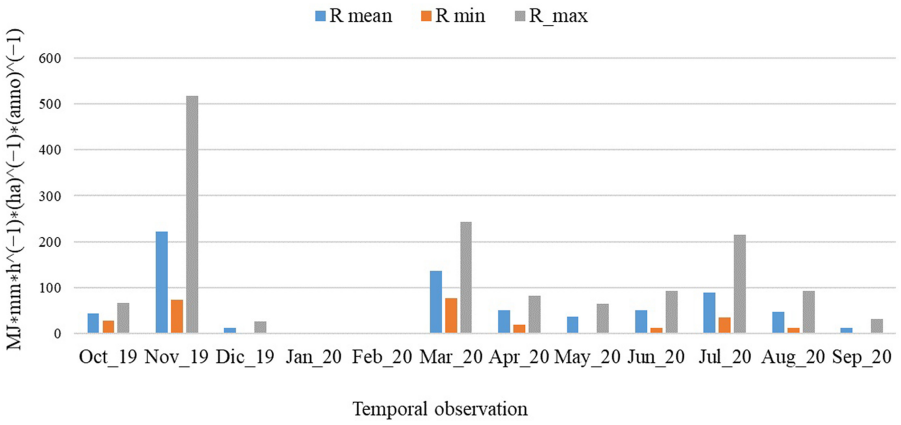

Fig. 3. R factor

By analyzing the graph of (Fig. 4), however, the average value of A in the month of March is very high. This means that despite the vegetation cover, the soil is significantly eroded by rain.

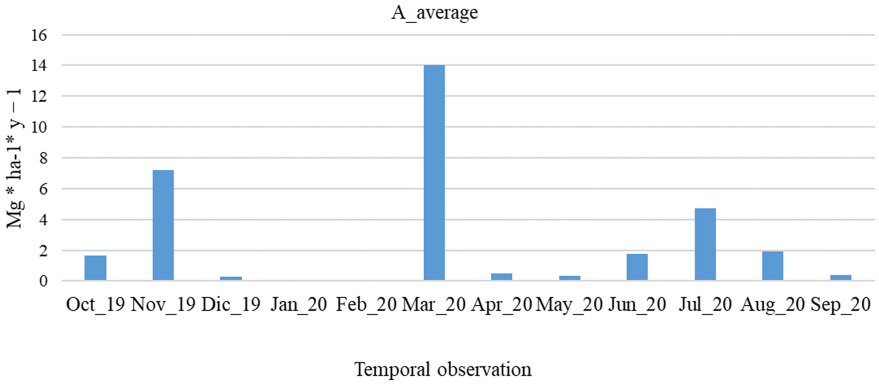

Fig. 4. A average

Finally, the trend of the C factor is also reported (Fig. 5), which shows a very low value of C which corresponds to a discrete vegetation cover.

It was therefore decided on the basis of the analysis of the monthly averages of the R, A and C factors to understand if there was a very strong relationship between them in reference to the month of March 2020 where the values show a high erosion compared to a coverage of the soil already advanced.

The methodology starts from the concept that in order to highlight if there is a proportionality between the erosion value of A and the factor C, this must be verified by trying to keep the other factors contributing to the final erosion value in a certain range.

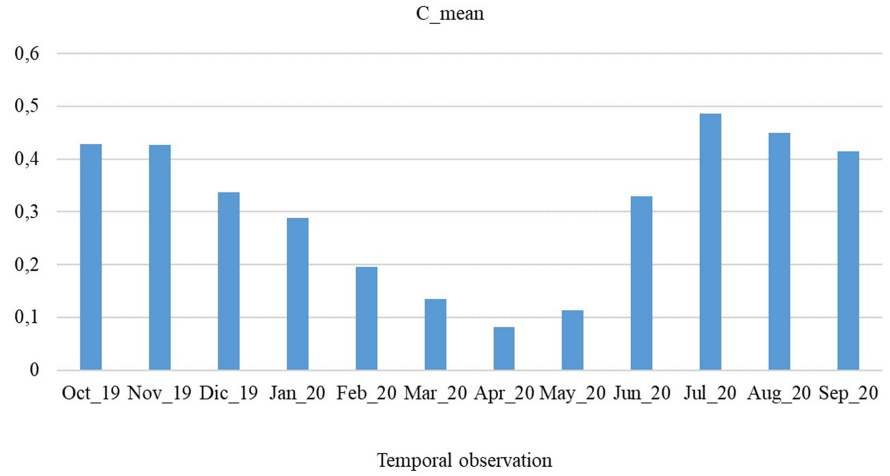

Fig. 5. C_average

To do this, it was decided to use the slope and the rainfall erosivity map divided into classes and to analyze the values of A in a range set by the classes for both slope and erosivity [22]. The following Fig. 6, shows the input maps of the proposed methodology.

