Computers and Electronics in Agriculture 236 (2025) 110474

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Identification, assessment and management of nitrogen load hotspots from livestock farming: Comparative analysis using regional land-use data and ESA World cover product[☆]

Raffaele Grieco [a,b], Oscar Rosario Belfiore [b], Elena Cervelli [b], Marco Bovo [a], Stefania Pindozzi [b,*], Ester Scotto di Perta [b], Patrizia Tassinari [a], Daniele Torreggiani [a]

[a] *Department of Agricultural and Food Sciences, University of Bologna, Bologna, Italy*
[b] *Department of Agricultural Sciences, University of Naples Federico II, Portici (NA), Italy*

ARTICLE INFO

Keywords:
Nitrogen pollution
Livestock manure
Land Use Land Cover
Geographic Information Systems
ESA WorldCover

ABSTRACT

Efficient nitrogen (N) management is essential for environmental sustainability, soil fertility, and the long-term viability of the livestock sector by reducing nutrient losses, improving resource efficiency, and mitigating environmental impacts. However, accurately estimating N loads and managing them spatially remains challenging. This study evaluates the impact of using two different data sources, traditional land-use maps (CUAS09) and satellite-derived land cover data (WC20), to estimate N loads at a large scale, focusing on livestock manure in the Campania Region, Southern Italy. Specifically, the study aims to assess how differences in spatial resolution and classification accuracy between these datasets influence N load estimation and the identification of suitable manure spreading areas. Furthermore, we investigate the role of Geographic Information Systems (GIS) in integrating multiple data sources to improve spatial analysis. Spatial analyses compared the data sources under two scenarios: (S1) traditional manure spreading techniques and (S2) advanced methods involving rapid manure incorporation. Results showed notable differences in N load estimation and the area identified as suitable for manure spreading. In Caserta, traditional land-use maps identified 21,899 ha, while satellite-based data estimated 20,571 ha. In Salerno, satellite-based data identified 11,019 ha, compared to 9,706 ha using land-use maps. The total N produced in the two study areas amounted to approximately 4,877 Mg. The overall accuracy (OA) between the two data sources was moderate (51.38 %), with a Kappa Coefficient (K_C) of 23 %, indicating discrepancies in spatial agreement. These differences highlight the importance of selecting appropriate data sources for N load estimation and their implications for developing precise N management strategies. The findings emphasize the need for integrating advanced and up-to-date spatial datasets to improve accuracy, identify N hotspot zones, and support sustainable agricultural practices.

1. Introduction

The livestock sector is expanding and developing very quickly, especially in developing nations (Awasthi et al., 2019). Large volumes of manure have also been produced as a result of the increase in livestock production, frequently in locations without the proper landscape conditions to absorb the additional loads. Although manure has a high potential for nutrients and can help improve soil structure and fertility (Font-Palma, 2019), it can actually have detrimental effects on the environment if it is not used and managed properly. The analysis of nitrogen (N) loads is a crucial issue for environmental and agricultural management, as N is a fundamental element for plant growth, food production, and industrial products (Hutchings et al., 2014) but when released in excess it can have negative impacts on natural ecosystems and water quality, affecting biodiversity, livelihoods, and human health (Hansen et al., 2024). In particular, the agricultural and livestock sectors produce large amounts of reactive N (N_r). An effective approach to monitoring and managing these loads is the identification of 'hotspot zones', i.e. areas characterised by high N concentrations. Identifying these zones allows management interventions to be focused and

---

[☆] This article is part of a special issue entitled: 'Precision Nutrient Management' published in Computers and Electronics in Agriculture.

[*] Corresponding author.

E-mail address: stefania.pindozzi@unina.it (S. Pindozzi).

https://doi.org/10.1016/j.compag.2025.110474
Received 18 December 2024; Received in revised form 3 April 2025; Accepted 27 April 2025

appropriate policies to be developed. Estimating N loads is often a complex process, mainly due to the lack of accurate, high-quality data at more detailed scales. Geographic Information System (GIS) techniques are an essential tool to identify and map N load hotspots accurately and are widely used to assist policy makers in spatial planning, to support Strategic Environmental Assessment (SEA)(González et al., 2011), and in precision farming technologies. The use of GIS also makes it possible to combine data from different sources, such as satellite images, land use land cover (LULC) data, and field data, to provide precise mapping of areas at risk. In addition, GIS techniques facilitate the spatial analysis of data, making it possible to model N distribution, simulate management scenarios, evaluate the effectiveness of targeted interventions, such as the promotion of sustainable agricultural practices, and identify areas suitable for the development of treatment plants. Spatial analyses are greatly affected by the type of input data and the accuracy of the data used, just as the importance of defining a suitable spatial resolution is important to obtain information with adequate accuracy (Serra et al., 2019). In the absence of detailed data on N loads from livestock farms, and without knowing the areas subject to agronomic manure use or high-resolution spatial dataset, this study aims to assess the impact of different LULC data sources on N load estimation and manure spreading area identification. Specifically, we compare traditional land-use maps (CUAS09) with satellite-derived land cover data (WC20) in the Campania Region, Southern Italy. The objective is to evaluate how variations in spatial resolution and classification accuracy influence N distribution modeling, the identification of critical areas, and the estimation of suitable manure spreading zones. To achieve this, we integrate GIS-based spatial analyses, including density and network analysis in ArcGIS (ESRI, 2024a), to identify livestock-dense areas and estimate N loads. Spatial information inherent in LULC was used to identify areas suitable for application (Paudel et al., 2009; Saha et al., 2018). The information in LULC maps is valuable for various applications in spatial planning, conservation biology, climate modeling, water management, food security, hydrology, and agriculture (Ban et al., 2015; Xu et al., 2024). In addition, the demand for remote sensing data for mapping LULC has grown considerably, especially to describe the impact of LULC changes (Macarringue et al., 2022). Estimating N loads from livestock manure requires accurate spatial data, but different LULC datasets can yield significantly different results. Conventional CUAS09 and WC20 differ in spatial resolution and classification accuracy, affecting N load estimation and manure spreading area identification. This study presents the first comparative analysis of these datasets in the Campania Region, an aspect missing in previous research (Cervelli et al., 2021; Scotto di Perta et al., 2024), evaluating their influence on N distribution modeling. By integrating advanced GIS techniques, including density and network analysis, we enhance N hotspot identification and demonstrate how dataset selection impacts spatial planning. Our findings contribute to improving N load assessment, providing valuable insights for policymakers and highlighting the implications of using global versus regional datasets for sustainable land management. The study intended to find more dependable spatial data because, in the literature, different authors have provided geospatial information on LULC, and these sources may have differing spatial resolutions, which could produce results that are incorrect or entirely different. Indeed, a number of the literature's articles incorporate Corine Land Cover (CLC) data with local authority data (Scotto di Perta et al., 2024) for their different analyses, or they employ land use information from sources including remote sensing images (Yan et al., 2021) (Miralha et al., 2021), data from the Ministry (Yalcinkaya, 2020), local authorities (Liu et al., 2022), and land use planning offices (Sliz-Szkliniarz and Vogt, 2012). Given the increasing reliance on global satellite-derived datasets, this study also examines the implications of using such products versus regional land-use maps in N load estimation. Ultimately, this research provides an approach applicable in contexts where data availability is limited, offering insights into the selection of spatial datasets for N management. The findings aim to enhance the reliability of N load assessments from livestock production and contribute to more precise and sustainable agricultural and environmental planning.

2. Material and methods

The procedure for obtaining the study area was structured as shown in Fig. 1. The first part of the diagram illustrates the data collection process, followed by the estimation of N production and the construction of the dataset (*I* − Fig. 1). This dataset was then imported into ArcGIS Pro 3.2.2 (ESRI®) for the creation of a geodatabase and data visualization. Next, two geoprocessing analyses, Kernel Density (KD) and Network Analysis (NA) (*II* − Fig. 1), were performed to obtain an intermediate result (*III* − Fig. 1). This intermediate output was then combined with two different LULC maps to identify and compare the areas suitable for N spreading. In the following step, two scenarios were compared (S1 − traditional manure spreading techniques and S2 − advanced methods involving rapid manure incorporation.). Finally, an accuracy assessment was conducted using Tabulate Area in ArcGIS Pro and a Cross Tabulation Matrix (CTM) (*IV* − Fig. 1). Tabulate Area was used to compute the spatial overlap between different LULC categories, while the CTM provided key accuracy metrics such as Overall Accuracy (OA) and Kappa Coefficient (K_C). This analysis enabled a quantitative evaluation of the agreement between the two LULC maps.

