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Analysis of trends in productivity metrics in assessing land degradation: A case study in the Campania region of southern Italy

Marco Di Leginio [a], Antonietta Agrillo [b], Luca Congedo [a], Michele Munafò [a], Nicola Riitano [a], Fabio Terribile [c,d], Piero Manna [b,*]

[a] Italian Institute for Environmental Protection and Research (ISPRA), Rome, Italy
[b] Institute for Mediterranean Agricultural and Forestry Systems (ISAFOM), National Research Council (CNR), Portici, NA, Italy
[c] CRISP Research Center, Department of Agriculture, University of Napoli Federico II, Portici, Naples, Italy
[d] Department of Agriculture, University of Napoli Federico II, Portici, Naples, Italy

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ABSTRACT

Land degradation is a critical issue at a global level and its progressive increasing greatly reduces soil ecosystem services. In this context, the 2030 Agenda for Sustainable Development, adopted by all United Nations Member States in 2015, defined the Sustainable Development Goals (SDGs) and indicated some targets of particular interest for a territory to be integrated into short- and medium-term national programs. Target 15.3, which aims to end desertification and restore degraded lands, is currently monitored by indicator 15.3.1, measured as the combination of three sub-indicators (trends in land cover change, land productivity and carbon stocks) as suggested by the United Nations Convention to Combat Desertification (UNCCD), the custodian agency for the SDG indicator. In our opinion, this assessment shows some weakness that are generally caused by a lack of information from direct field observations. The greatest limitation regards land productivity dynamics linked to the NDVI trajectory adopted by the UNCCD methodological approach. For this reason, the paper proposes an alternative approach that consists of using annual maximum NDVI value assessments instead of annual mean values for trajectory calculation. To come to these conclusions, the study addresses a reliability assessment by using remote sensing techniques via the Google Earth Engine (GEE) and analysing the NDVI evolution over time at 450 locations spread around the Campania region (southern Italy). To this end, a customised Graphical User Interface (GUI) was built on the GEE platform and a Google Earth time slider tool was applied to visualize land cover changes which occurred at each location over a period of 18 years (2001–2018). The survey was carried out on MODIS and Landsat 7 collections and showed that the new approach had a better performance than the UNCCD approach (90 % vs 62 % of successful reliability tests, up to 96 % considering results from Landsat images). The application of maximum NDVI values to assess productivity dynamics spatially shows, with regard to UNCCD data, more than double the percentages of degraded and stable lands and a drastic reduction in improved areas within the Campania region. Overall, this innovative approach appears to agree more closely with ground truth and the use of finer resolution data is more suitable for investigating land degradation processes within a regional context.

1. Introduction

Land degradation is one of the biggest global challenges with significant consequences for both ecosystems and human populations. It is defined as the many human-caused processes that are causing the decline in or loss of biodiversity, ecosystem functions or ecosystem services in any terrestrial and associated aquatic ecosystem (IPBES, 2018). The definition has changed over time moving from “desertification” (UNCCD, 1994) to the concept of “land degradation” (UNCCD, 2017), which takes into account a much wider approach and includes land cover dynamics as a main driver of degradation. The complexity of land degradation processes and the interplay of biophysical and socioeconomic causes (climate change, soil depletion, landscape modifications and biodiversity decline) make assessment of the phenomenon particularly challenging (Salvati, 2022).

In October 2015, the UNCCD (United Nations Convention to Combat

* Corresponding author.
E-mail address: piero.manna@cnr.it (P. Manna).

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Desertification) adopted the concept of Land Degradation Neutrality (LDN) as a part of the 2030 Agenda within the Sustainable Development Goals (SDGs). LDN is defined as "a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems (Decision 3/COP.12, UNCCD, 2015). Target 15.3 aims, by 2030, to "combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world": it is monitored through the evolution of degraded land as a percentage of total land area (SDG indicator 15.3.1). This indicator is measured as a combination of three sub-indicators which were adopted at the eleventh session of the UNCCD Conference of the Parties: 1) status and change in land productivity; 2) land cover and land cover change, 3) change in above- and below-ground carbon stocks (with the stock of soil organic carbon -SOC- as the initial metric). The indicator result is derived from a classification of land condition (i.e., degraded, stable or not degraded) and is based primarily, and to the largest extent possible, on comparable and standardized official national data sources. As a result, changes in the sub-indicators are depicted as positive or improving; negative or declining, stable or unchanging (UN, 2022, Sims et al., 2017).

The UNCCD recommends using global datasets to estimate the sub-indicators in the absence of reliable national estimates (Sims et al., 2019). Global datasets, although freely available, are not so appropriate for LDN policy action at country level because of, amongst other limitations, their coarse resolution. For this reason, the UNCCD recommends a 'tiered approach' for countries to compute the three indicators, which can use data from three levels (Global Mechanism, 2016; UNCCD, 2018), namely i) Earth observations, geospatial information and modelling, ii) national statistics and iii) field surveys and ground measurement.

In addition, the recent proposal for a Directive on Soil Monitoring and Resilience in Europe (Soil Monitoring Law) also encourages earth observation in order to support Member States in monitoring the relevant soil descriptors (COM (2023) 416 final).

Earth observation (EO) is most frequently employed to monitor the above-ground vegetation processes by using the readily available satellite time-series data covering the past three decades and nearly all the world (Mbow et al., 2015). Thus, remote sensing has become a crucial tool in the mapping of land degradation and, to this purpose, vegetation productivity indicators derived from time-series satellite images may be the most useful proxy for assessing land degradation on regional or global scales (Veron S.R. et al., 2006, Fensholt et al., 2013, Huang S. et al., 2016). However, the volume of remote sensing big data (RSBD sensu Ma et al., 2015) far exceeds the capacity of standalone storage hardware so major geo-big data analytics are currently developing on cloud platforms, an efficient way of storing, accessing and analysing datasets on very powerful servers which "virtualize supercomputers" for the user (Amani et al., 2020; P. Perez-Cutillas et al., 2023). To tackle these issues and bridge the gap between users' expectations and current Big Data analytical capabilities, EO Data Cubes (EODC) are a new paradigm revolutionizing the way users can interact with EO data and a promising solution to store, organize, manage and analyse EO data (Giuliani G. et al., 2019).

Among free cloud EODC computing services, the Google Earth Engine (GEE) stands out as it allows an analysis-ready data catalogue of several petabytes with a high-performance computational service. The public data catalogue hosts over 40 years of remotely sensed data, such as Landsat, Modis, National Oceanographic and Atmospheric Administration Advanced Very High-Resolution Radiometer (NOAA-AVHRR), Sentinel 1, 2, 3 and 5-P; and Advanced Land Observing Satellite (ALOS) data (Gorelick et al., 2017).

Within Modis collections, an additional ready-to-use vegetation index, NDVI, is also available not requiring the download of raw images (Kumar and Mutanga, 2018; Tamiminia et al.,2020, Tucker, 1979). This index is calculated by the difference of near infrared (NIR) and red (R) reflectance and normalized by their sum: it shows a high correlation with the vegetation cover percentage and green leaf biomass (Purevdorj et al., 1998, Gitelson et al., 2003).

For computation of SDG indicator 15.3.1, it is common to use Trends Earth, a free open-source QGIS plugin that exploits EO data in a desktop and cloud-based system.[1] On this platform, a single sub-indicator or all three sub-indicators combined may be assessed through global default data or a specific national dataset (Sims et al., 2021). This approach is a reference element, that becomes the standard for preparation of the reporting process established by the UNCCD (PRAIS - Performance Review and Implementation System[2]). A broad range of users (Girma et al., 2023, Kust et al., 2023, Paredes-Trejo et al., 2023, Cherif et al., 2023, Assennato et al., 2020, Gonzalez-Roglich et al., 2019, Bayouli et al., 2021) is currently applying Trends.Earth in projects ranging from the planning and monitoring of restoration efforts to tracking urbanization and developing official national reports for submission to the UNCCD every four years (decision 15/COP.13). All these elements strive to help in the monitoring and evolution of the landscape, supporting decision-makers in identifying and mapping current and future land degradation problems (IPBES, 2018).

As stated before, the methodology proposed by the UNCCD assesses degraded, stable or improved areas by considering *land productivity*, *land cover change* and *change in carbon stocks*.

In the present work, we focus on the "land productivity" criteria and ignore the second and third sub-indicators. This has been done for the following reasons:

- The "land productivity" is the biological productive capacity of the land, the source of all the food, fiber, and fuel that sustains humans. To assess this indicator, Net Primary Production (NPP) is usually used. However, it is time-consuming and costly to estimate (Giuliani et al., 2020). Hence, remotely sensed proxies are commonly used to derive indicators of NPP with a rather objective approach, i.e., by exploiting the measurement and monitoring of primary production through the evaluation of NDVI dynamics that can be quantified and spatialized. On the contrary, the second and third sub-indicators are classified through a much more empirical approach which assumes that changes in land use classification are linked to SOC stock variations and thus connected either to land degradation or land improvement as a consequence of the "change direction" (Minelli et al., 2017, Orr et al., 2017, Sims et al., 2020).
- Land cover dynamics widely depend on the classification system and acquisition scale of data; the matrix for identifying stable, improving or degraded areas might be ambiguous and needs to be adapted to different contexts (Sims et al., 2021): only those situations leading to an evident ecosystem reduction, such as vegetation loss or urban expansion, are classified as "degraded", but all changes involving a new management system or switching crop production have to be investigated through the repeated collection of soil sampling data over a time interval to establish possible degradation/improvement phenomena.
- The monitoring of carbon stock changes lacks a harmonized topsoil dataset and suffers from a scarcity of soil profiles and the absence of soil samples collected in the same period (FAO, 2018).
- Land productivity greatly affects the final assessment of land degradation, while land cover and carbon stock have minor impacts; in this sense, the "one out all out" approach enhances the great weight of land productivity changes (see next chapter).