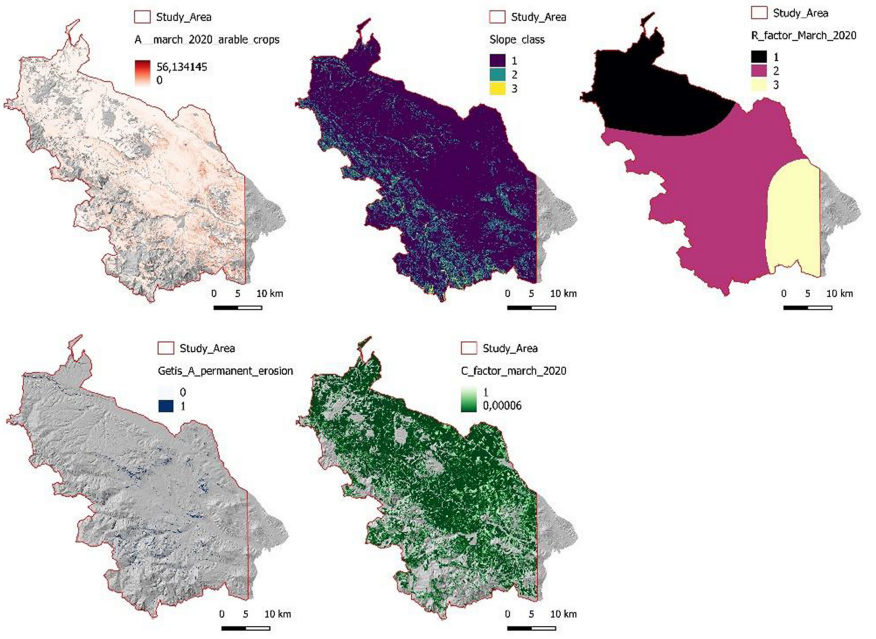

Fig. 6. Input map: erosion A in the upper left, the slope in 3 classes in the upper center, the erosion factor R in 3 classes on the right, the permanent erosion of Getis in the lower left and finally the factor C

The block diagram (Fig. 7) shows the methodology developed for the identification of potentially degraded areas. Arable land covered by vegetation is certainly more protected from erosion because the leaf surface present interposes a physical barrier to the impact of rain and the effect of debris sliding downstream [23]. Identifying the cultivated agricultural areas in which the erosion phenomenon is high, especially in the periods of growth of the vegetation, implies that that area could over time show problems caused by a not very luxuriant vegetation and an increasingly scarce growth and therefore decide to abandon that land or use it for another use For this reason, by isolating the C factor from the other factors and linking it to A in the periods of maximum vegetative activity, it is possible to obtain degraded areas as they show a high rate of erosion despite the soil being covered by vegetation.

Subsequently, the combination of all possible couples was elaborated, obtaining 9 layers of the erosion value A which fall into the same class for S slope and R erosivity. Referred to March 2020. Since the goal is to search for the correlation between A and the factor C was chosen to compare them through the linear regression analysis tool by means of which the residual map for each pair regr [A_ (i, j), C] was obtained.

In the following Table 1 the value of the correlation coefficient R has been reported for each comparison, which has moderate values only for some pairs.

The residual maps A_res (i, j) quantifies the error pixel by pixel Ɛ calculated on the difference between the estimated value of A and real A.

$$Y = AX + B + \epsilon \tag{2}$$

The direct proportionality (2) is given by the points closest to the regression line and therefore by the points where the value of the residuals Ɛ is small in absolute value. Having chosen the most correlated layers $R > 0.25$, it was assumed to set a threshold on the choice of residuals and therefore on the error since the coefficient R is not very high. To select the values of A in which the error Ɛ can be considered minimum, a threshold was defined (3)

$$\epsilon = |\text{Yreal} - \text{Yest}| < 2 \tag{3}$$

around the regression line by selecting only the pixels of A most correlated with C. Finally, a threshold value greater than o equal to 5 [Mg * ha-1- * y − 1] has been chosen. The last step was to compare the map thus obtained with the permanent erosion map A, the result of which represents those agricultural areas in degradation.