2.1. Overview of the study area

Campania (40°49′34″ N, 14°15′23″ E) (Fig. 2) is a region in southern Italy with an area of approximately 13,600 km2, making it one of Italy's medium-sized regions. Agriculture in Campania is particularly developed due to the mild climate and fertile soils. The most productive agricultural areas are in Salerno and the Volturno plains. The region is famous for the production of high-quality typical products, such as San Marzano tomatoes and Buffalo Mozzarella, fruit, and grapes. Livestock farming also plays an important role, especially buffalo, from which the famous Mozzarella di Bufala Campana DOP (protected denomination of origin) is made, one of the region's most famous products. There are also cattle, sheep, and pig farms. In 2020, 13,391 livestock farms (16.9 % of all active farms) were located in Campania (Assessorato Agricoltura Regione Campania, 2020). On the same date, there were 1,088 buffalo farms with 300,229 heads (a 15 % increase in heads but a 34 % decrease in the number of farms compared to the 2010 census); there were 6,146 cattle farms with cattle, with 158,885 heads (a 34 % decrease in the number of cattle farms and a 13 % increase in the number of heads compared to 2010) (Assessorato Agricoltura Regione Campania, 2020). Excellence in the high-quality food industry is still growing in Italy. With 9.4 %, Campania is one of the regions that produces the most high-quality processed foods, followed by Emilia-Romagna (18 %) and Tuscany (13.8 %). Additionally, 46.5 % of processors in Campania work in the fresh meat industry (ISTAT, 2022). This region was chosen as the study area due to the presence of a significant number of livestock farms, the availability of precise location data for these farms, and its relevance to pressing environmental issues that require targeted support. Additionally, the collaboration with regional authorities played a key role in facilitating data access and ensuring the study's applicability to local policies. Moreover, the buffalo farming sector in the Campania region is rapidly expanding within increasingly concentrated areas, further highlighting the importance of assessing its environmental impact.

2.2. Data collection and calculation method

The first step in the flowchart involved creating the dataset, which included preparing the livestock data and performing the necessary calculations for N estimation (Fig. 1).

Livestock Data: Detailed livestock (cattle, buffalo, and pig) data were gathered related to 2020, including the number of animals, their type, production method, and geographic distribution. These data were

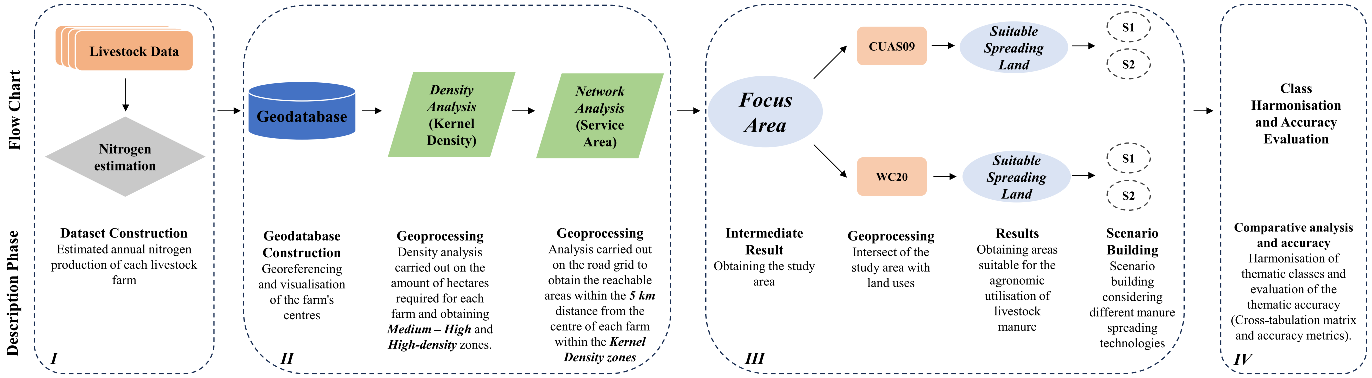


Fig. 1. Flow chart and description phase of analysis.

Fig. 2. Location of the study area – Campania Region (Italy).

obtained from a national database. The data were analysed and arranged in a Microsoft Excel spreadsheet.

Nitrogen estimation: Using the following formula (**Eq.** (1) (Cervelli et al., 2021; Scotto di Perta et al., 2024), the N produced by each individual farm was first determined in order to quantify the N load per hectare produced by the various farms in the various municipalities of the region:

$$N_p = \sum (n_a * N_a)_i \tag{1}$$

Where: N_p is the expected amount of N produced annually (t y^{-1}); n is the number of animals; N is the amount of N generated by each animal (t y^{-1}); a is the animal's age and i is the type of production. The value of N was derived from the II table (Nitrogen produced by livestock) available of the Italian Ministerial Decree 5046/2016, which provides information on the annual amount of effluent produced and the corresponding N concentration for different animal categories, considering their age and housing type. The full decree is available on the Gazzetta Ufficiale website (https://www.gazzettaufficiale.it/eli/id/2016/04/18/16A02762/sg). The livestock dataset includes age classifications of the animals, which allowed us to calculate the annual N content of the slurry and manure based on the age group of the animals. For this purpose, we considered N excretion rates expressed as kg N/t live weight/year for both slurry and manure. In our N load estimation model, we assume that the values provided by Ministerial Decree 5046/2016 accurately represent N excretion rates for different livestock categories. N excretion is considered constant within each age group and livestock type, without accounting for variations in diet or farm-specific management differences, as we assume uniform practices across farms. Additionally, we do not consider any transformations prior to land application, assuming that all excreted N remains available for spreading. After estimating the amount of N produced annually by each farm, only farms producing more than 1000 kg N ha^{-1} per year were selected. For these farms, the number of hectares required to ensure adequate application of the total amount of manure produced was calculated. This was done by dividing the amount of N produced annually by the individual farm by the maximum amount of N (Kg N ha^{-1}) that can be applied in the zone in which the farm location point falls, i.e. by 340 kg N ha^{-1} if the farm is in an ordinary zone (OZ) or by 170 kg N ha^{-1} if it is in a nitrate vulnerable zone (NVZ).

2.3. *Geodatabase building and geoprocessing methods*

Next, the geodatabase was constructed (Fig. 1) using ArcGIS Pro, operated under a valid license provided by the Alma Mater Studiorum – University of Bologna, by integrating the prepared farm dataset with additional layers, including the administrative boundaries, NVZs, the digital elevation model (DEM), and the road network (Table 1). All data have been converted to the Universal Traverse Mercator (UTM) Zone 33 projected coordinate system of the World Geodetic System 1984 (WGS 1984). The construction of the geodatabase was a crucial step to enable two subsequent geoprocessing analyses, highlighted in green within the flowchart (Fig. 1): *Density Analysis* and *Network Analysis*.

Density Analysis: The value of the required hectares was used as a

Table 1
Campania Region spatial data.

Data Type	Source	Year	Format
Livestock Data	National Livestock Database	2020	Excel Table
Administrative Boundaries	Campania Region Geoportal	2004	Shapefile
NVZs	Campania Region Geoportal	2017	Shapefile
DEM	National Italian Geoportal	2001	Raster
Road Network	Campania Region Geoportal	2015	Shapefile
CUAS09	Campania Region Geoportal	2009	Shapefile
WC20	ESA WorldCover 10 m v100	2020	Raster

variable to conduct the density analysis. The density of point features surrounding each output raster cell is computed using KD. The density value is greatest at the point position and becomes zero at the search radius distance from the point as it moves farther out from the point. The location of each farm serves as the representation of the point in the study, and a maximum search radius of 5 km was chosen in order to account for each farm's direct influence on a zone with a diameter of 5 km.

The following formula (**Eq.** (2) is used to determine the expected density at each point (x,y):

$$Density = \frac{1}{(radius)^2}\sum_{i=1}^{n}\left[\frac{3}{\pi}{*}pop_i\left(1-\left(\frac{dist_i}{radius}\right)^2\right)^2\right] \tag{2}$$

Where: $i, \ldots, n$ are the input points. Include points in the sum only if they are within the (x,y) radius distance; the optional parameter pop_i is the population field value of point i and $dist_i$ is the distance between point i and the (x,y) location (ESRI, 2024b).

A spatial density analysis was carried out to identify the areas with the highest N loads. The ArcGIS tool *KD* was used to calculate the N density on a continuous surface, highlighting the 'hot areas' with the highest accumulations (Cervelli et al., 2021; Scotto di Perta et al., 2024). The result was divided into 5 classes (low, medium–low, medium, medium–high, and high) using the Natural Breaks (Jenks) classification (ESRI, 2024c). The areas identified as medium–high and high were selected and the farms located in these areas were identified. By calculating the density, we were able to map the expected distribution of N load per hectare across the region and identify critical areas with higher concentrations. This analysis was essential for estimating N distribution more accurately, as it provides a spatially continuous representation rather than relying solely on farm locations. KD provides a continuous surface representation of spatial density, avoiding artificial effects caused by rigid cell-based divisions. This allows for the identification of hotspots or areas of higher concentration. Additionally, KD is well-suited for datasets of varying density and scale, as it applies a kernel function at each point to smooth the distribution. KD is a valuable tool for estimating probability distributions, identifying hotspots, and predicting spatial or event patterns. (Krisp and Špatenková, 2010). Moreover, it served as a fundamental step for the subsequent NA, allowing us to define key areas where N flows, and potential environmental pressures are most significant.

Network Analysis: Without knowing the actual area available to each farm, the NA tool was used. The NA tool in ArcGIS is an effective tool that may help optimize the management of livestock effluent by identifying locations that are really accessible to livestock farms (Grieco et al., 2024) and helps solve the maximum service area problem (MSAP), allowing the area that can be served by a set of facilities to be determined (Indriasari et al., 2010). Starting from the attention area obtained from the KD, the farms falling within this area were identified. From these farms, a network analysis was then carried out to determine the accessibility of the agricultural areas in relation to the N source (livestock farms). The *Service Area* analysis tool in ArcGIS was used to delineate service areas around the N source points (ESRI, 2024d), taking into account the transport infrastructure. This process helped to identify the areas where N application is most logistically feasible. The analysis was carried out taking into account areas within 5, 10, and 15 km of the farms.