On the basis of these premises, the general objective of this study was

[1] https://docs.trends.earth/en/latest/index.html.

[2] https://www.unccd.int/news-stories/stories/prais-4-reporting-platform-live.

to test the effectiveness of the SDG 15.3.1 sub-indicator output when following two methodologies: the widespread Trends.Earth plugin method and an alternative approach using a different NDVI metric. The results were compared with the "ground truth" obtained from observation of true colour satellite images.

The research was carried out in Campania, southern Italy: the choice of the site was especially useful because (i) the region has high territorial variability which potentially overlaps with a geographical distribution of degraded areas (ii) the authors had access to a large dataset (e.g. soil, geology, land use, climate etc.) that proved to be useful for this specific research. These conditions facilitated the testing of the productivity sub-indicator included in the SDG 15.3.1 indicator.

2. Materials and methods

2.1. Study area

The region of Campania is in the southern part of the Italian Peninsula; it has a population of 5,834,056 people and a total area of 13.595 km^2. Campania is the second most populous and the most densely populated region of Italy. Forest and semi-natural areas cover more than 37 % of land in the region (about 5.000 km^2) and comprise the areas in which land use is at its least human dominated. Arable land occupies around 55 % and artificial areas about 7.5 % of the total area (CLC, 2018). However, data from the SNPA (National Environmental Protection System in Italy) which indicates that artificial land cover accounts for about 10.5 % of land use in the region, clearly above the national average value (i.e. 7,14 %, ISPRA/SNPA, 2023), shows that this information is probably underestimated.

The climate regime of the region is typically Mediterranean, hot-dry summers and cool-wet winters, with some evident differences because of the significant orographic effects on precipitation (Longobardi, 2022). High precipitation (up to 2,000 mm) is typical in high relief areas of the central part of the Apennines during winter periods, while lower values (900 mm) are generally recorded in the western and eastern parts of the region. The mean annual temperatures range from 12 °C in February to 29 °C in August. The morphologically heterogeneous territory of the region translates into great soil, land and land use variability whose responses to and effects on degradation phenomena can potentially differ greatly.

2.2. Data source and processing

2.2.1. The UNCCD procedure

The starting point of the study was the result obtained when applying the UNCCD procedure to Campania through the Trends.Earth plugin using as input the default data: i) ESA CCI land cover maps classified in 7 classes according to IPPC Land Use Categories, ii) SoilGrids at 250 m resolution as reference to carbon stocks for the first 30 cm of the soil profile and iii) productivity elaborated from bi-weekly data from MODIS with 250 m resolution (Trends.Earth. Conservation International. Available online at https://trends.earth. 2022).

As stated above, the comparison of the three sub-indicator values clearly shows the great weight of productivity on the final evaluation 15.3.1 (see Table 1).

Moreover, in order to interpret land productivity change, the UNCCD recommends applying three metrics based on NDVI:

- *Trend or trajectory*: measures the rate of change over a period of at least 15 years;
- *State*: detection of recent changes in primary production as compared to a baseline period.
- *Performance*: local productivity relative to other areas with similar land cover or bioclimatic regions.

The aggregation of the three metrics according to the "One-out, all out (1OAO)" method proposed by the methodology gives values at pixel scale as indicated in Fig. 1.

More specifically, following the 1OAO rules, the "trend or trajectory" metric distinctly appears to be highly important if compared with the other two metrics (state and performance): considering the 18 possible different combinations, more than 80 % of the final evaluation follows the trajectory classes.

Furthermore, trend is here considered to be the most objective parameter as it is used as a statistical significance test to determine the rate of NDVI changes over time, whereas the determination of significance in the state and performance metrics is more arbitrary (Sims et al., 2019).

Table 1
Percentage of Indicator 15.3.1 and related three sub-indicators assessed in Campania by applying Trends.Earth default data. The summary of change in productivity shows values similar to the final assessment.

	Summary of SDG 15.3.1 Indicator (final assessment)	Summary of change in ***productivity***	Summary of change in ***land cover***	Summary of change in ***soil organic carbon***
Improved land area	65.95 %	67.93 %	1.59 %	0.64 %
Stable Land area	22.85 %	25.05 %	94.48 %	98.50 %
Degraded Land area	11.02 %	6.84 %	3.93 %	0.85 %
Land area with no data	0.17 %	0.17 %	0.00 %	0.00 %

2.2.2. Our approach

Considering the above, the assessment in the Campania region focused on the analysis of trend metrics to evaluate the productivity sub-indicator. We studied this item to achieve the dual objective of i) testing the reliability of the SDG 15.3.1 sub-indicator through a procedure for verifying the results obtained by applying the Trends.Earth plugin, and ii) testing the reliability of a revised version according to a new approach.

In doing this, we required access to the codes of the Trends.Earth plugin, which is supported by several Python scripts that allow calculation of the various indicators on the GEE. These codes are freely available on GitHub.[3]

As already shown in the previous paragraph, the GEE is currently one of the best tools for interpreting the performance of vegetation indices and their seasonal dynamics (maximum value, minimum value, range, mean, etc) at different spatial and temporal resolutions (i.e., MODIS, Landsat, Sentinel).

Hence, we assessed the trajectory of NDVI in the GEE environment at pixel level for the whole Campania region over the 2001 – 2018 period. The calculation code applied by Trends.Earth was reproduced, and new trend metric was tested by also running the scripts on Landsat products with a finer spatial resolution.

To be more precise, the MODIS13Q1 V6.1 product (bi-weekly, spatial resolution 250 m) and the Landsat 7 (16 days, spatial resolution 30 m, with a temporal observation that is compatible with the studied period) dataset were used to analyse NDVI values over the 2001–2018 period. According to the official methodology, the mean annual NDVI values were used to compute a linear regression at the pixel level to identify areas experiencing changes in primary production.

A Mann-Kendall non-parametric significance test was then applied to check statistically whether the variable of interest had a monotonic

[3] https://github.com/ConservationInternational/trends.earth-algorithms.

Trend	State	Performance
Improving	Improving	Stable
Improving	Improving	Degrading
Improving	Stable	Stable
Improving	Stable	Degrading
Improving	Degrading	Stable
Improving	Degrading	Degrading
Stable	Improving	Stable
Stable	Improving	Degrading
Stable	Stable	Stable
Stable	Stable	Degrading
Stable	Degrading	Stable
Stable	Degrading	Degrading
Degrading	Improving	Stable
Degrading	Improving	Degrading
Degrading	Stable	Stable
Degrading	Stable	Degrading
Degrading	Degrading	Stable
Degrading	Degrading	Degrading

5 Classes	3 Classes
Improving	Improving
Improving	Improving
Improving	Improving
Improving	Improving
Improving	Improving
Moderate decline	Degrading
Stable	Stable
Stable	Stable
Stable	Stable
Stressed	Stable
Moderate decline	Degrading
Degrading	Degrading
Degrading	Degrading
Degrading	Degrading
Degrading	Degrading
Degrading	Degrading
Degrading	Degrading
Degrading	Degrading

Fig. 1. Land productivity metrics aggregated into three or five classes according to UNCCD methodology (Source: Trends.Earth. Conservation International. Available online at: http://trends.earth. 2022).

upward or downward trend over time (Mann, 1945, Kendall, 1975). The Mann-Kendall 'Z' score can be used to determine the significance of the Trend slope (Onyutha, et al. 2016): positive Z scores indicate a trend of increasing productivity; negative scores indicate decreasing productivity. The Z score represents the number of standard deviations from the mean of the sample, so it reflects the magnitude of the slope with larger positive or negative scores indicating a more statistically significant slope. Results obtained from Trends.Earth are expressed as integers from −3 to 3 through a range of pixel values representing the significance statistics of the trend slope as reported in the list below.

In the present work, pixel values were assigned with the following significance thresholds according to the same approach as trajectory trends elaborated by Trends.Earth plugin (Sims et al., 2021):

- declining (Z score $<$ -1.96; Trends Earth pixel value = -3 and −2)
- stable ($-1.96 \leq$ Z score ≤ 1.96; Trends Earth pixel value = -1, 0, 1)
- increasing (Z score $>$ 1.96; Trends Earth pixel value = 2 and 3)

The stable class (not significant in Z score variations) is associated with all pixels that do not fall into the degradation or improvement classes.

Following the above procedure and using both MODIS and Landsat 7 stacks of images, we introduced a new metric by applying the codes to calculate the pixel-based trends by using the maximum annual NDVI values instead of the mean ones. In this way, we obtained 4 trajectory evaluations (2 resolutions with MODIS and Landsat x 2 metrics with mean and max NDVI values) for the Campania region for the observed period (2001–2018) (see Fig. 2).