5 Result and Discussion

The use of software that can implement very complex calculation procedures allows to obtain very accurate processing with few hardware resources available. All this in order to be able to monitor areas at risk of degradation in the shortest possible time.

Thanks to the interoperability of the available datasets, it is possible to aggregate multiple sources and expand the potential of remote sensing techniques for safeguarding the soil resource.

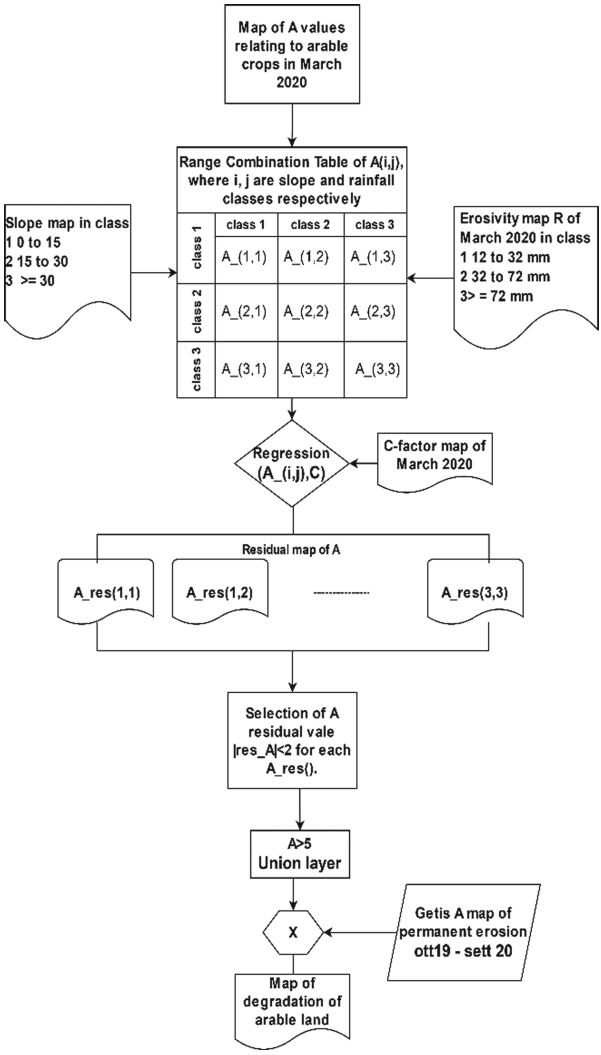

Fig. 7. Flow chart methodology

In this context, the proposed methodology aims to be able to give an innovative approach in the study of the phenomenon of land degradation. The first step in defining the methodology is the calculation of erosion A.

In fact, starting from this data and analyzing the factors that make up the RUSLE, a raster map was developed that identifies those agricultural areas potentially in degradation and showing conditions of poor productivity. The Fig. 8 shows the study area on the left, while details on some municipalities affected by the degradation phenomenon have been reported on the right by submitting the most recent orthophoto.

The following Table 2 shows for each municipality of the study area the estimated surface of the degraded area, the average value of potential erosion A relative to the

Table 1. R coefficient

regr(A_(i,j),C)	R
regr(A_(1,1),C)	−0.061179
regr(A_(1,2),C)	−0.182321
regr(A_(1,3),C)	**−0.265939**
regr(A_(2,1),C)	−0.18986
regr(A_(2,2),C)	**−0.314881**
regr(A_(2,3),C)	**−0.464801**
regr(A_(3,1),C)	0.060026
regr(A_(3,2),C)	**−0.367359**
regr(A_(3,3),C)	**−0.466316**