2.4. *Identifying areas suitable for spreading and assessing nitrogen loads*

The geoprocessing phase outlined above defined the study area (Intermediate Results in Fig. 1), serving as the basis for the subsequent geoprocessing steps described below. The area within 5 km of the farms was used to identify the intermediate focus area, i.e. the study area for evaluating the differences resulting from the use of the Campania region Agricultural Land Use Map (CUAS09) with global satellite-based Land Cover Map provided by ESA (ESA WorldCover 10 m 2020 v100 –WC20) (Zanaga et al., 2021) (Fig. 1) (Table 2).

The CUAS09 was obtained through field surveys of the agroforestry landscapes of Campania by the staff of the former Agricultural Inspectorates, and the latest available version dates back to 2009, with a representation scale of 1:100,000. On the other hand, for 2020 a freely accessible global land cover product with a spatial resolution of 10 m has been used (Table 2). The WC20 dataset is derived from remotely sensed data acquired by Sentinel-1 and Sentinel-2 sensors from 1 January to 31 December 2020, together with other auxiliary data, used as input data in a supervised classification process, based on Sentinel-1 and Sentinel-2 data (Zanaga et al., 2021). This procedure, implemented also for 2021 (Zanaga et al., 2022), has its roots in previous ESA experiences such as GlobCover and the European Space Agency's Climate Change Initiative Land Cover (CCI Land Cover), which formed the basis for the WorldCover product (ESA, 2017)(Arino et al., 2008). The accessible area within 5 km was intersected with the two land use datasets mentioned above. On these obtained areas, as described in Fig. 1, two different scenarios were constructed: the first scenario (S1: Use of constraints) was created by applying the restrictions foreseen by the DGR decree of the Campania Region (Table 2 – S1) regarding the correct agronomic use of zootechnical effluents; the second scenario (S2: Use of innovative techniques), on the other hand, took into account the use of spreading techniques involving the rapid incorporation of the effluent, which, if applied, could eliminate some of the restrictions contained in the DGR n. 585 of the Campania Region (Table 2 – S2). This intersection resulted in the final study areas. The decision to focus on two scenarios, S1 and S2, was made to ensure clarity and relevance in the analysis, while also considering data availability and the specific objectives of the study. Finally, the assessment of the N load was carried out using the following formula (**Eq.** (3):

$$N_{load} = (ha_{av} \times N_{max}) - N_p \tag{3}$$

Where: N_{load} is the part of the maximum applicable N that is replaced by N from the effluent; ha_{av} is the area suitable for application (ha); N_{max} is the maximum applicable N of 170 and 340 kg N ha^{-1} y^{-1} in NVZs and OZs, respectively; N_p is the N produced annually by livestock farms (kg N y^{-1}). Where $N_p > (ha_{av} \times N_{max})$, it indicates an exceedance of the maximum applicable N.

For both geospatial data sets, not all agricultural land is suitable for application, so areas not suitable for application were removed and buffer analyses were applied to ensure the required distances from roads, lakes, rivers, and urban settlements. For the WC20, a manual geoprocessing analysis was carried out to distinguish greenhouses, farms, and large urban settlements within the built-up class; it was important to know the large urban settlements as the distances to be respected for spreading were only applied to this class, while the buffer analysis was not used to greenhouses and farms/isolated houses. The areas suitable and unsuitable for spreading were determined based on the regulations included in DGR no. 585 of the region of Campania, in which the spatial constraints in OZs and NVZs are listed. Table 3 shows the constraints applied and excluded areas. In addition, both scenarios

Table 2
Comparison of CUAS09 and WC20 Land Use Data.

Data Type	Temporal coverage	Map Scale	Spatial coverage	Accuracy
CUAS09	2009	1:100,000	Regional (Campania region)	Not Available
WC20	2020	1:20,000 (pixel size: 10 m)	Global	Global: 74.4 % ± 0.1 %; Europe: 76.8 % ±0.2 (Zanaga et al., 2021)

Table 3
Exclusion areas and scenarios.

Land Cover	Excluded areas	S1: Use of constraints NVZ	OZ	S2: Use of innovative techniques constraints NVZ	OZ
CUAS09	Shrubland, Urban settlement, Sparse vegetation, Water body, Forest, Poplar wood, willow, Other broadleaved, Outcropping rocks, Beaches, Dunes and Sands	< 10 m from a surface watercourse, < 100 m from an urban settlement, < 30 from lakes and coastal areas, < 10 m from roads and Land with a slope greater than 10 %	< 10 m from a surface watercourse, < 100 m from an urban settlement, < 10 from lakes and coastal areas, < 10 m from roads and Land with a slope greater than 10 %	< 10 m from a surface watercourse, < 30 from lakes and coastal areas and Land with a slope greater than 10 %	< 10 m from a surface watercourse, < 10 from lakes and coastal areas and Land with a slope greater than 10 %
WC20	Shrubland, Built – up, Bare/sparse vegetation, Snow and Ice, Permanent water body, Herbaceous wetland, Mangroves, Moss and Lichen				

Table 4
Nomenclature harmonization between WC20 and CUAS09.

New Label	WC20	CUAS09
Tree cover	10. Tree cover	Coniferous forests Hardwood forests Orchards and minor fruits Olive groves Vineyards Poplar groves, willow groves, and other broadleaf trees
Shrublands	20. Shrublands	Areas with sclerophyllous vegetation Bushes and shrublands
Grassland	30. Grassland	Natural grassland and high-altitude meadows Grasslands Temporary grasslands Permanent meadows, mixed meadows and pastures
Cropland	40. Cropland	Autumn/winter cereals associated with grain crops Fodder crops associated with autumn grain cereals Autumn/winter arable crops – grain cereals Spring/summer arable crops – grain cereals Spring/summer arable crops – industrial crops Spring/summer arable crops – vegetables Complex cropping systems and plots
Built Up	50. Built Up	Urban settlements and artificial surfaces Protected crops – Floriculture, ornamental plants and nurseries Protected Crops – Horticulture and Fruit Growing
Bare/Spare vegetation	60. Bare/Spare vegetation	Areas with sparse vegetation Bare rocks and outcrops Beaches, dunes, and sands
Permanent water bodies	80. Permanent water bodies	Water bodies
Herbaceous wetlands	90. Herbaceous wetlands	

(S1 and S2) have been evaluated to consider the increase in the number of hectares available for application in the case of innovative application techniques involving the rapid incorporation of the spilled effluent. The use of such techniques, in accordance with the DGR decree of the Campania Region, allows the elimination of the distances to be respected from urban settlements and roads, as shown in Table 3.

2.5. Comparative analysis and accuracy

In the final step of the flowchart (Fig. 1), the differences between the two sets of geodata were assessed by analysing the variations in their classifications. ArcGIS Pro software was used to calculate the cross and overlap areas between the two polygon shapefiles, plotted using the *Tabulate Area* tool. *Tabulate Area* is a spatial analysis tool that calculates the area of intersection between categorical raster or polygon datasets, producing a matrix that quantifies how different land use categories overlap across layers. In this study, *Tabulate Area* was applied to compute the proportion of each CUAS09 land use category within the corresponding WC20 classes, allowing a quantitative assessment of their spatial relationships. By calculating the percentage of CUAS09 that falls within WC20, we were able to determine the degree of agreement between the two datasets and identify potential discrepancies in land use classification. This method provided a structured way to compare different sources of spatial information, ensuring a more detailed evaluation of land use consistency across datasets.

Table 5
Description and hectares in the S1 – CUAS09 study area.

CUAS09 Class	*WC20 Class	Caserta	Salerno	Total
Autumn/winter cereals associated with grain crops	Cropland	–	471.62	471.62
Fodder crops associated with autumn grain cereals	Cropland	–	1,081.89	1,081.89
Grasslands	Grassland	2,318.08	316.21	2,634.29
Orchards and minor fruits	Tree cover	7,414.06	616.23	8,030.29
Olive groves	Tree cover	15.26	1,776.65	1,791.90
Autumn/winter arable crops – grain cereals	Cropland	4,196,85	537,30	4,734.15
Spring/summer arable crops – grain cereals	Cropland	4,133.53	3,800.12	7,933.65
Spring/summer arable crops – industrial crops	Cropland	2,944.49	13.38	2,957.86
Spring/summer arable crops – vegetables	Cropland	876.70	894.23	1,770.93
Complex cropping systems and plots	Cropland	–	192,25	192.25
Vineyards	Tree cover	–	6.72	6.72
Total		21,898.97	9,706.59	31,605.56

Table 6
Description and hectares in the S1 – WC20 study area.

Land Cover Class	Caserta	Salerno	Total
Tree cover	1,739.07	3,127.51	4,866.58
Grassland	2,671.39	1,789.14	4460.53
Cropland	16,160.86	6,102.02	22,262.87
Total	20,571.31	11,018.67	31,589.98

In the next step, concerning the two spatial datasets, in this case CUAS09 and WC20, a thematic comparison was carried out. First, CUAS09 was transformed into a raster data model with a spatial resolution of 10 × 10 m, using the WC20 product as a reference.

The thematic comparison can be divided into 3 stages:

1. Before carrying out the comparison, the nomenclature of the product classes had to be harmonised. This step is of paramount importance

as different definitions of classes may describe different landscapes (Duarte et al., 2023). This harmonisation was necessary to reduce the discrepancies between the two spatial datasets, improving class coherence and making the results comparable. At this stage, in view of the difficulty of distinguishing between greenhouses, they were considered to be part of the built-up.