The performance evaluation of the approaches coupling different metrics and resolutions was computed by combining GEE and Google Earth (https://earth.google.com/) and using a network of 490 ground truth test points (390 for testing MODIS and 100 for Landsat images) from a random selection over different landscape units (combining geological setting, morphology, topography, climate and land use) (Fig. 3). These "ground truth" test points were analyzed by photointerpretation over true colour images and about 5 % of these points were validated by field evaluation (visual assessment by experts, including authors who had personal knowledge of these areas).

3. Results

3.1. The analysis in the Google Earth Engine (GEE)

Land productivity was firstly assessed through analysis of the NDVI

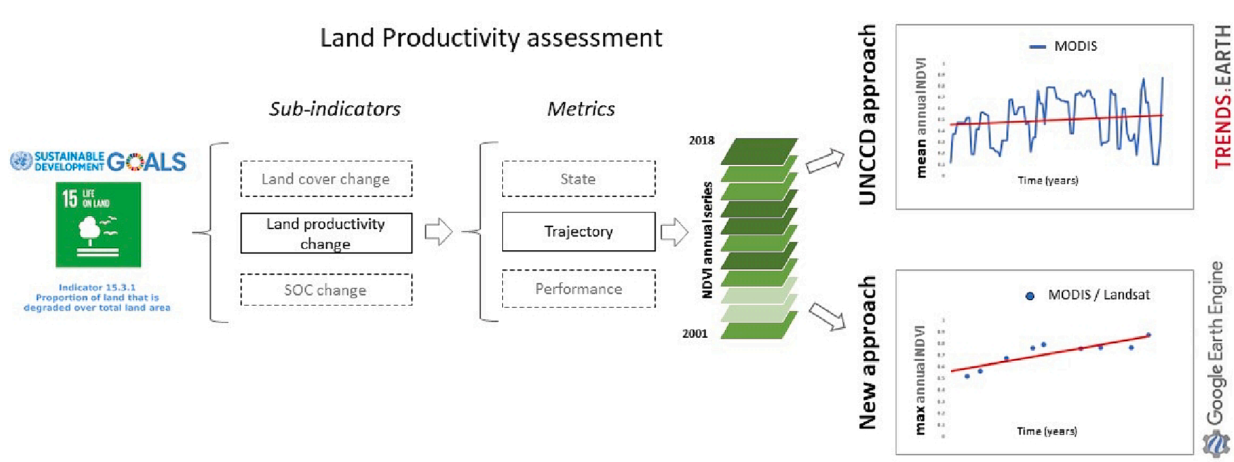


Fig. 2. General workflow adopted in the present work: starting from land productivity sub-indicators, we only considered the trajectory metric within a testing area (the Campania region). We compared the traditional UNCCD approach (based on mean yearly NDVI data) for the 2001–2018 period with an alternative metric based on maximum yearly data, using both MODIS and Landsat data sources.

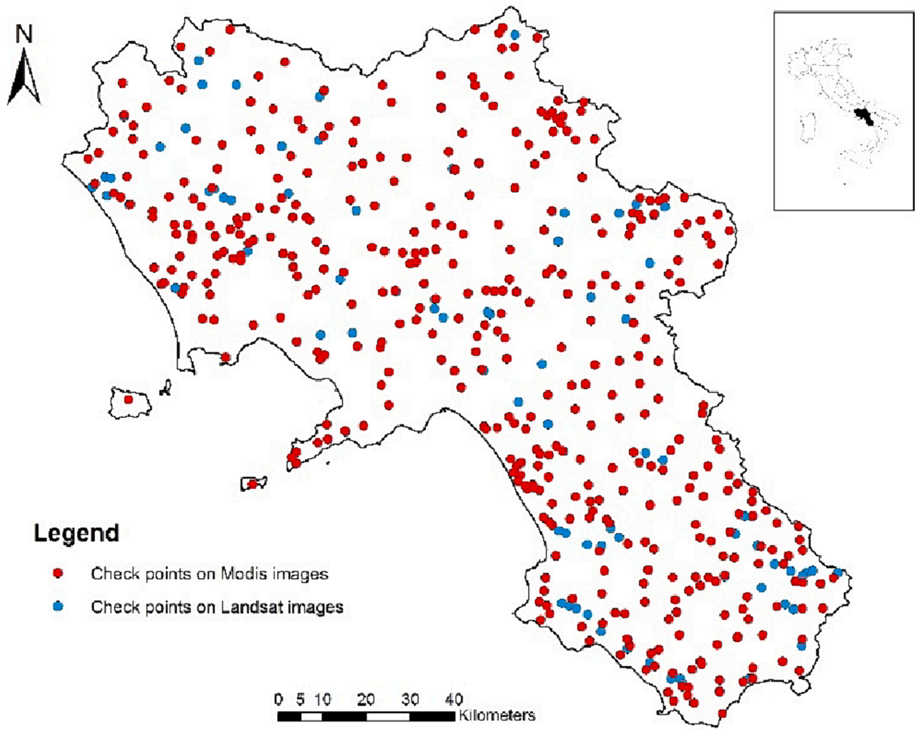


Fig. 3. Locations of testing points within the Campania region.

trends over the selected 2001–2018 period by using the Trends.Earth plugin. The result was a multiband raster containing all the information regarding productivity sub-indicators (trajectory, state, performance, mean annual NDVI integral, etc.). The data corresponding to trajectory were clipped within a GIS environment over the study area (the Campania region) and uploaded onto the GEE through the client-side user interface: the map showed a predominance of the "improvement" class which occupied almost 68 % of the total surface; only 2.5 % of the territory was classified as "degraded" and about 30 % fell into the "stable" class (Fig. 4).

In order to explore the official procedure applied by Trends.Earth in producing trajectory metrics, we reproduced the codes in the GEE by considering the same data source, study area and observation period. Finally, we applied the original styled layer descriptor (SLD) and obtained a raster map that was completely comparable with the Trends. Earth output, so confirming the correct reproduction of the official procedure.

For the sake of clarity, it should be emphasized that, even though land productivity appears to be the main sub-indicator in defining the state of land, the assessment obtained is more of an investigation into the evolution of the state of canopy/plant vigour over time than a strict analysis of land degradation/improvement, which cannot be based on the observation of NDVI trends alone (G.T. Yengoh et al., 2015, Schillaci et al., 2023). Cases where the NDVI trends alone identify degradation or improvement phenomena are those that can be defined as "striking", such as intense soil erosion affecting production, soil sealing or land use changes between distant classes (forest/agriculture).

However, from here on, in following the coding of the official methodology, we will mention the degraded, improved and stable classes even though only referring to the trend metric.

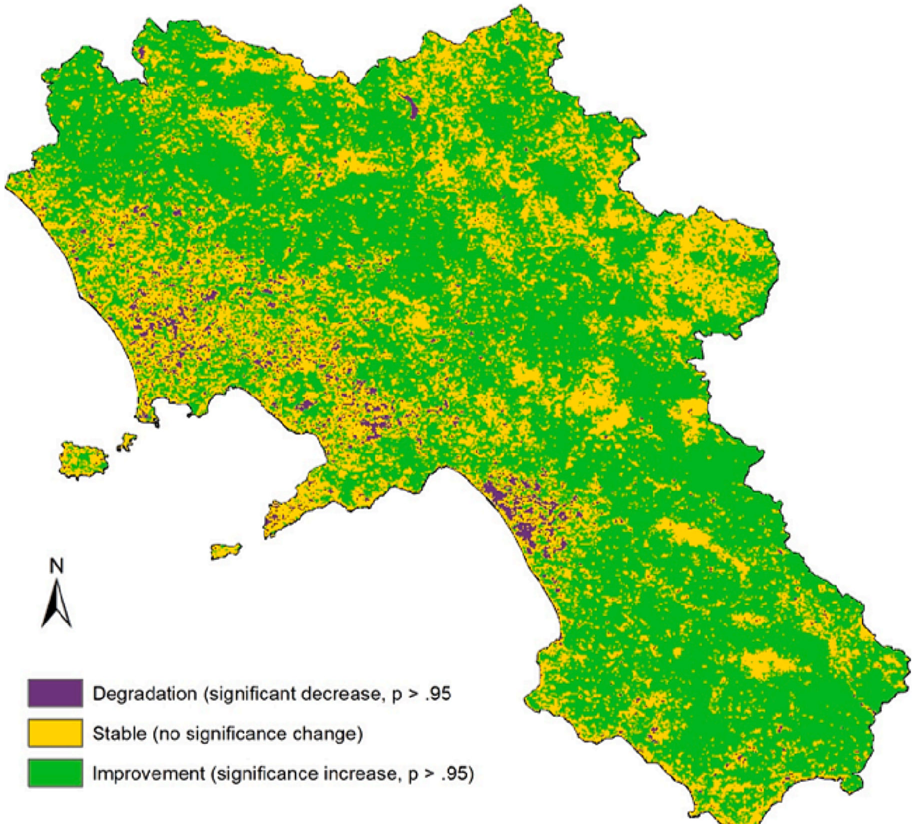
3.2. The logical framework

With the GEE tool at our disposal, equipped with a customized Graphical User Interface (GUI) including (see Fig. 5) a map visualization panel, an inspector tool and a code editor, we were able to perform the reliability tests for the indicator and to test new metrics at different spatial resolution.