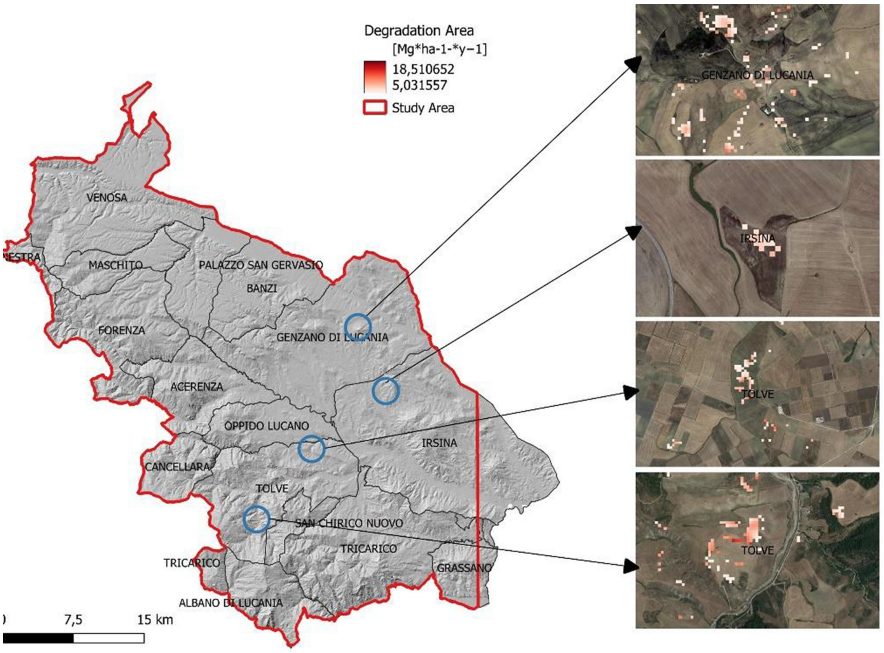

Fig. 8. Degradation Map. On the left side the Study area - In the right, particular of degradation area detected in red in the ortophoto (2017)

month of March 2020 and finally the ratio between the identified degraded area. by the algorithm and the cultivated area for each municipality. The municipality with the highest degraded surface is Tolve with 70.32 (ha) with a degraded area and agricultural area ratio of approximately 1%, followed by Genzano di Lucania with approximately 64 (ha). If the data of Genzano di Lucania may be obvious due to the very large crops land

area, in the case of the municipality of Tolve the phenomenon already seems to have a greater weight.

Compared to the data of the relationship between degraded area and crops land area, an interesting fact to note refers to the municipality of San Chirico Nuovo which shows the highest percentage 1.48% compared to all the municipalities in the study area to which particular attention should be paid.

The surface of the degraded areas is approximately 250 hectares, totaling 0.25% of the entire area intended for arable land.

Table 2. Surfaces of the degraded areas -Summarize

Municipality	Degradation of arable land (ha)	Arable lands area (ha)	RUSLE (A) Average	Degradation Area/Arable land (%)
Tolve	70.32	7255.937701	7.367268234	0.9691373176
Genzano di Lucania	63.48	17918.38498	6.952897228	0.3542729999
Tricarico	36.2	8520.473156	9.066046735	0.4248590347
Irsina*	19.48	14953.27964	8.579731184	0.130272425
Forenza	14.72	6461.095185	7.3275489	0.2278251531
Acerenza	13	4497.243118	6.867987696	0.2890659824
San Chirico Nuovo	12.52	841.4932548	7.653385216	1.487831296
Venosa	6.44	11430.60733	5.785923422	0.05633996352
Banzi	3.08	6786.586724	6.46151887	0.04538363872
Oppido Lucano	2.68	3909.054331	6.709750104	0.06855878105
Ginestra	2.24	536.6577852	5.937695989	0.417398212
Cancellara	2.12	2205.97083	7.614363337	0.09610281202
Palazzo San Gervasio	1.68	4584.127325	6.926314922	0.03664819672
Albano di Lucania	0.76	1445.747507	7.738875188	0.05256796199
Maschito	0.48	3569.221851	5.673954447	0.01344830946
Grassano*	0	1231.173906	0	0
TOTAL	**249,2**	**96147.05462**	**0**	**0.259186307**

*. the data relating to the two municipalities is partial

6 Conclusion

Large-scale satellite monitoring and the availability of open data offers innovative support for the development of environmental monitoring methodologies thanks to which it is now possible to address the phenomenon of soil degradation with more in-depth analyzes. In this work, attention has been focused on the phenomenon of erosion because it is both a consequence and a cause of the phenomenon of soil degradation.

This kind of approach is not tied to any particular software or data but can be easily replicated with new generation images of greater detail.

Finally, it could be useful to investigate the land degradation phenomenon with respect to the other factors that determine potential erosion A.

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