2. Visual analysis of the differences between the maps of the two study areas of Caserta and Salerno;
3. A CTM was generated for each of the study areas obtained, by comparing two maps using the WC20 as a reference. The decision to use the WC20 spatial data as a reference is based on the fact that we know the overall accuracy of this spatial data, which is reported to be 76.7 % (Xu et al., 2024). For CUAS09 the accuracy is not known. The CTM was carried out both on a single study area, located in Caserta and Salerno, and on the total study area given by the combination of the two areas. According to (Duarte et al., 2023), this makes it possible to calculate user and manufacturer accuracy when using one of the maps as a reference. The following accuracies and statistics were computed in this analysis: i) OA, which measured the overall percentage of correctly classified samples of the CUAS09 data in comparison to the WC20 data; ii) Producer's Accuracy (PA), which measured the degree to which the CUAS09 spatial data reliably covered the WC20 reference classes; iii) User's Accuracy (UA), which measured the degree of reliability of each CUAS09 class in comparison to the reference (WC20) and iv) K_C, quantifies how far the level of agreement between CUAS09 and WC20 exceeds casual agreement (Comber, 2013; Islami et al., 2022; Smits et al., 1999). The CTM was carried out with the software RStudio (version 2024.09.1).

3. Results

3.1. Regional hotspot area identification

It was feasible to determine which areas are impacted by the existence of farms with a significant N load thanks to the density analysis. For the following analysis, the areas designated as Medium-High and High were employed. These two categories contain the farms that require more than 114 ha to use the effluent for agronomic purposes in a sustainable way, that is, under the Nitrates Directive. A significant part of these areas, which are not uniformly dispersed throughout the region, fall into NVZs. The majority of the large farms are situated in these locations because of their importance for agriculture and the topography of the terrain. The land reachable in 5, 10, and 15 km from each farm from the farm complex is shown in Fig. 3b. Those reachable in 5 km represent the intermediate result of the analysis. It is important to note that the areas reachable by the farms are not entirely suitable for the spreading of effluents, in fact, the area identified in the province of Caserta and Salerno that can be reached within 5 km is 43,105.5 ha, for this reason, it is important to know the LULC. In the undivided KD areas, 346 livestock farms are producing more than 1000 kg N y^{-1}, of which 307 are buffaloes and 39 are cattle. This figure makes it clear that in the Campania region the majority of livestock is buffalo. In fact, in these areas, there are about 94,989 buffalo heads against 3,714 cattle heads.

3.2. Potential nitrogen distribution in the identified area

The clear distribution of hotspot areas in the Campania region and the display of areas suitable for spreading can be seen in Figs. 4 and 5. These hotspot areas have already been identified by Scotto di Perta et al. (2024) and Cervelli et al. (2021) in previous studies.

The results shown in Figs. 4 and 5 indicate that in all scenarios the N loads from the livestock sector do not exceed the maximum load that the soil can support according to the Nitrates Directive. However, the approach used does not take into account the fact that there are additional farms in the areas reachable by the farms within 5 km that could be included in the N loads contributed. These farms were not taken into account because they were found to be outside our study area. For the study area of Caserta and Salerno, differences were obtained using land use maps or satellite images (Figs. 4 and 5). In the study area of the Caserta province, satellite data showed a decrease in the area suitable for spreading. There is a reduction of 1,328.7 ha in the S1 scenario (Figs. 4 and 5). In the study area of the Province of Salerno, the result is the opposite, where the use of satellite data showed a greater availability of suitable land in S1, with 1,312.1 ha more than the use of land use maps (Figs. 4 and 5). Furthermore, the S1 – CUAS09 scenario, which is located in the province of Salerno, shows that the N load from livestock farming almost completely covers the maximum amount of N that can be applied. In fact, the N from the livestock sector covers 96 % (N_p/N_{max}) of the potentially applicable N (Fig. 4). This high N_p/N_{max} ratio in Salerno indicates a more critical and potentially riskier management of the nutrient balance. On the contrary, the S1 – CUAS09 scenario in the province of Caserta has a lower N_p/N_{max} ratio (Fig. 4). Another critical aspect is the distribution of areas within NVZs. In Caserta, the entire agricultural area is included in NVZs in both the constrained and unconstrained scenarios. In Salerno, on the other hand, only a part of the territory falls within NVZs. The analysis's findings indicate that, in addition to other advantages, the use of quick effluent incorporation enables the extension of areas that are ideal for spreading. In actuality, the number of appropriate surfaces increases significantly in all cases. In particular, in the province of Caserta, the use of innovative techniques allows an increase in available hectares of 8 % in the S1 – CUAS09 scenario and 7 % in the S2 – WC20 scenario. On the contrary, in the province of Salerno, the increase in hectares is much higher, at 28 % and 25 % in S1 – CUAS09 and S2 – WC20, respectively. There is also an

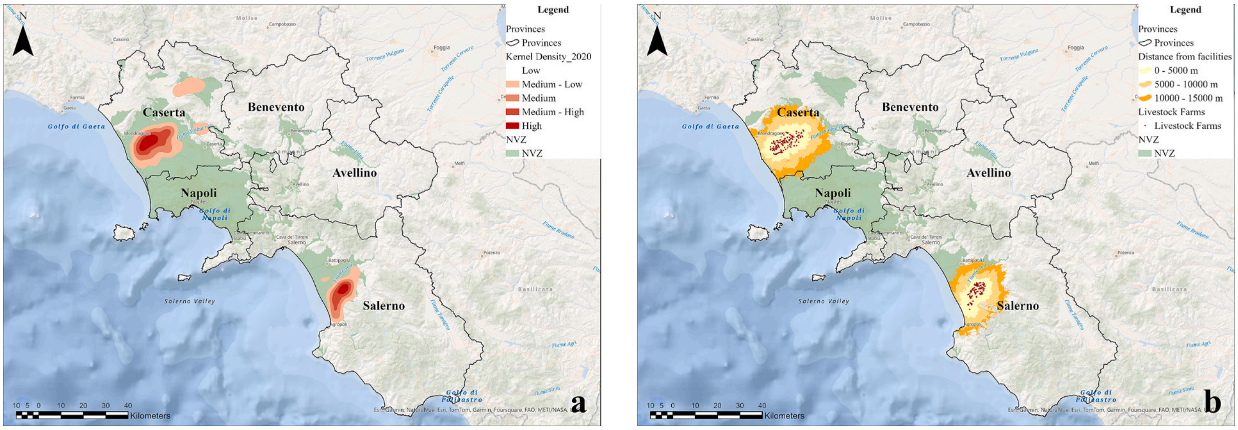
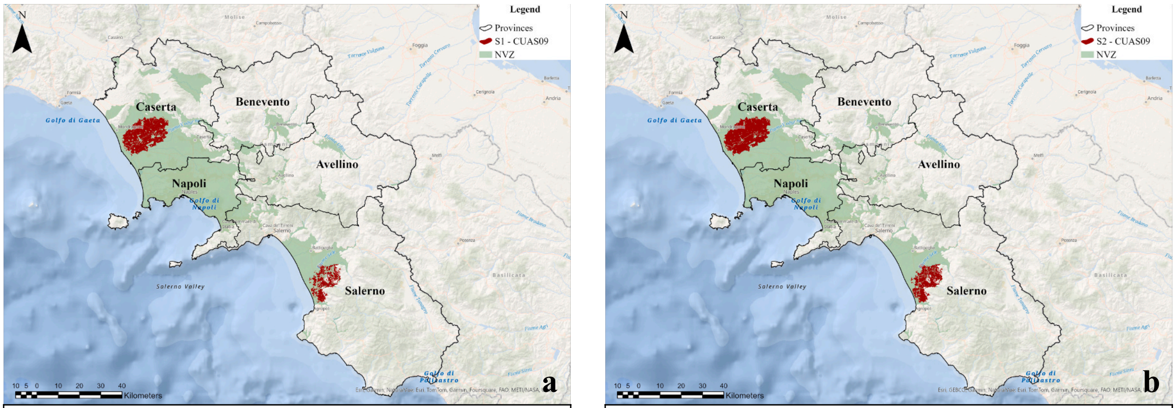


Fig. 3. Density analysis (a) and Service Areas (b).



	Caserta	Salerno
Scenarios	**S1 – CUAS09: Constraints**	
Ha Totali	21,899.0	9,706.6
Ha in NVZ	21,899.0	7,552.0
Ha in OZ	0.01	2,155
N_{max} (Kg)	3,722,825.0	2,016,396.9
N_p (Kg)	2,936,819.1	1,939,819.9
N_p/N_{max}	**79%**	**96%**

	Caserta	Salerno
Scenarios	**S2 – CUAS09: No Constraints**	
Ha Totali	23,667.1	12,385.7
Ha in NVZ	23,667.1	9,970.5
Ha in OZ	0.01	2,415
N_{max} (Kg)	4,023,401.2	2,516,148.1
N_p (Kg)	2,936,819.1	1,939,819.9
N_p/N_{max}	**73%**	**77%**

Fig. 4. Scenarios results: S1 – CUAS09 (a) and S2 – CUAS09 (b).

increase in the number of hectares in OZ in Salerno. In Fig. 6, the differences in the area suitable for spreading obtained can be visually observed by means of the overlay.

