



# Unravelling the influence of projected land use/land cover on surface water ecological status in Italian watersheds

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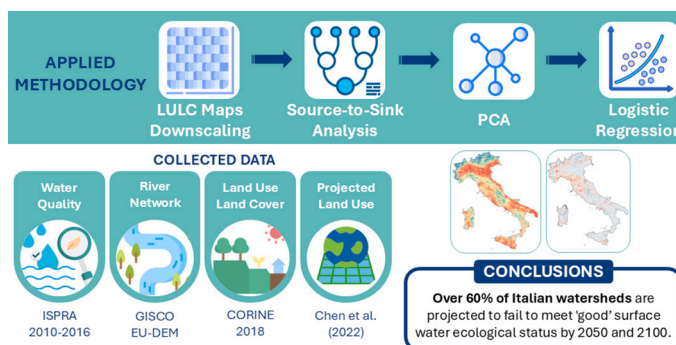
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## HIGHLIGHTS

- Source-to-sink extraction of key landscape metrics
- Dimensionality reduction using Principal Component Analysis
- BLR model with 90 % accuracy in predicting SWES at riverine scale
- Over 60 % of Italian watersheds are projected to fail “good” SWES by 2050 and 2100.
- Natural land cover expansion is associated with improved SWES.

## GRAPHICAL ABSTRACT



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## ABSTRACT

This research examines the influence of land use and land cover (LULC) on water quality in Italian watersheds, with a focus on predicting the likelihood of achieving good surface water ecological status (SWES) under future scenarios (SSP2-RCP4.5 and SSP5-RCP8.5) for the years 2050 and 2100. The developed methodology includes remapping future LULC, conducting Principal Component Analysis to examine the interactions between land use classes and the impact of upstream LULC on downstream SWES, and regression analysis to predict future SWES. Future projections indicate a decline in SWES in human-influenced areas, but potential improvements in natural regions with conservation efforts. For both scenarios, over 60 % of Italian watersheds are expected to fail to achieve good SWES by 2050 and 2100, emphasizing the need for targeted land management strategies to mitigate these effects. This analysis represents valuable support for the development of adaptive strategies that safeguard water resources and ensure the long-term sustainability of freshwater ecosystems.

## 1. Introduction

Freshwater is one of the planet's most critical resources, yet it represents only a small fraction of the Earth's total water. Despite its limited

availability, demand is steadily increasing due to population growth, agriculture, industry, and urbanization (United Nations, 2023). This rising pressure leads to two major challenges: water scarcity, as many regions already face shortages and uneven distribution (Jones et al.,

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2024), and water quality degradation, driven by pollution, over-abstraction, and land use change (Shi et al., 2017). Climate change further amplifies these issues by intensifying droughts, floods, and altering hydrological cycles. These global pressures are also evident in Europe, where, despite long-standing policy efforts, water resources remain under stress, affecting both human health and sustainable development (Vigiak et al., 2021). The EU addressed this with the Water Framework Directive (WFD), which aimed for 'good' ecological status across European waters by 2015 (European Commission, 2015; Water Frame Directive, 2000). By that year, however, nearly half of the EU's surface waters had not reached this target, underscoring the need for stronger measures (Vigiak et al., 2021).

In this context, Land Use and Land Cover Change (LULCC) directly affect ecosystems and biodiversity, influencing SWES. Urbanization increases runoff and pollutant load in water bodies (Alamdari et al., 2022; Sun and Zhang, 2025), while agriculture can degrade water quality through fertilizer and pesticide runoff, leading to eutrophication (Buonocore et al., 2021; Locke, 2024). Moreover, the alteration of natural landscapes disrupts the natural hydrological cycle, further exacerbating water quality issues (Botter et al., 2021; Dou et al., 2023). Understanding the LULC-SWES relationship is critical for sustainable management and policy-making.