To this end, we started by adapting the GUI to our needs, which consisted of being able to observe the trajectories of the NDVI values at the pixel scale at any point on the map in real-time. Therefore, we added new lines of code to i) calculate the maximum annual NDVI data (as suggested by Markos et al., 2023) in order to use these values to produce a new trajectory metric, as already done for the mean values following the official procedure; ii) add panels to the GUI to host two charts which have to be created on the-fly every time a user clicks on a location of interest on the map (i.e. pixel) by using the inspector tool. The charts show the normal NDVI values and the maximum yearly NDVI values as collected from the multi-temporal stack of images and corresponding to the clicked-on location, both provided with trend lines (Fig. 6). Moreover, in order to simplify the "on the ground" check of the results obtained after the classification of the NDVI trends (degraded, stable or improved areas), we added a specific code to iii) print the path to visualize the point selected in Google Earth by generating a link to kml files and iv) obtain the single scene of MODIS NDVI collection corresponding to each selected date.

The graphs coupled with the trajectory map allowed us to observe the NDVI trends over time at each point of the study area so as to discover their shapes, anomalous peaks, ascending and descending periods, phenological phases (green-up, maturity and senescence) during the year and deduce the possible causes. Moreover, uploading the observation points onto Google Earth allowed us to use the *time slider* tool to observe on a true colour image timeline how the surrounding landscape/canopy changed over time. We made a photointerpretation by applying at each point a buffer of approximately 250 m as the resolution of the MODIS images. With this logical framework, we were able to deduce whether the classification of trends for the 2001–2018 period was correct or not for each observation point by making a comparison between what was reported on the map, what was shown by the NDVI graphs and what was shown by the Google Earth images (true colour).

The procedure described above, was repeated with images at a better resolution, the Landsat7 Collection characterized by a timeline



2001 - 2018	Trends Earth
Degraded areas	2.5 %
Stable areas	29.7 %
Improved areas	67.8 %

Fig. 4. The Campania region classified through trend metrics according to the methodology proposed by the UNCCD (Trends.Earth) and considering the 2001–2018 period. Different colours represent a classification of trend metrics at pixel level after a Kendall test. At the bottom left, the surfaces are reported (%) classified with reference to the total surface.

compatible with the studied period (USGS Landsat 7 Collection 2 Tier 1 TOA Reflectance). In this case, we focused the photointerpretation on a buffer of 30 m, which was coherent with the pixel size of Landsat images. The working scheme described in Fig. 5 was again applied to the images in this collection: the observation points superimposed onto the trend maps can be "clicked" on to obtain on the-fly the graphs of the NDVI variations over time both for the normal values and the yearly maximum values covering the 2001–2018 period.

3.3. The reliability tests

In the first phase, the reliability test which regarded the MODIS multi-temporal NDVI images, calculates both the mean NDVI yearly values as reported by the official method and the maximum yearly values according to the new proposed metric. To this end, the analysis was carried out on 390 ground truth points that were selected within the Campania region according to the criteria described above.

In a second phase, the tests were performed by using the trend results from the Landsat 7 collection with the aim of verifying the metric improvement at a higher resolution. In the present work, the term "reliability" means the comparison carried out, at each observation point, between what was classified according to the applied trend metrics, what we deduced by observing the NDVI charts and what it was possible to deduce in terms of degradation/non-degradation from the true colours satellite images provided by Google Earth.

The results of this study – based on the comparative evaluation of the two UNCCD- based procedures- will be shown through the relevant case studies described below. Fig. 7 shows the map of Campania classified according to the methodology relating to trajectory sub-indicators proposed by the UNCCD, with some highlighted areas corresponding to the cases discussed. To be more precise, rather than representing new metric applications, case A addresses a procedure applied to all the cases in order to improve the quality of NDVI data.

Case A - The greenhouses

The first attempt to improve the trajectory output regarded the selection of good quality images from the MODIS collection. Pixel quality can be negatively affected by clouds or other atmospheric conditions and, so, each image should be pre-processed to remove the unusable values. Each MODIS image contains quality assurance (QA) information that can be used to identify which pixels to remove. We used a specific function in the GEE to get the required pixel quality and mask the pixels to be removed, so ensuring the absence of potential outliers caused by clouds or other noises. This masking procedure changed our results greatly in comparison with the official metric, particularly along the coastline where there are often scattered or densely aggregated greenhouses. Example A in Fig. 7 shows an area in the southern part of the Salerno municipality where there is a dense concentration of greenhouses. The frequent seasonal presence of growing tents make NDVI signals unclear and the following statistical test not unbiased: as a consequence, the approach with the mask recognizes stable areas

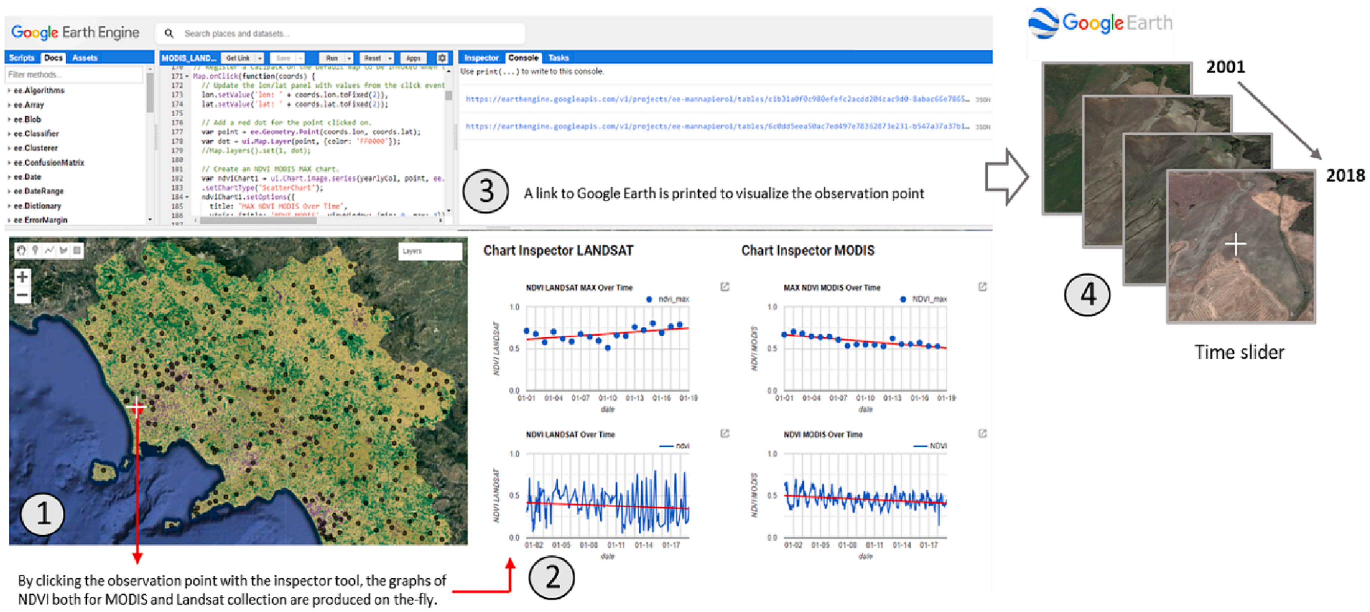


Fig. 5. The gee logical framework applied to check whether the classification of trends referring to the 2001–2018 period was correct or not. 1) the 450 observation points (black dots) distributed over the study area and superimposed on the metrics maps. The graphs of NDVI for both the MODIS and Landsat collections are produced on the-fly by clicking each position within the territory; 2) an example of the graphs produced representing the NDVI data for the 2001–2018 period; 3) a link to Google Earth is produced for each position clicked to visualize the observation point through high resolution true colour satellite images over time by using the time slider tool (4);

instead of degraded ones. According to the official approach assessed by Trends.Earth, these territories are classified as degraded while, when applying the quality filter to mask noises, most of the pixels are classified as stable. It is interesting to note that, according to the UNCCD approach, almost 25 % of the total regional degraded area is localized in this sector of the region. In other words, using a good quality pixel filter can significantly change the scenario.

Case B - Overestimation of improved areas

These cases represent the most common subject matter for applying a different metric: the analysis carried out at the observation points by applying the logical framework described above highlighted the significant difference between the UNCCD approach and the approach proposed in the present study on the assessment of areas identified as "improved" or "potentially improved". We observed a frequent overestimation of areas classified as improved in the UNCCD approach. The common presence of peaks in the lower minimum value at the beginning of an observation period induces an increasing trend line which confers an improvement status on the pixels. In the same way, their presence at the end of the observed period attributes a decreasing trend line which highlights potentially degraded pixels. The latter case should be masked with the second sub-indicator of land productivity referred to as "state", which is able to detect recent changes in primary production as compared with an initial period; however, the third and fourth rows of Fig. 1 do not confirm this assumption due to the greater weight assumed by trajectory, aggregating land productivity metrics. Low minimum values were observed in the presence of clouds, often encountered in mountain areas, and bare soils, mainly found in cropland and connected to growth cycles of plants and/or soil management practices. We have also observed cases where the amplitude of NDVI curves over time tended to shrink to minimum values (higher minimum values), probably as a result of crop management practices or due to crop rotation (these aspects deserve additional studies).