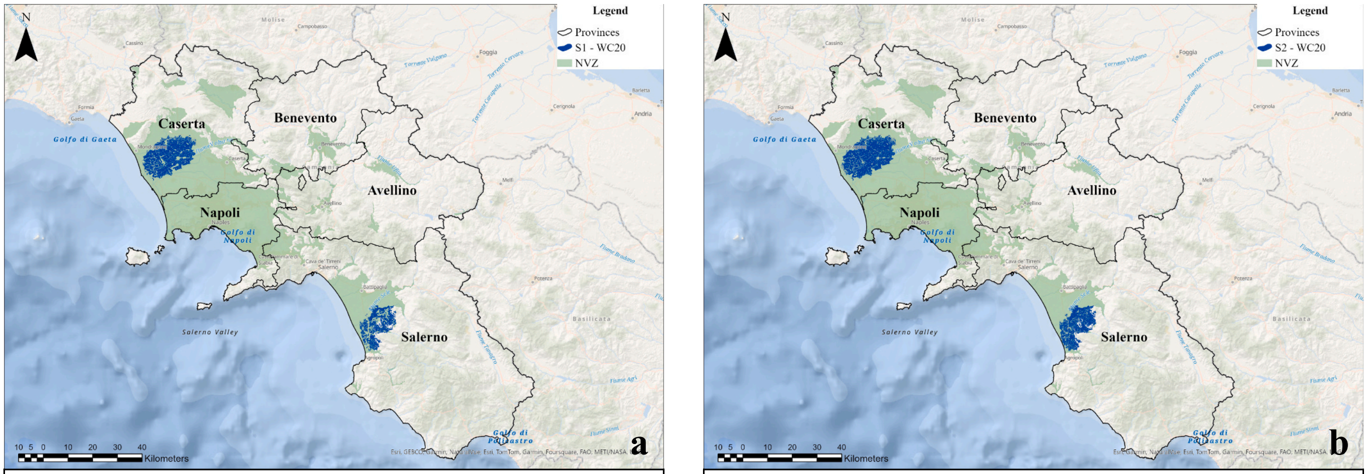
3.3. Difference, visualisation, and evaluation between CUAS09 and WC20

In Table 4, the harmonization performed can be observed. The CUAS09 dataset, being a land use dataset, provides a more detailed classification compared to WC20. As shown, the newly created “Built-Up” label also includes protected crops due to the difficulty in isolating them. In terms of hectares, as seen in Figs. 4 and 5 for Scenario S1, the two spatial datasets yield different results, and when calculating the hectares for each class, significant differences arise (Tables 5 and 6), especially for the “Tree Cover” class in the study area of Caserta. The same analysis, using the Tabulate Area tool (Table S1), revealed results indicating discrepancies between the two spatial datasets. This discrepancy was also confirmed by the CTM discussed later.

Fig. 7 shows examples of the difference between the two products (CUAS09 and WC20) in more detail with a real colour image. From this visualisation, it is easy to see that the regional CUAS09 data provide less detail than the ESA data. In particular, in Caserta, a large area (green area in Fig. 7) classified as “Tree cover” in CUAS09 there is no correspondence in WC20.

3.3.1. Cross tabulation matrix between CUAS09 and WC20

The results of the CTM revealed differences between the areas analysed. For the combined area of Caserta and Salerno, the OA was 51.38 %, indicating a moderate level of accuracy, while the K_C was 23 %, reflecting a relatively low classification agreement. Although an accuracy of 51.38 % may be acceptable in complex geospatial analyses, the low K_C suggests that the observed accuracy could be influenced by chance, highlighting the weak agreement between classifications. In Caserta alone, the OA was lower, with a value of 47.01 %, showing a slight decrease in accuracy compared to the combined area. The K_C for Caserta was 12.95 %, indicating a weak correlation in the classifications. Conversely, Salerno exhibited the highest performance among the areas examined, with an OA of 57.8 %. The K_C for Salerno was also higher at 37.42 %, reflecting a stronger classification agreement compared to Caserta and the combined area. The evaluation of the PA and UA is based on the comparison between the CUAS09 dataset, and the WC20 dataset used as a reference. The results highlight significant differences between the two classifications, varying both by classes and geographical areas (Salerno + Caserta, Salerno, and Caserta) (Fig. S2), reflecting discrepancies in the representation of LULC categories between the two datasets. For the “Tree Cover” class in the combined Salerno and Caserta area, a PA of 32.69 % and a UA of 56.84 % were recorded, indicating a moderate discrepancy between CUAS09 and WC20 (Fig. S2). However, when the two areas are analysed separately, notable differences emerge: in Caserta, the PA drops to 12.74 %, while in Salerno it rises to 68.47 %. This suggests that in CUAS09, forested areas are better represented and correspond more closely to WC20 in Salerno, where they are likely characterized by a more recognizable spatial pattern compared to Caserta. The Shrublands class shows very low performance in both classifications (Fig. S2). In the combined area, the PA is 3.42 % with a UA of just 0.56 %. Similar values are observed in Salerno (PA 3.42 %, UA 2.35 %) (Fig. S2), while in Caserta the class was not identified, suggesting a complete lack of correspondence with WC20. This could indicate a misclassification of shrubland areas in CUAS09, likely confused with other categories such as Grassland or Bare/Spare Vegetation. For the Grassland class, the PA in the combined area is 18.52 % and the UA is 10.97 % (Fig. S2), highlighting significant discrepancies between the two spatial datasets. In Salerno, the PA further decreases to 11.49 % with a UA of 2.81 %, while in Caserta, the PA is slightly higher (15.01 %) with a UA of 11.49 %. This suggests that grasslands in CUAS09 are likely overestimated or poorly defined compared to WC20, possibly due to confusion with other classes such as agricultural land or shrublands. The Cropland class shows the best correspondence between



	Caserta	Salerno
Scenarios	**S1 – WC20: Constraints**	
Ha Totali	20,571,3.0	11,018.7
Ha in NVZ	20,571,3.0	8,565.3
Ha in OZ	0.00	2,453
N_{max} (Kg)	3,497,122.9	2,290,247.7
N_p (Kg)	2,936,819.1	1,939,819.9
N_p/N_{max}	**84%**	**85%**

	Caserta	Salerno
Scenarios	**S2 – WC20: No Constraints**	
Ha Totali	22,112.9	13,730.4
Ha in NVZ	22,112.7	11,014.5
Ha in OZ	0.17	2,716
N_{max} (Kg)	3,759,222.2	2,795,864.8
N_p (Kg)	2,936,819.1	1,939,819.9
N_p/N_{max}	**78%**	**69%**

Fig. 5. Scenarios results: S1 – WC20 (a) and S2 – WC20 (b).

the two datasets (Fig. S2). In the combined area, the PA is 69.84 % and the UA is 64.34 %. Higher values are recorded in Caserta (PA 73.88 %, UA 57.49 %) compared to Salerno (PA 64.11 %, UA 79.91 %). The higher UA in Salerno suggests that agricultural areas are better delineated in CUAS09. For the Built-Up class, the PA in the combined area is 36.14 %, with a UA of 60.66 % (Fig. S2). In Caserta, the PA is similar (36.41 %), but the UA decreases to 54.00 %, whereas in Salerno, the PA drops to 30.45 %, and the UA significantly increases to 67.07 % (Fig. S2). These differences indicate that urban areas in Caserta are less represented in CUAS09 compared to Salerno, where there is greater consistency with the satellite data. The Bare/Spare Vegetation class is among the most challenging to harmonize. In the combined area, the PA is 5.66 % with a UA of just 0.05 % (Fig. S2). In Caserta, the class is not recognized (PA and UA are 0 %), while in Salerno, the PA increases to 12.77 % (Fig. S2), although the UA remains null. This highlights the poor representation of areas with sparse or no vegetation in CUAS09. Finally, for the Permanent Water Bodies class, the PA in the combined area is 32.12 %, with a UA of 8.50 % (Fig. S2). In Caserta, the values improve (PA 42.45 %, UA 90.37 %), whereas in Salerno, the PA drops dramatically to 7.07 %, with a UA of 49.40 % (Fig. S2). This suggests that water bodies are better defined in CUAS09 for Caserta compared to Salerno, where mapping accuracy for water surfaces is likely lower.