To understand these interactions, researchers use statistical analysis, GIS mapping, and hydrological models. Statistical analyses reveal correlations between LULC types (e.g., urban, agricultural) and water quality indicators (Chiang et al., 2021; Ding et al., 2016; Zhang et al., 2020). GIS maps LULC changes, identifying areas where alterations impact water quality (Zhang et al., 2023). Models like SWAT and BASINS simulate LULC effects on hydrology and water quality (Ross and Randhir, 2022; Shree and Kumar, 2023; Zhu et al., 2023), requiring extensive data in order to predict changes over time. Despite the potential for modelling and forecasting current and future water conditions, these detailed approaches can dilute and obscure the specific impact of land use structure and landscape patterns as an individual predictor of water quality. Additionally, many studies are constrained by their focus on relatively small areas with simplified or limited river networks (Camara et al., 2021; Ding et al., 2016; Shree and Kumar, 2023), or on larger areas where the analysis is based on generalized watersheds that do not account for the nuances of individual river branches (Vigiak et al., 2021). This highlights a need for research that accounts for detailed spatial variations in river networks and land use across different landscapes and various scales.

When studying the relationship between landscape patterns and water quality, researchers typically use Digital Elevation Models (DEMs) to divide a watershed into smaller sub-watersheds, where landscape metrics or water samples are accounted for analysis. Then, statistical methods were utilized to explore the relationships between landscape metrics and water quality. Several observational studies have demonstrated how LULC changes directly affect both water quantity and quality in diverse regions. For example, Shukla et al. (2023) showed that in the Rur basin (Germany), forest-to-urban conversions increased runoff by up to 43 %, particularly in upstream areas, heightening local flood risks, while forest-to-grassland conversions reduced runoff and soil erosion. In Argentina, Bonansea et al. (2021) reported that agricultural intensification and rapid urban expansion around Los Molinos reservoir led to significant water quality degradation, with more frequent algal blooms observed through NDVI analysis. Similarly, Rahmani and Fattahi (2024) documented that LULC alterations combined with hydrological drought in Iran's Helle river increased water hardness and salinity by 13.7 % and 16.1 %, respectively, while reducing pH and altering the predictability of several key parameters. Further insights come from studies in China. Lu et al. (2024) found that water quality in the Ganjiang River Basin was strongly influenced by the composition of land types within upstream buffer zones, with cropland and settlements degrading water quality, while forests and grasslands improved it. Landscape metrics such as patch density and shape complexity were also

linked to nutrient pollution and turbidity. Liu et al. (2021) highlighted that in subtropical agricultural catchments, the integration of land use, soil, and geomorphological factors provided strong explanatory power for TN and TP levels, underscoring the combined influence of landscape composition and configuration. Similarly, Zhang et al. (2020) showed that in the Daning River Basin of the Three Gorges Reservoir Region, the effects of land use on water quality varied across watershed and riparian zones, with diversity and shape indices of land cover strongly influencing nitrogen and phosphorus concentrations.