In these cases, we found that the new metric further reduces the effects due to minimum NDVI data by "cleaning" the signals over time and changing the output from significant improvement or degraded classes to stable ones (i.e. no significant NDVI change over the time period) (Fig. 7, case B and Fig. 8, on the right).

Case C - Soil erosion

In the hilly arable inland areas of Campania, near the boundaries with the regions of Molise and Puglia, the new metric based on max NDVI highlights "striking cases", i.e. evidently degraded areas that are not revealed by the Trends.Earth results. The forms of land degradation in these areas involved soil loss due to water action and are mostly found in small areas affected by stream channel erosion as shown in Fig. 8. We collected several Google images at the observation points where the erosion phenomena affecting the areas are evident. Unlike the official approach (Fig. 9, bottom right), the proposed metric (Fig. 9, bottom left) shows a slight but constant reduction in maximum annual NDVI values from year to year, which results in degraded pixels as shown in Fig. 7 (case C).

Case D - Forest environment.

Several observations from forest areas showed a significant reductions in NDVI values so giving a declining trend slopes, the indicator of degradation. We found that, in some cases (striking), these declines were connected to fire events that occurred during the observation period, as confirmed by the regional database on forest fires which has been available since 2002 (Carabinieri-CUFAA, 2021[4]). Moreover, in other cases, we observed that the typical form of local land management was chestnut tree coppicing (Iovino et al., 2020). Hence, either because of fire or coppicing, the trend reduction are the result of a sudden drop in NDVI values, which are generally extremely high in forest environments. However, we often only noticed these descending trends, classified as forms of degradation by the indicator, through the new proposed metric while Trends.Earth classified the observations as stable or improved (Fig. 7, case D, and Fig. 10).

3.4. Land degradation assessment through a higher resolution approach (Landsat)

NDVI time series from 2001 to 2018 were calculated using the

[4] https://geoportale.incendiboschivi.it/portal/apps/sites/#/geoportale-incendi-boschivi.

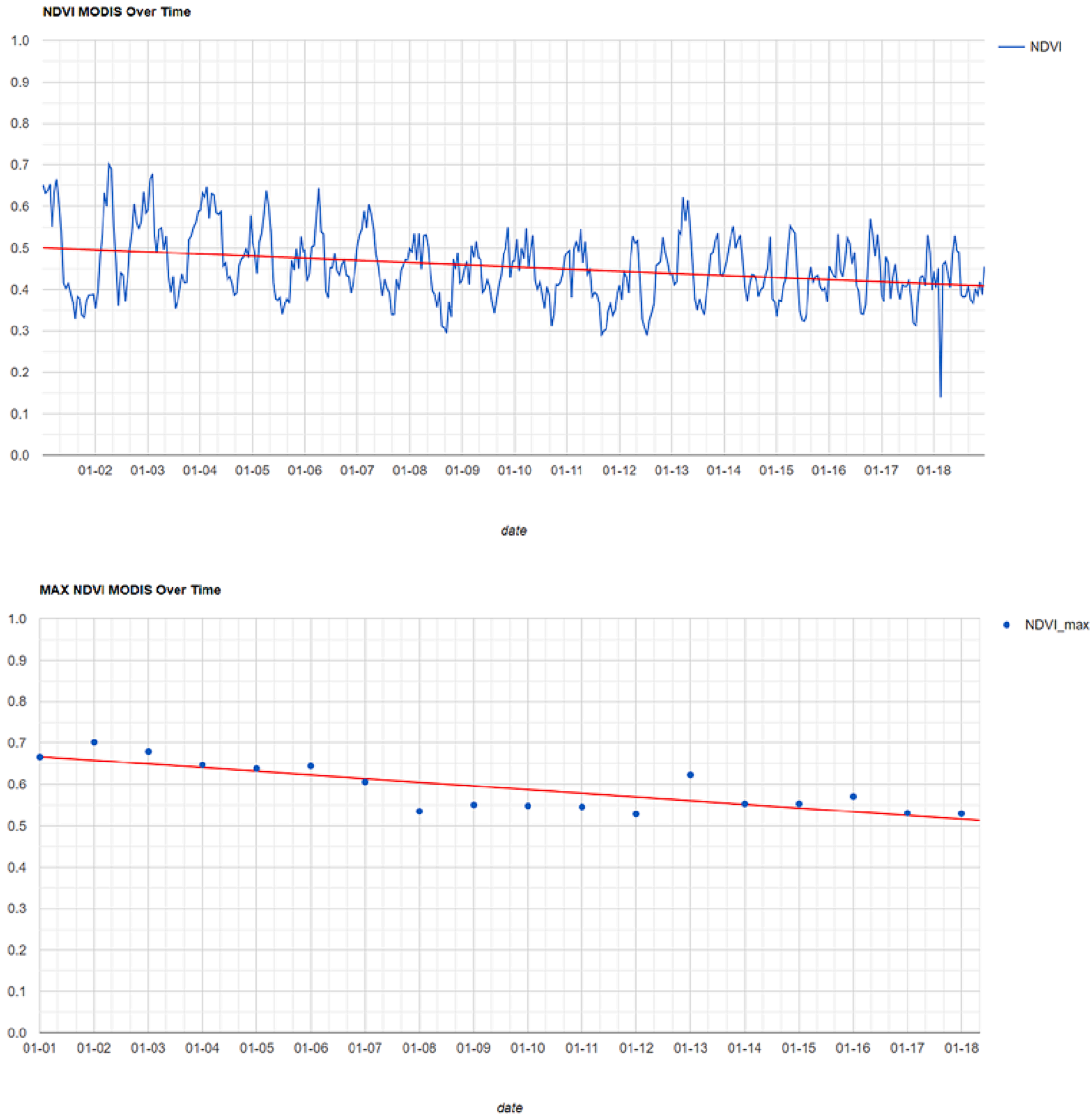


Fig. 6. Example of charts produced showing the modis ndvi values overtime from 2001 and 2018 (above) and the corresponding yearly maximum values (below). trendlines in red. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Landsat7 Collection too. We applied the overall GEE procedure described for the MODIS images to observe the results and reliability of the metrics at higher resolution (30 m). In this case the reliability tests were performed by using 100 additional observation points that were widely distributed over the regional territory. As expected, the tests confirmed higher reliability of the new metric; the finer resolution of the Landsat NDVI signal permits a better vison of land use change over time while also identifying landscape fragmentation in *peri*-urban areas due to urban development and infrastructure construction. Fig. 11 shows a testing phase at one of the observation points, comparing Landsat and MODIS images. In addition to the greater detail and variability of the data obtained using the Landsat images, the added value of the new metric is also more evident: the same point classified as degraded with MODIS is considered as improved with the Landsat images, although the surrounding areas were subjected to new urbanization during the observed period.

3.5. Comparative evaluation of the UNCCD trajectory and new assessment approach

The results of the reliability tests highlighted the better performance of the proposed metric. After starting from 390 observation points and discarding 40 due to dubious interpretations, the remaining 350 points gave us the following results: 313 confirmed the reliability of the new metric and 216 supported the quality of the Trends.Earth assessment (there was total agreement between the two approaches at 178 points).

Table 2 below summarizes these results and the better performance of the new metric compared with the official methodology is self-evident (90 % vs. 62 %). A further phase conducted on an additional 100 points showed that the level of accuracy increased up to 96 % when using Landsat images with a higher resolution.

In Table 3 below, the surfaces of the Campania region are shown and classified as degraded, stable or improved, according to the official methodology compared with the proposed new approach using the MODIS and Landsat datasets: stable and degraded areas significantly