4. Discussion

4.1. Use of different spatial LULC data

A crucial aspect that emerged from the analysis is that in Caserta, the entire area falls within NVZs, while Salerno shows a partial integration of the entire area within NVZs. However, Salerno comes closest to the maximum allowable N load (96 % in the constrained scenario), suggesting a more critical nutrient management situation than in Caserta. These differences highlight the need for territorially specific mitigation strategies to optimize livestock sector sustainability and reduce environmental impacts. The CUAS09 local data analysis revealed significant differences in similarity to the WC20 dataset. These differences can be attributed to several factors, including the complexity of the landscape and the different quality of class representation in the two datasets. Similarly, Zhang et al. (2023) identified significant discrepancies while testing the classification accuracy and spatial coherence of five LULC datasets, highlighting the challenges associated with LULC comparisons. In addition, discrepancies may result from misalignment of spatial data or using different classification schemes. The challenge of harmonizing the nomenclature of two different spatial datasets was also highlighted by Duarte et al. (2023), which presented a comparison between global and national land cover maps. The CTM results showed differences between the analysed areas. In Caserta and Salerno, the OA was 51.38 %, indicating moderate accuracy, while the K_C was 23 %, suggesting weak classification agreement. This outcome was expected, as the analysis compared land use data from 2009 (CUAS09) with land cover data from 2020 (WC20) due to the lack of more recent or comparable datasets for the Campania region. Given these differences in sources and timeframes, the objective was not to assess absolute accuracy but rather to highlight classification discrepancies. This limitation emphasises the need for local authorities to improve and update their LULC datasets. Finally, a limitation of the ESA WC20 dataset is its inability to distinguish greenhouses from the built-up class. As it was not possible to extract greenhouses, they were conservatively classified as unsuitable for

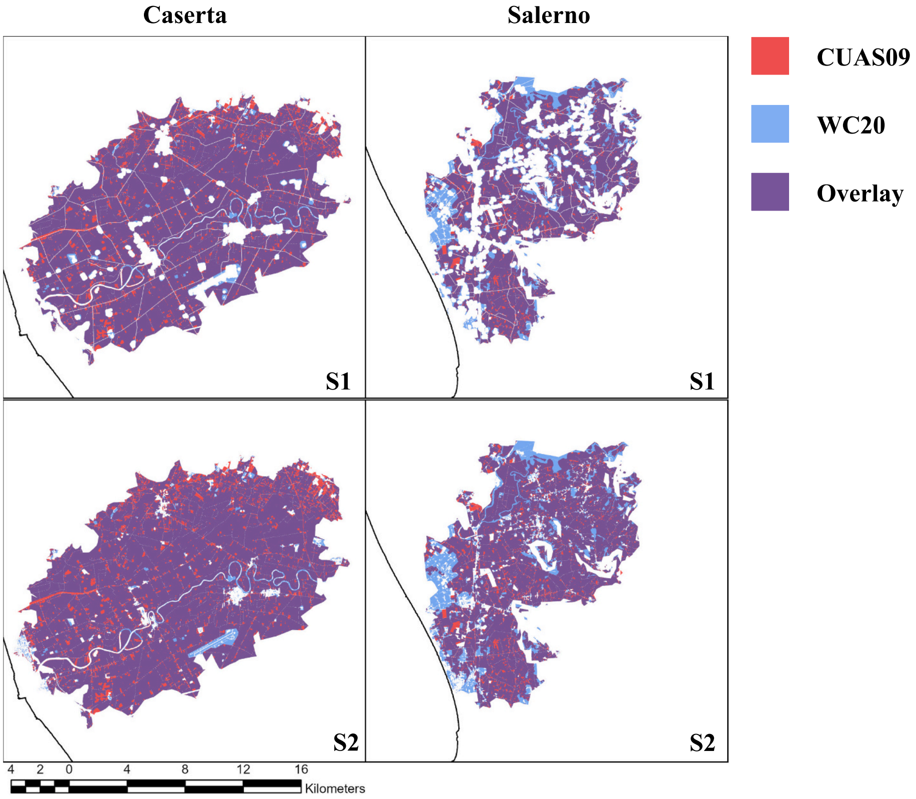


Fig. 6. Spatial overlay of N distribution differences between CUAS09 and WC20 in Scenario 1 and 2.

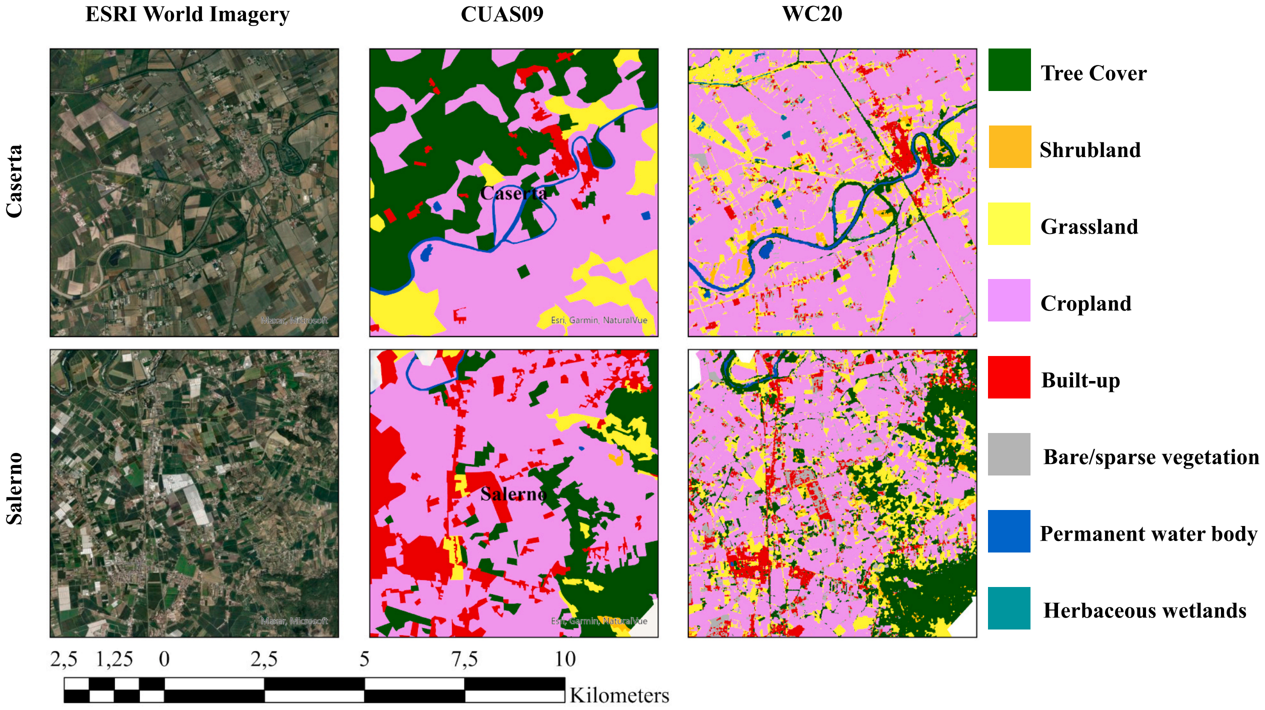


Fig. 7. Comparing Caserta (41°04′23″ N, 14°19′52″ E) and Salerno (40°40′57″ N, 14°46′05″ E) spatial representation.

manure application. Overcoming this challenge in the future, using a secondary classification process based on a dedicated spectral index such as the Plastic Greenhouse Index (PGHI)(Ji et al., 2020) already tested in the considered study area (Belfiore et al., 2024) datasets would greatly improve the accuracy of such analyses.

4.2. *Implications for manure distribution*

The lack of data on the specific fields associated with each farm for manure application is a significant limitation. In this study, it was assumed that all livestock manure was spread evenly over the available fields. However, not knowing which fields are more or less accessible to farmers could lead to under- or overestimation of actual N loads. Knowledge of farm-specific field layouts and distances, combined with NA, can help to optimise manure distribution strategies. In this study, we have assumed that, on average, farmers consider an area within a 5 km radius to be suitable for spreading. However, this assumption would require farm- and site-specific analysis. Our results confirmed that large farms are often located in areas with limited land access, meaning that manure may have to be transported further, sometimes across municipal boundaries. This calls for a better understanding of the balance between economic and environmental sustainability. Manure application techniques, such as sprinkling or direct soil injection. Techniques that minimize manure exposure to air generally reduce ammonia (NH_3) and odour emissions (Chadwick et al., 2011). However, as Webb et al. (2010) reported, lower NH_3 emissions may lead to an increase in nitrous oxide (N_2O) emissions, but the differences are often insignificant. In this context, digestate from biogas treatment plants offers a promising solution to reduce environmental impacts (Duan et al., 2020; Khoshnevisan et al., 2021). For this reason, the adoption of livestock manure application technologies should itself be encouraged by supportive policies that enable farm modernisation.

4.3. Implications for government, community, and development

The results of this research can significantly contribute to land-use planning and management by government authorities. In particular, the analysis of areas with high N loads from livestock effluents provides crucial information for formulating more targeted policies. This analysis can help define specific zones where sustainable effluent management techniques should be applied. Public institutions could use these findings to update regulations and criteria for livestock effluent management, thus contributing to more effective planning. Cameira et al. (2019), emphasize that, in municipalities with high livestock production, efficient manure management is essential to reduce N surplus. Their study highlights the importance of spatial modeling in assessing the environmental and economic impacts of management strategies. An additional tool for improving effluent management is NA, which enables the study of distances and optimal routes for transporting livestock effluents from farms to agricultural fields or suitable treatment facilities. This approach can assist authorities in: i) Optimizing transport routes, reducing logistical costs and the environmental impact associated with transportation; ii) Identifying well-served areas and those with limited accessibility, suggesting strategies to improve road infrastructure or optimize the distribution of treatment facilities and iii) Evaluating alternative scenarios for sustainable effluent management, such as establishing regional treatment centers based on the location of farms and the available road network. The introduction of innovative spreading techniques, combined with logistics optimization through NA, could not only enhance agricultural productivity but also reduce environmental risks and promote more sustainable farming practices. For example, the local agricultural community could benefit from training programs or financial support to adopt advanced technologies, while simultaneously mitigating the risk of water pollution. Additionally, access to this information could raise awareness and engage the local community in responsible nutrient management, thereby strengthening the link between agriculture and environmental protection. This is also important for farmers, who play a crucial role in reducing N pollution from agricultural sources, as they are the direct implementers of mitigation measures (Iversen et al., 2024). From a development perspective, the findings of this research provide valuable insights for improving territorial and agricultural management in the region. Support policies, such as funding for purchasing innovative effluent treatment equipment, could incentivize the adoption of more eco-friendly techniques.

4.4. Availability and potential of up-to-date LULC datasets

One of the main implications of this study is the need to update land use maps in the Campania region by integrating satellite data for more accurate planning. The differences observed in the use of CUAS09 and WC20 to identify areas suitable for manure application highlight the importance of updating LULC data or integrating satellite data into livestock manure management strategies. Indeed, LULC mapping can benefit greatly from the fusion of remote sensing datasets, geospatial big data, physical big data, and socio-economic data (Zhang and Li, 2022). Future improvements in N loading modeling could make use of higher resolution remote sensing data, more frequent updates of land use maps, and the inclusion of additional variables, such as crop type, to account for annual variations. A fundamental assumption of this study is that all land is suitable for manure application. However, this does not account for crop types that prohibit manure application. Detailed knowledge would make it possible to identify areas unsuitable for manure application more accurately and determine the maximum applicable N loads for each crop. Combining this approach with advanced logistical strategies, such as NA, could help reduce environmental costs and improve land use efficiency, benefiting farmers, local communities, and governments alike.

5. Conclusion and recommendations for future research

This study demonstrated how the choice of spatial data sources significantly influences the estimation of N loads from livestock manure and the identification of suitable spreading areas. Given the variability in land-use data sources highlighted in the literature, our findings emphasize the importance of selecting appropriate spatial datasets to ensure accurate and reliable N load assessments. The comparison performed with the cross-tabulation matrix between the local land use map (CUAS09, 2009) and the satellite-based map used as reference (WC20, 2020) reveals significant differences between the two spatial datasets considered. These differences are denoted by the moderate OA (51.38 %) and the low K_C (23 %). These results indicate that the CUAS09 dataset, not coeval with the livestock data (2020) and at a lower resolution than the WC20 data, introduces uncertainty in the identification of suitable spreading areas. In line with the study's objective of assessing the implications of using global satellite-derived datasets versus regional land-use maps, our findings show that different spatial information sources can yield significantly different results in identifying areas suitable for manure spreading. As illustrated in Fig. 6, there are clear differences in the suitable spreading area obtained using the two different spatial datasets. The integration of GIS made it possible to identify critical areas in N distribution, particularly in the province of Salerno, which is approaching the maximum allowable N load. Furthermore, NA demonstrated how the logistics of effluent spreading can impact sustainable N management. These findings directly address the study's objective of evaluating the impact of different land-use data sources on N management and identifying key spatial factors affecting nutrient distribution. However, a major limitation remains the lack of precise data on the specific fields where each farm applies manure, as well as the crop type cultivated on each field, which is essential to exclude crops unsuitable for manure application. This uncertainty affects the accuracy of N load estimates and the feasibility of mitigation strategies. Without detailed knowledge of field locations, N pressure in different areas could be over- or underestimated. To overcome this challenge, future research should prioritize obtaining or integrating farm-specific data to refine spatial analyses and improve nutrient management strategies. Beyond improving data accuracy, these insights have broader implications for spatial planning and agricultural policies. Adopting advanced manure spreading techniques and promoting GIS tools for resource management could enhance manure use efficiency while reducing pollution risks. Local institutions should encourage farm modernization through financial support policies and the updating of land-use data with satellite-derived information. Future studies should also explore the integration of spectral indices and remote sensing techniques to improve the classification of agricultural land and further enhance N management strategies.

CRediT authorship contribution statement

Raffaele Grieco: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Oscar Rosario Belfiore:** Writing – review & editing, Supervision, Software, Methodology, Data curation, Conceptualization. **Elena Cervelli:** Writing – review & editing, Supervision, Formal analysis, Conceptualization. **Marco Bovo:** Writing – review & editing, Supervision, Formal analysis. **Stefania Pindozzi:** Writing – review & editing, Supervision, Funding acquisition, Formal analysis. **Ester Scotto di Perta:** Writing – review & editing, Supervision. **Patrizia Tassinari:** Writing – review & editing, Funding acquisition. **Daniele Torreggiani:** Writing – review & editing, Supervision.

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.

Acknowledgments

This study was financed by the European Union - NextGenerationEU through the Italian Ministry of University and Research under PNRR – Mission 4 Component 2, Investment 3.3 “Partnerships extended to universities, research centres, companies and funding of basic research projects” D.M. 352/2021 – CUP J33C22001860002. This study was carried out within the Next Generation EU Contributo alla spesa a valere sulla Missione 4 – Componente 2. Dalla Ricerca all’Impresa - Investimento 1.1 Fondo per il Programma Nazionale della Ricerca (PNR) e Progetti di Ricerca di Rilevante Interesse Nazionale (PRIN): “Limit DGGas” funded by Italian Miur, CUP E53D23010780006 and the Agritech National Research Center and received funding from the European Union Next-Generation EU (PIANO NAZIONALE DI RIPRESA E RESILIENZA (PNRR) —MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.4—D.D. 1032 17/06/2022, CN00000022). Moreover, this study was carried out under the agreement “SPORFASS” (CUP B22D24000060002) of the Campania Region. This manuscript only reflects the authors’ views and opinions, and neither the European Union nor the European Commission can be considered responsible for them.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2025.110474.

Data availability

Data will be made available on request.

References

Arino, O., Bicheron, P., Achard, F., Latham, J., Witt, R., Weber, J.L., 2008. GlobCover the most detailed portrait of Earth.

Assessorato Agricoltura Regione Campania, 2020. 7° censimento generale dell’agricoltura [WWW Document]. accessed 11.29.24. https://agricoltura.regione.campania.it/statistica/statistica_VII_censimento.html.

Awasthi, M.K., Sarsaiya, S., Wainaina, S., Rajendran, K., Kumar, S., Quan, W., Duan, Y., Awasthi, S.K., Chen, H., Pandey, A., Zhang, Z., Jain, A., Taherzadeh, M.J., 2019. A critical review of organic manure biorefinery models toward sustainable circular bioeconomy: Technological challenges, advancements, innovations, and future perspectives. Renewable and Sustainable Energy Reviews 111, 115–131. https://doi.org/10.1016/j.rser.2019.05.017.

Ban, Y., Gong, P., Giri, C., 2015. Global land cover mapping using Earth observation satellite data: Recent progresses and challenges. ISPRS Journal of Photogrammetry and Remote Sensing 103, 1–6. https://doi.org/10.1016/j.isprsjprs.2015.01.001.

Belfiore, O.R., Cavallo, S., Aquino, A., Falanga Bolognesi, S., De Michele, C., Della Monica, C., Alali, Q., Mula, I., Pizzolante, A., D’Urso, G., 2024. Satellite-based monitoring of groundwater utilization for irrigation: a case study in Southern Italy, in: Neale, C.M., Maltese, A., Nichol, C., Bostater, C.R. (Eds.), Remote Sensing for Agriculture, Ecosystems, and Hydrology XXVI. SPIE, p. 35. Doi: 10.1117/12.3031728.

Cameira, M.R., Rolim, J., Valente, F., Faro, A., Dragosits, U., Cordovil, C.M., 2019. Spatial distribution and uncertainties of nitrogen budgets for agriculture in the Tagus river basin in Portugal – Implications for effectiveness of mitigation measures. Land Use Policy 84, 278–293. https://doi.org/10.1016/j.landusepol.2019.02.028.

Cervelli, E., Di Perta, E.S., Mautone, A., Pindozzi, S., 2021. The landscape approach as support to the livestock manure management. the buffalo herds case-study in Sele plain, Campania region. In: 2021 IEEE International Workshop on Metrology for Agriculture and Forestry. https://doi.org/10.1109/MetroAgriFor52389.2021.9628616.

Chadwick, D., Sommer, S., Thorman, R., Fangueiro, D., Cardenas, L., Amon, B., Misselbrook, T., 2011. Manure management: Implications for greenhouse gas emissions. Anim Feed Sci Technol 166–167, 514–531. https://doi.org/10.1016/j.anifeedsci.2011.04.036.

Comber, A.J., 2013. Geographically weighted methods for estimating local surfaces of overall, user and producer accuracies. Remote Sensing Letters 4, 373–380. https://doi.org/10.1080/2150704X.2012.736694.

Duan, N., Khoshnevisan, B., Lin, C., Liu, Z., Liu, H., 2020. Life cycle assessment of anaerobic digestion of pig manure coupled with different digestate treatment technologies. Environ Int 137, 105522. https://doi.org/10.1016/j.envint.2020.105522.

Duarte, D., Fonte, C., Costa, H., Caetano, M., 2023. Thematic Comparison between ESA WorldCover 2020 Land Cover Product and a National Land Use Land Cover Map. Land (basel) 12. https://doi.org/10.3390/land12020490.

ESA, 2017. Land Cover CCI Product User Guide Version 2.

ESRI, 2024a. ArcGIS Pro geoprocessing tool reference [WWW Document]. URL https://pro.arcgis.com/en/pro-app/latest/tool-reference/main/arcgis-pro-tool-reference.htm (accessed 12.16.24).

ESRI, 2024b. How Kernel Density works [WWW Document]. URL https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/how-kernel-density-works.htm (accessed 11.11.24).

ESRI, 2024c. Data classification methods [WWW Document]. URL https://pro.arcgis.com/en/pro-app/latest/help/mapping/layer-properties/data-classification-methods.htm (accessed 11.11.24).

ESRI, 2024d. Network analysis workflow [WWW Document]. URL https://desktop.arcgis.com/en/arcmap/latest/extensions/network-analyst/network-analysis-workflow.htm (accessed 11.11.24).