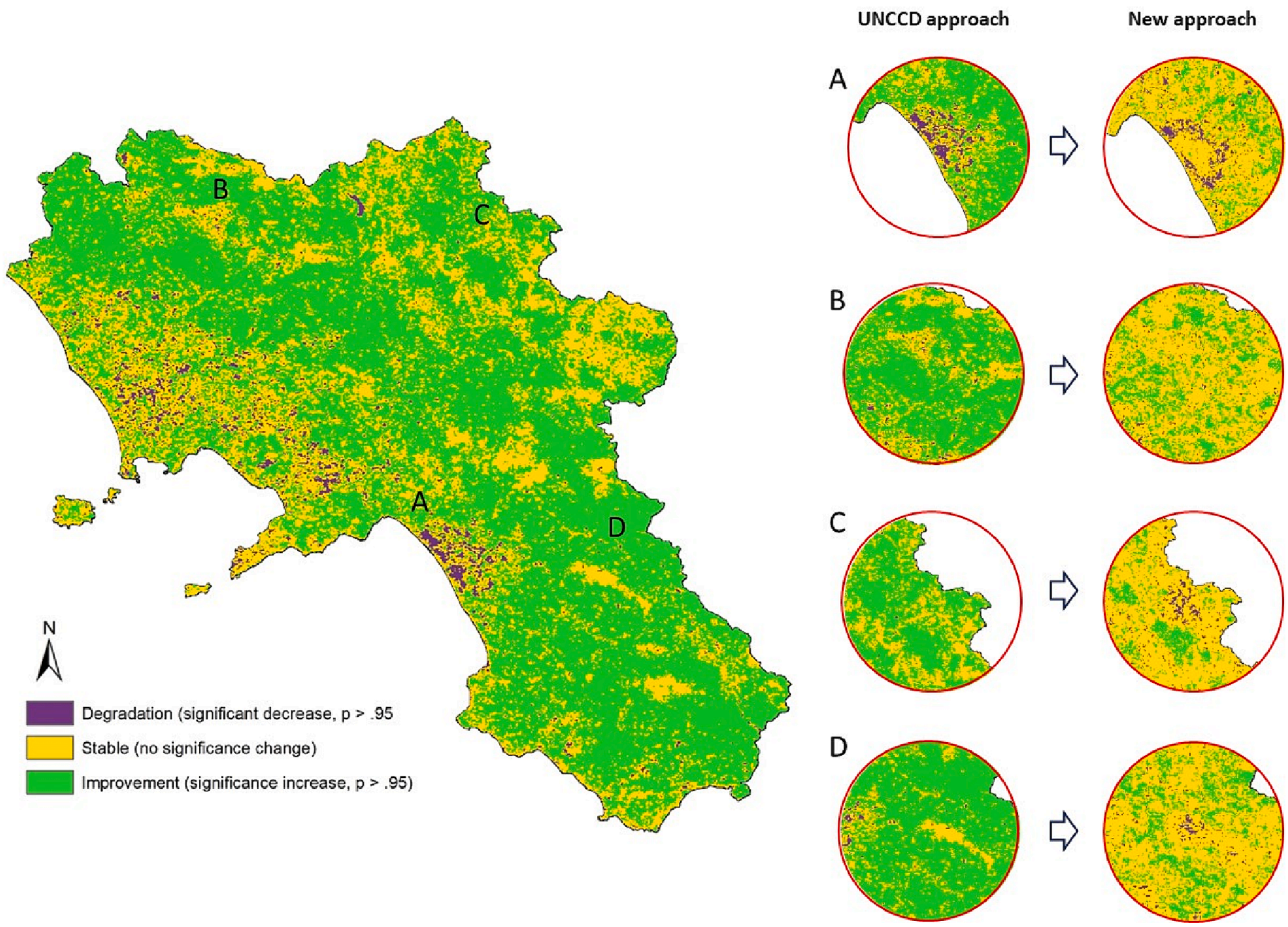


Fig. 7. The map of campania classified according to the methodology proposed by the unccd. different colours represent pixels classified as degraded, stable or improved areas during the 2001 – 2018 period. circular spots (a – d) highlight the areas referred to in the cases discussed.

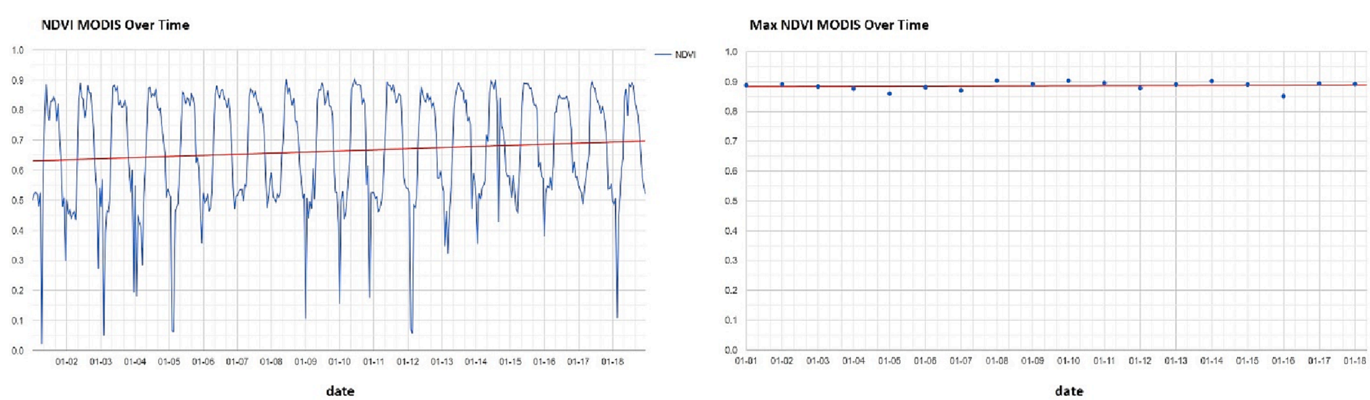


Fig. 8. Examples of NDVI trajectories over time for the same location from 2001 to 2018 calculated through the two approaches. Left side, NDVI data with a positive mean values trend (red line) classified as improving. Right side, yearly maximum NDVI data with horizontal trend (red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

increase at the expense of those showing improvement, which decrease by about one-third.

Considering the above, if the new proposed metric were applied, the results of the land degradation assessment in the Campania region for the 2001–2018 period would be significantly different. In particular, the degraded and stable classes would have their values more than doubled in terms of occupied surfaces, while the improved class would be more than halved. As already stated, the results obtained by observing just the NDVI trajectories describe the behaviour of the canopies rather than the state of health of the underlying soils.

However, the results shown in Table 2 and the differences reported in Table 3 highlight in one hand the benefits of higher spatial resolution (250 vs 30 m) capable to both, reduce the noise effects of adjacent pixels and consequently have greater precision in the representation of the spatial variability of the data. On the other hand, differences between approaches are associated to different sensitivity to NDVI values. In fact,

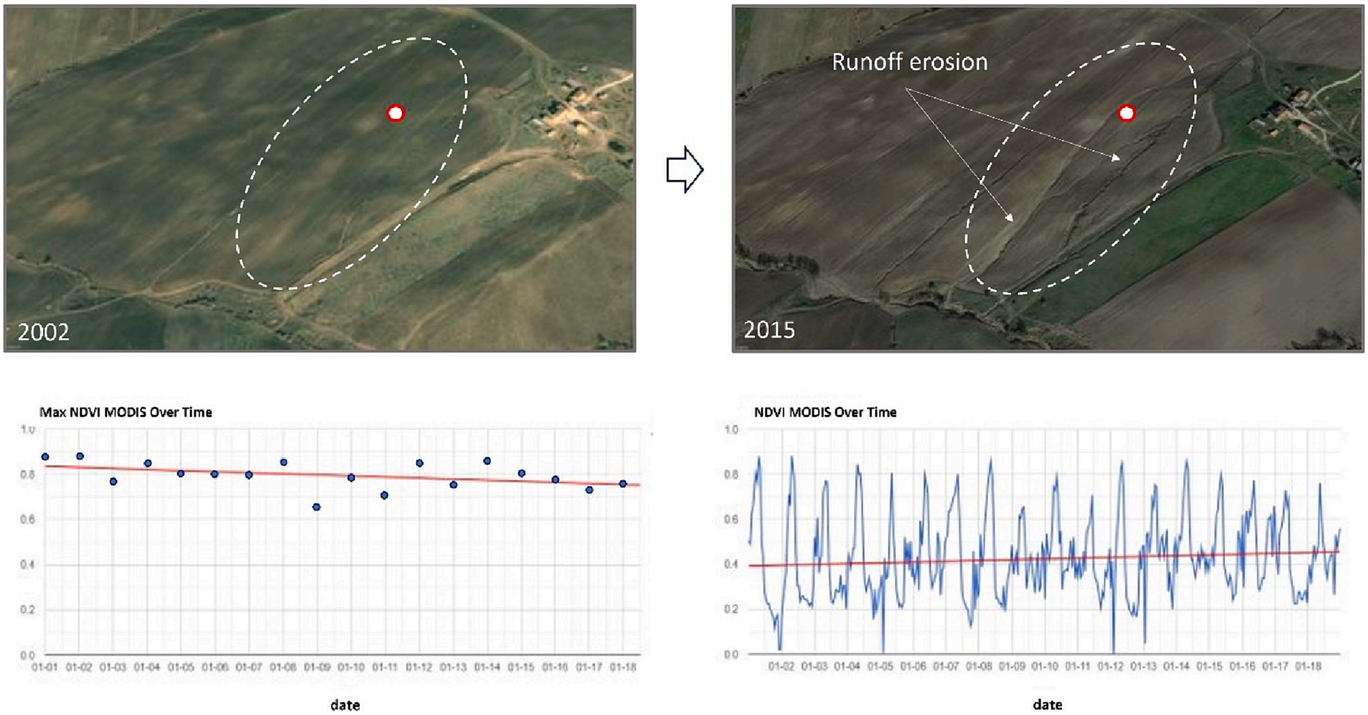


Fig. 9. Example of degraded areas due to soil water erosion. The two images from Google Earth highlight the phenomena from 2002 to 2015. Bottom left, NDVI chart produced with the proposed new approach. Maximum yearly NDVI values show a slight but constant reduction (trend line) classified as degradation (Fig. 7, C). Bottom right, mean values of NDVI show a slight positive trend (trend line) classified as improvement. The white circle identifies the point selected to produce the charts. Dotted line highlights part of the eroded area recognized as degraded through the new approach.