Font-Palma, C., 2019. Methods for the Treatment of Cattle Manure—A Review. C 2019, Vol. 5, Page 27 5, 27. Doi: 10.3390/C5020027.

González, A., Gilmer, A., Foley, R., Sweeney, J., Fry, J., 2011. Applying geographic information systems to support strategic environmental assessment: Opportunities and limitations in the context of Irish land-use plans. Environ Impact Assess Rev 31, 368–381. https://doi.org/10.1016/j.eiar.2010.12.001.

Grieco, R., Cervelli, E., Bovo, M., Pindozzi, S., Scotto, E., Tassinari, P., Torreggiani, D., 2024. The role of geospatial technologies for sustainable livestock manure management : A systematic review. Science of the Total Environment 954, 176687. https://doi.org/10.1016/j.scitotenv.2024.176687.

Hansen, B., Aamand, J., Blicher-Mathiesen, G., Christiansen, A.V., Claes, N., Dalgaard, T., Frederiksen, R.R., Jacobsen, B.H., Jakobsen, R., Kallesøe, A., Kim, H., Koch, J., Møller, I., Madsen, R.B., Schaper, S., Sandersen, P.B.E., Voutchkova, D.D., Wiborg, I., 2024. Assessing groundwater denitrification spatially is the key to targeted agricultural nitrogen regulation. Sci Rep 14, 1–13. https://doi.org/10.1038/s41598-024-55984-9.

Hutchings, N.J., Nielsen, O.K., Dalgaard, T., Mikkelsen, M.H., Børgesen, C.D., Thomsen, M., Ellermann, T., Højberg, A.L., Mogensen, L., Winther, M., 2014. A nitrogen budget for Denmark; Developments between 1990 and 2010, and prospects for the future. Environmental Research Letters 9. https://doi.org/10.1088/1748-9326/9/11/115012.

Indriasari, V., Mahmud, A.R., Ahmad, N., Shariff, A.R.M., 2010. Maximal service area problem for optimal siting of emergency facilities. International Journal of Geographical Information Science 24, 213–230. https://doi.org/10.1080/13658810802549162.

Islami, F.A., Tarigan, S.D., Wahjunie, E.D., Dasanto, B.D., 2022. Accuracy Assessment of Land Use Change Analysis Using Google Earth in Sadar Watershed Mojokerto Regency. IOP Conf Ser Earth Environ Sci 950. https://doi.org/10.1088/1755-1315/950/1/012091.

ISTAT, 2022. In aumento i prodotti riconosciuti dalla Ue.

Iversen, S.V., Dalgaard, T., Graversgaard, M., 2024. Discordance between farmers and scientists - Perspectives on nitrogen reduction measures in Denmark. J Environ Manage 352, 119877. https://doi.org/10.1016/j.jenvman.2023.119877.

Ji, L., Zhang, L., Shen, Y., Li, X., Liu, W., Chai, Q., Zhang, R., Chen, D., 2020. Object-Based Mapping of Plastic Greenhouses with Scattered Distribution in Complex Land Cover Using Landsat 8 OLI Images: A Case Study in Xuzhou, China. Journal of the Indian Society of Remote Sensing 48, 287–303. https://doi.org/10.1007/s12524-019-01081-8.

Khoshnevisan, B., Duan, N., Tsapekos, P., Awasthi, M.K., Liu, Z., Mohammadi, A., Angelidaki, I., Tsang, D.C.W., Zhang, Z., Pan, J., Ma, L., Aghbashlo, M., Tabatabaei, M., Liu, H., 2021. A critical review on livestock manure biorefinery technologies: Sustainability, challenges, and future perspectives. Renewable and Sustainable Energy Reviews 135, 110033. https://doi.org/10.1016/j.rser.2020.110033.

Krisp, J.M., Špatenková, O., 2010. Kernel density estimations for visual analysis of emergency response data. Lecture Notes in Geoinformation and Cartography 395–408. https://doi.org/10.1007/978-3-642-03442-8_27.

Liu, B.L., Li, G., Yang, C.X., Ma, J., Zhao, Y., Yu, S.P., Dong, J., Guo, H., 2022. Spatial Suitability Evaluation of Livestock and Poultry Breeding: A Case Study in Wangkui County, Heilongjiang Province. China. Sustainability (switzerland) 14. https://doi.org/10.3390/su14127464.

Macarringue, L.S., Bolfe, É.L., Pereira, P.R.M., 2022. Developments in Land Use and Land Cover Classification Techniques in Remote Sensing: A Review. Journal of Geographic Information System 14, 1–28. https://doi.org/10.4236/jgis.2022.141001.

Miralha, L., Muenich, R.L., Schaffer-Smith, D., Myint, S.W., 2021. Spatiotemporal land use change and environmental degradation surrounding CAFOs in Michigan and North Carolina. Science of the Total Environment 800. https://doi.org/10.1016/j.scitotenv.2021.149391.

Paudel, K.P., Bhattarai, K., Gauthier, W.M., Hall, L.M., 2009. Geographic information systems (GIS) based model of dairy manure transportation and application with environmental quality consideration. Waste Management 29, 1634–1643. https://doi.org/10.1016/j.wasman.2008.11.028.

Saha, G., Raj, C., Elliott, H., Gall, H., Shortle, J., Alber, D., 2018. Geospatial landscape analysis for livestock manure management in Western Pennsylvania. In: ASABE 2018 Annual International Meeting 2–13. https://doi.org/10.13031/aim.201801218.

Scotto di Perta, E., Cervelli, E., Grieco, R., Mautone, A., Pindozzi, S., 2024. GIS-based analysis to assess biogas energy potential as support for manure management in Southern Italy. Acta IMEKO 13, 1–6. https://doi.org/10.21014/actaimeko.v13i1.1688.

Serra, J., Cordovil, C.M. d. S., Cruz, S., Cameira, M.R., Hutchings, N.J., 2019. Challenges and solutions in identifying agricultural pollution hotspots using gross nitrogen balances. Agric Ecosyst Environ 283, 106568. Doi: 10.1016/j.agee.2019.106568.

Sliz-Szkliniarz, B., Vogt, J., 2012. A GIS-based approach for evaluating the potential of biogas production from livestock manure and crops at a regional scale: A case study for the Kujawsko-Pomorskie Voivodeship. Renewable and Sustainable Energy Reviews 16, 752–763. https://doi.org/10.1016/j.rser.2011.09.001.

Smits, P.C., Dellepiane, S.G., Schowengerdt, R.A., 1999. Quality assessment of image classification algorithms for land-cover mapping: A review and a proposal for a cost-based approach. Int J Remote Sens 20, 1461–1486. https://doi.org/10.1080/014311699212560.

Webb, J., Pain, B., Bittman, S., Morgan, J., 2010. The impacts of manure application methods on emissions of ammonia, nitrous oxide and on crop response-A review. Agric Ecosyst Environ 137, 39–46. https://doi.org/10.1016/j.agee.2010.01.001.

Xu, P., Tsendbazar, N.E., Herold, M., de Bruin, S., Koopmans, M., Birch, T., Carter, S., Fritz, S., Lesiv, M., Mazur, E., Pickens, A., Potapov, P., Stolle, F., Tyukavina, A., Van De Kerchove, R., Zanaga, D., 2024. Comparative validation of recent 10 m-resolution global land cover maps. Remote Sens Environ 311, 114316. https://doi.org/10.1016/j.rse.2024.114316.

Yalcinkaya, S., 2020. A spatial modeling approach for siting, sizing and economic assessment of centralized biogas plants in organic waste management. J Clean Prod 255, 120040. https://doi.org/10.1016/j.jclepro.2020.120040.

Yan, B., Li, Y., Yan, J., Shi, W., 2021. Spatial site selection for a centralized treatment center of livestock excreta: Taking Nantong Town as an example. Comput Electron Agric 180. https://doi.org/10.1016/j.compag.2020.105885.

Zanaga, D., Van De Kerchove, R., Daems, D., De Keersmaecker, W., Brockmann, C., Kirches, G., Wevers, J., Cartus, O., Santoro, M., Fritz, S., Lesiv, M., Herold, M., Tsendbazar, N.E., Xu, P., Ramoino, F., Arino, O., 2022. ESA WorldCover 10 m 2021 v200. Meteosat Second Generation Evapotranspiration (MET). https://doi.org/10.5281/zenodo.7254221.

Zanaga, D., Van De Kerchove, R., De Keersmaecker, W., Souverijns, N., Brockmann, C., Quast, R., Wevers, J., Grosu, A., Paccini, A., Vergnaud, S., Cartus, O., Santoro, M., Fritz, S., Georgieva, I., Lesiv, M., Carter, S., Herold, M., Li, L., Tsendbazar, N.-E., Ramoino, F., Arino, O., 2021. ESA WorldCover 10 m 2020 v100 (Versión v100). Zenodo. https://doi.org/10.5281/zenodo.5571936.

Zhang, C., Li, X., 2022. Land Use and Land Cover Mapping in the Era of Big Data. Land (basel) 11. https://doi.org/10.3390/land11101692.

Zhang, W., Tian, J., Zhang, X., Cheng, J., Yan, Y., 2023. Which land cover product provides the most accurate land use land cover map of the Yellow River Basin? Front Ecol Evol 11, 1–17. https://doi.org/10.3389/fevo.2023.1275054.