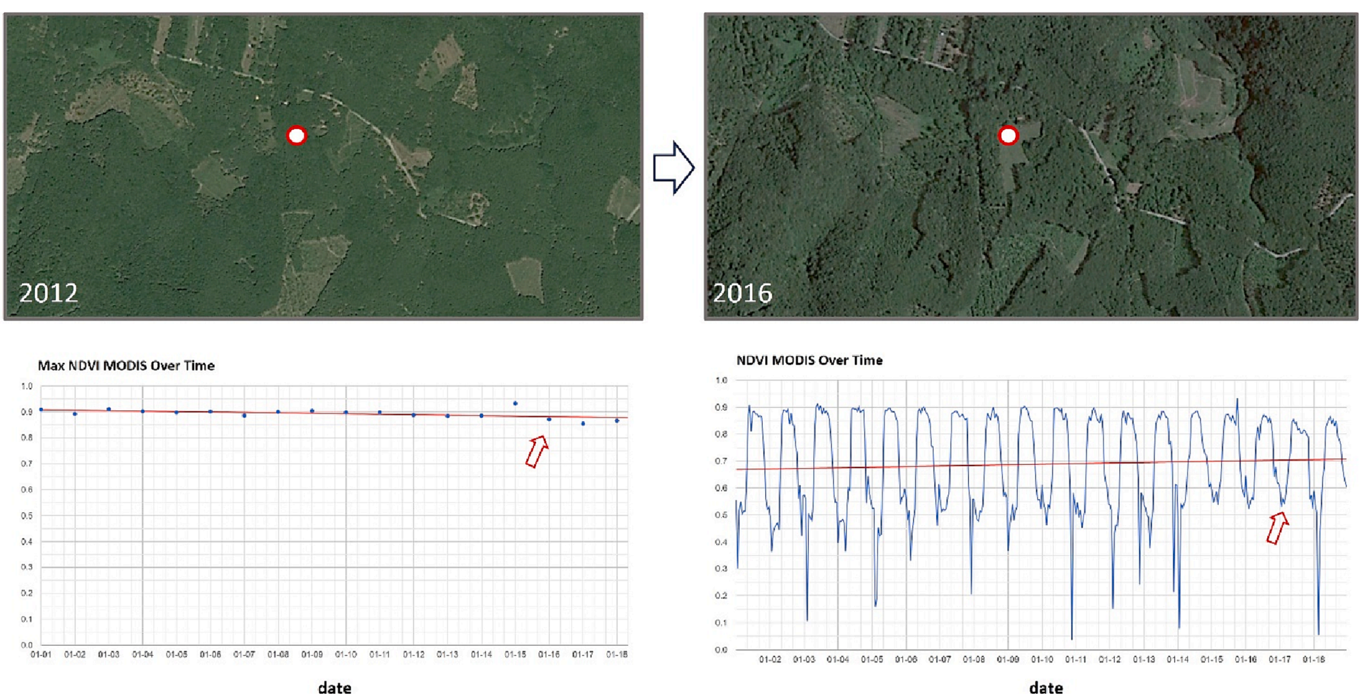


Fig. 10. Example of areas subjected to coppice management. The two images from Google Earth highlight the presence of several areas given over to coppicing from 2012 to 2016. Bottom left, NDVI chart produced through the proposed new approach. Maximum yearly NDVI values show a reduction during the 2016–2018 period (red arrow), which is recognised as a degradation (Fig. 7, D). Bottom right, mean values of NDVI show a slightly positive trend that is classified as improvement (trend line) even though the amplitude of the curves appears reduced during the 2016 – 2018 period (red arrow). The white circle identifies the point selected to produce the charts. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

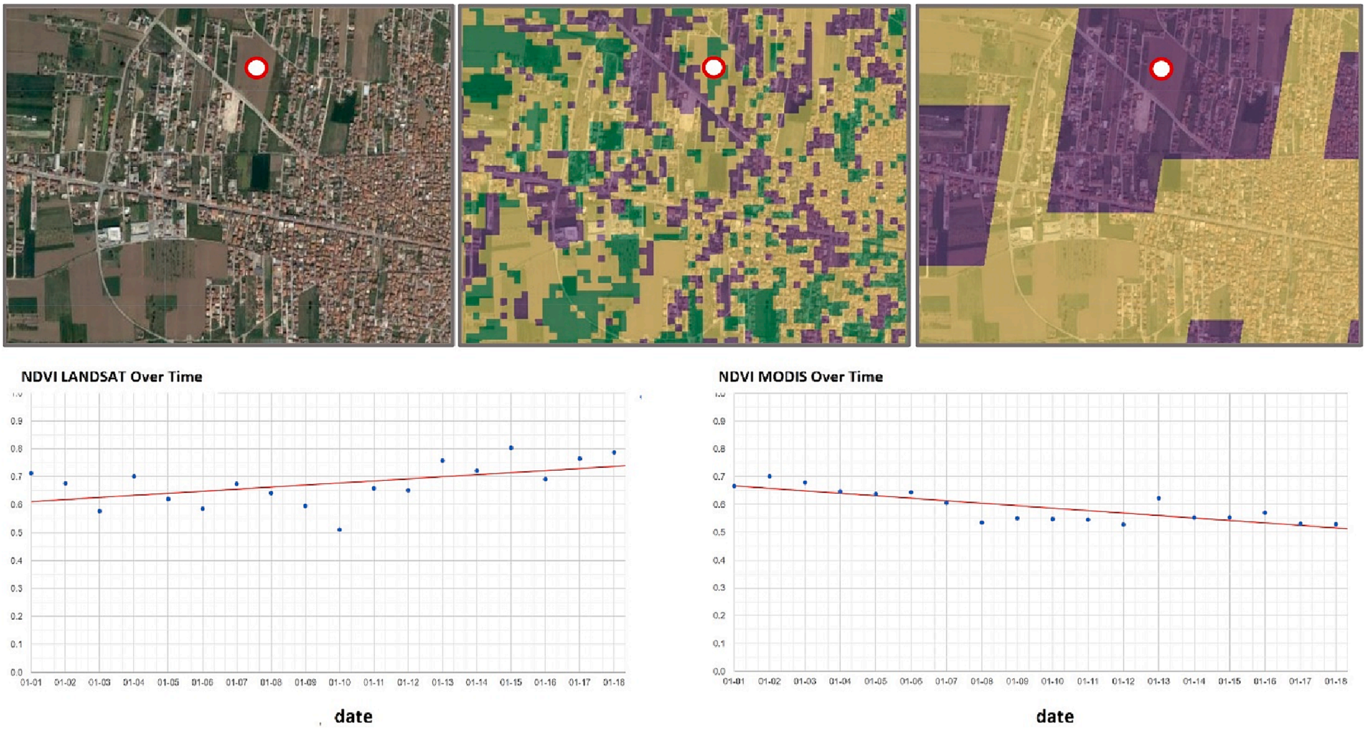


Fig. 11. Example of comparison between Landsat and MODIS images used as datasets for the calculation of the proposed new metric. The images from left to right are from Google Earth true colour, Landsat and MODIS new metric. The white circle identifies the point selected to produce the charts. In this example, the same metric returns conflicting results due to different image resolution. Evidently, in the case of MODIS images on the right, the observation point corresponds to a pixel whose value was influenced by the fact that the surrounding areas were subjected to urbanization (degradation). On the other hand, for the same location, Landsat data at finer resolution returns some pixels that are classified as improved, probably due to a local change in land use during the observation period.

Table 2
Results of the reliability tests conducted on 450 (350 + 100) observation points.

MODIS – UNCCD approach	*GEE MODIS – new approach*	*GEE Landsat – new approach*
62 %	*90 %*	*96 %*

Table 3
Percentages of degraded, stable and improved areas using different approaches and data sources.

	MODIS – UNCCD approach	*GEE MODIS – new approach*	*GEE Landsat – new approach*
Degraded	2,5%	6,1%	4,5%
Stable	29,7%	73,3%	68,1%
Improved	67,8%	20,6%	27,4%

as already discussed, we observed that the proposed new metric, based on the yearly maximum NDVI values, appears to be less sensitive to the outliers of minimum NDVI values and more sensitive to striking cases of degradation or improvement (e.g., soil consumption, intense erosion in agricultural environments, fires or changes between agricultural/forest land uses) where the metric could even replace the SDG indicator 15.3.1. Nevertheless, in the case of stable trajectories or slight sloping in a positive or negative direction, which is true in the majority of the analyzed cases, it is very hard to assess the state of the land with any certainty.

In the latter cases, there is a clear need to integrate NDVI trajectories with additional indices and/or data and datasets suitable to the scale of the analysis and capable of adding further information on possible drivers of degradation or early signs of soil degradation that are not recognisable through the approaches currently used.

4. Discussion

Nowadays, the land degradation issue is at the centre of the EU Agenda for environmental policies, as is confirmed by the new proposal for a Directive on soil monitoring and resilience (Soil Monitoring Law). At the same time, the research community has turned its attention to the definition of indices/indicators that are capable of describing land degradation in order to permit the monitoring and achieving of sustainable development goals (SDGs. Reaching these targets necessarily requires common, implementable, and comparable methodologies worldwide. For this reason, the United Nations has established the monitoring of indicator 15.3.1 with the support of three sub-indicators: productivity and its trend over time, land use/cover changes, and trends in carbon stock above and below ground. For its importance in the final assessment (see chapter 1 “Introduction”), this study focuses on land productivity and how it is measured by the international scientific community. Although the term “productivity” refers to a soil’s capacity to provide yields and is closely related to the concept of physical, chemical, and biological fertility, the methodology adopted by the UNCCD proposes measuring this sub-indicator using the NDVI index, applied as a proxy for depicting the phenomenon over time.

In this context, remotely sensed data can surely play a significant role in determining land degradation processes by offering a list of undoubtable advantages, such as the speed of the analysis, low costs, the possibility to monitor land changes over time and quickly compare different landscapes, and the opportunity to evaluate the processes over large territories. One of the most important factors is the almost complete absence of surveys aimed at testing data obtained by remote sensing of direct field observations (Kirui et al., 2021, AbdelRahman, 2023, Gabriele & Brumana, 2023). Some cases have been recently studied at local level in Africa, in central Mediterranean areas and eastern Asia (Reith et al., 2021, Schillaci et al., 2023, Cherif et al., 2023, Von Maltitz et al., 2019, FAO, 2022) and these consider the overlapping of all the sub-indicators that mainly use global or national datasets as results of the SDG 15.3.1 indicator. Conflicting results are highlighted by using different input data sources and different scales of satellite images (Akinyemi et al., 2021, GEO-LDN Initiative, 2020, Jendoubi et al., 2019). With regards to land productivity, many case studies stress the accuracy of the NDVI trajectory as the best proxy for determining degradation phenomena coupled with other climatic/drought parameters or phenological and productivity-related variables (Prince, 2019, Schillaci et al., 2022, Rotllan-Puig et al., 2021, Xoxo et al., 2022), but the same Earth Observation (EO) data source can produce different results that lead to “false-positives” of apparent improvement trends for degraded areas and, conversely, “false-negatives“ (FAO, 2022, Thomas et al., 2023).

In this context, the present analysis highlights the greater effectiveness of the proposed new method in assessing the productivity sub-indicator. Contextually it is very interesting to highlight that the proposed approach – based just on the NDVI trend – is very high-performing and able, in specific cases, to replace the complex UNCCD approach, which includes soil and land use information. Moreover, it could be hypothesized that this approach, especially benefiting of higher spatial resolution EO data and the opportunity to produce at pixel level graphs on the-fly of indicators, could become a tool for local, regional and national-scale land degradation monitoring in compliance with the SDG15.3.1 indicator. Additionally, since the approach is based on open data, it is open to further improvements and can be replicated with ease over different territories and eventually using finer resolution data like free satellite images from Sentinel. However, there are some critical issues which are summarized below:

- The observation of trends and patterns of just NDVI data cannot automatically be interpreted in terms of land degradation and/or improvements, except for in striking cases.
- The relationships between soil degradation and productivity may not be linear, so additional parameters and/or indicators should be used contextually to NDVI.
- The availability of high-resolution data allows significant improvement of the analyses by reducing the noise effects of adjacent pixels and guaranteeing greater precision in the representation of the spatial variability of the data.
- A careful study of the signals and their trends at pixel level, by using representative samples of the full data, is necessary. This is fundamental in order to understand the system behaviour over time.
- Reliability analysis of the results is required, possibly by using quantitative in-situ measurements as ground truths. This issue is critical when approaches are transferred between scales.
- To confirm the robustness of the proposed procedure, it needs to be applied in pilot areas with different environmental conditions in Europe and elsewhere.

Finally, the results obtained in this work show the need to identify more sensitive approaches, either on the basis of the combination of remote sensing variables, as has already been proposed by other authors (Markos et al., 2023; Kussul et al., 2023), or by adding different trend analysis methods, for example, those based on the study of the fitting function parameters or on the usage of additional resources such as satellites with hyperspectral sensors, airborne data, etc. (Milewski et al., 2022).

5. Conclusions

In the present study, we have observed the SDG 15.3.1 land productivity sub indicator through the trajectory metric of NDVI in order to assess land degradation in Campania during the 2001 – 2018 period. We started with the assumption that the trajectory is the most representative metric. The analysis, performed by applying the official methodology through Trends.Earth software, showed widespread improvement in the land conditions and almost 68 % of the total surface was classified as improved; only 2.5 % of the whole territory appeared affected by degradation and about 30 % was apparently in a stable condition. These results are not in agreement with general trends of land degradation at national or European levels, although we are aware that the methodologies applied are different. Nevertheless, on the basis of this evidence, we tried to improve the analysis by developing the entire code in the GEE environment to reproduce the same steps followed by the official UNCCD methodology. We masked low quality pixels through the quality assurance of the MODIS images, so ensuring the absence of most of potential outliers due to signal noises. The application of the mask prevented the noise of several disturbed pixels from changing the results, mainly in correspondence with some municipalities located along the Campania region coastline. After this first attempt to improve the output, we exploited the potential of the GEE by developing a script to run real-time chart visualization which, on a pixel basis at selected observation points, represented the trends of the NDVI signal over time. We also wrote a code to upload the observation points via.kml files onto the Google Earth platform and used the time slider tool to “follow”, through true colours satellite images, the variations to which the canopies and eventually the surrounding land were subjected during the observation period. The working framework highlighted the need to identify a new metric that is capable of overcoming certain limitations shown by the UNCDD official methodology.

For this purpose, we proposed a novel procedure consisting of the assessment of NDVI maximum annual values instead of mean values for trajectory calculations. This new approach produced a map of Campania that, as opposed to the official approach, showed a significant increase in the stable areas, a decrease in those classified as improved and a slight increase in areas classified as degraded. These results, which were also confirmed by using higher resolution data collection, are most likely due to the lower sensitivity of the new metric to the outliers of the minimum NDVI values. Moreover, we noticed the better performance of the new metric in some specific striking cases, such as in the case of areas subjected to evident soil erosion, land use change and forest areas that were subjected to coppicing. Indeed, the verification of the approaches carried out by using a network of sample points scattered throughout the region, indicated a reliability of around 60 % for the official approach and 90 % in the case of the proposed new approach (up to 96 % by applying the new metric to Landsat 7 collection). The same best outcome can be observed in areas that remain “stable”, typically in natural or forested areas where the cover and density of the canopy are constant over time without showing clear signs of deterioration or reduction.

The reliability test was carried out considering the interpretation of the Google Earth true colours multi-temporal images as “ground truth”. This procedure is obviously not comparable to field measurements of degradation processes, but it presents certain advantages such as requiring less time to cover extended areas at a lower cost considering the free satellite image sources. Furthermore, it became clear that, through the proposed framework, the reliability analysis can mainly be conducted by observing evident and visible degradation phenomena, as in the case of intense soil erosion, soil sealing, fires, etc., or evident improvement phenomena, such as changes in land use (i.e. from agricultural to forestry or the restoration of urban areas which adopt nature-based solutions). All other forms of potential degradation/improvement which do not necessarily result in significant changes in NDVI, such as soil pollution, compaction, loss of organic matter, or the use of improved cultivation techniques, are less easily detectable even when using the finest spatial resolution of remote sensing. However, even considering the above, it is our opinion that the use of the trend metric based on maximum NDVI yearly values is more suitable than the official metric in determining degraded/improved or stable areas over the territory. This approach, combined with the higher resolution of the satellite imageries, reproduces the spatial variability of the metrics in greater detail and better assessment of potential land degradation processes within strongly fragmented territories like Campania. It is self-evident that the greater resolution translates into more useful information for planning purposes, especially on local scales, where it is particularly important to know where and how it is necessary to limit the degradation phenomena of the territories.

The proposed study aims to improve an already existing approach based on the trend metrics of a vegetational index. Although further insights are required, our results confirmed an improvement, paving the way for future studies addressed at applying the same approach to the other sub-indicators provided by the UNCCD methodology (state and performance). Moreover, the proposed approach which provide on the-fly pixel based indicators graphs and utilize open EO data even at high resolution, could become a easily replicable tool for local, regional and national-scale land degradation monitoring.

The world of remote sensing is constantly and very quickly evolving and tools such as the GEE allow very complex analyses at very low cost today. The spatial resolution and the number of bands of satellite resources are also continuously improving, so guaranteeing greater precision in the analyses and applicability of indicators to spatial scales that are appropriate for landscape planning and management. In this context, Sentinel-2 images, freely available for download since 2015, or the very high-resolution of unmanned aerial vehicles might permit better investigation of the effects of land management on soil degradation processes, even on a single farm scale.

CRediT authorship contribution statement

Marco Di Leginio: Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Antonietta Agrillo:** Methodology, Data curation. **Luca Congedo:** Writing – review & editing, Formal analysis, Conceptualization. **Michele Munafò:** Writing – review & editing, Supervision, Conceptualization. **Nicola Riitano:** Writing – review & editing, Methodology, Conceptualization. **Fabio Terribile:** Writing – review & editing, Visualization, Supervision, Methodology, Data curation, Conceptualization. **Piero Manna:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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