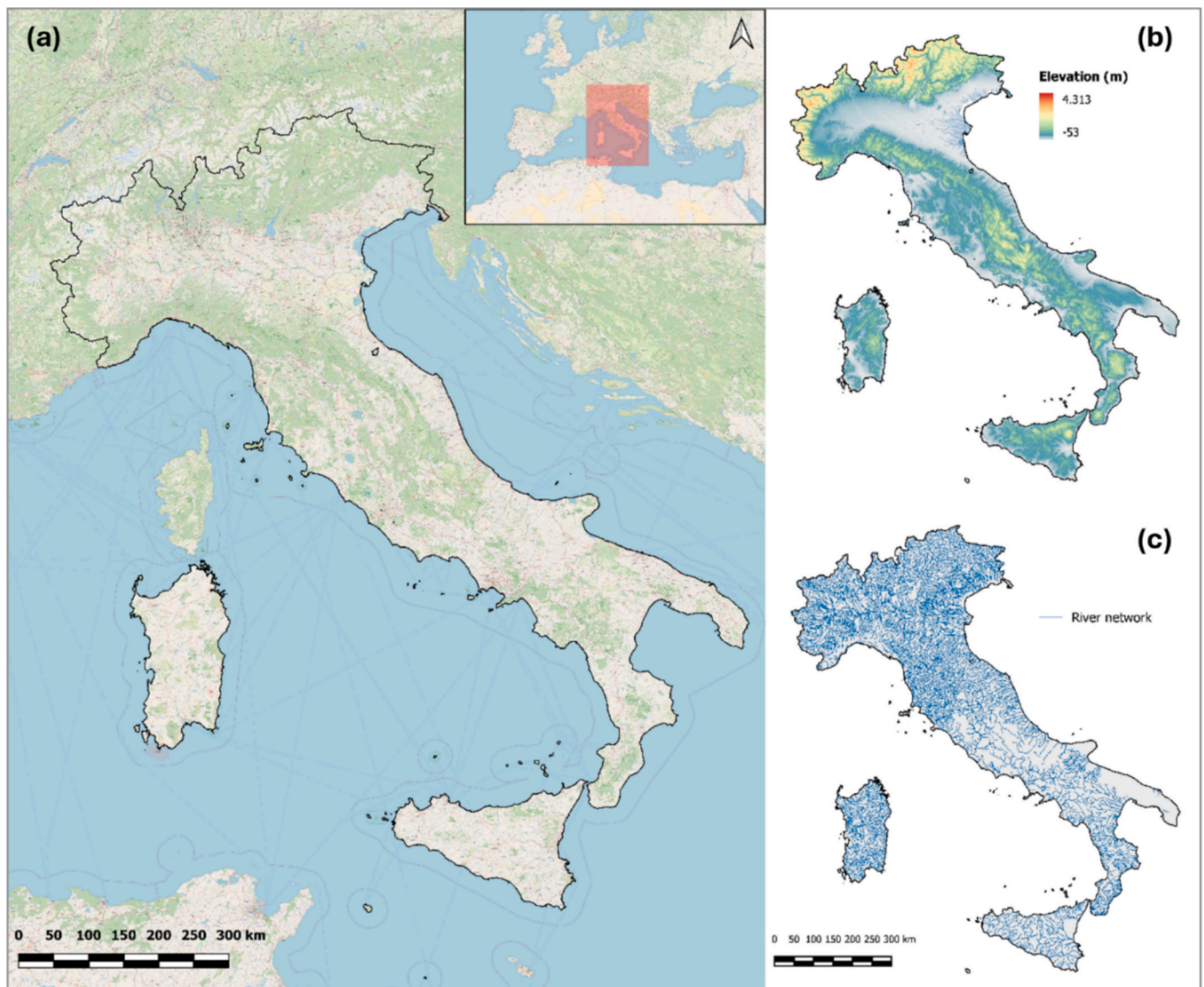
Two main approaches are currently used to link sub-watershed characteristics with water quality data. The first approach links the water quality of each monitoring site only to its specific sub-watershed, ignoring the upstream effects (Marisi et al., 2025; Zhang et al., 2022). The second approach, which has shown stronger landscape patterns to water quality, connects each monitoring site to all upstream sub-watersheds and their buffers, considering the cumulative impact of the upstream landscape on water quality (Ding et al., 2016; Liu et al., 2021; Wu and Lu, 2021). However, this upstream-to-downstream approach has not yet been used to forecast future water quality based on projected land use maps.

Although the studies mentioned above provide valuable insights into the impacts of land use changes on water quality, they have not adequately incorporated the comprehensive WFD classifications, which consider both chemical and biological indicators. Many of these studies tend to focus predominantly on bio-geochemical parameters, overlooking the WFD's holistic approach to ecological health, which includes aquatic flora, fauna, and habitat quality (European Commission, 2015; Water Frame Directive, 2000). Building on existing research, this study investigates the role of natural land covers and their spatial arrangement in shaping the ecological status of surface waters in the baseline and future scenarios. The central hypothesis is that ecological conditions improve in areas with extensive natural land covers, particularly where future projections indicate their expansion. This improvement is assumed to depend not only on the proportion of natural land covers but also on their spatial configuration, since the arrangement of patches across the landscape regulates hydrological connectivity, enhances nutrient retention, and supports habitat integrity (Moreno-De-Las-Heras et al., 2020; Yarnell and Thoms, 2022). To test this hypothesis, the methodology integrates future LULC projections with landscape metrics analysis and regression modelling, enabling the estimation of the probability of achieving good SWES under different SSP-RCP scenarios. A downscaling procedure was developed to harmonize datasets of different resolutions, reconciling high-resolution watershed boundaries with lower-resolution LULC data and generating fine-scale projections from coarser inputs. The influence of upstream land use configuration on downstream water quality is accounted for by tracing water flow from upland to lowland areas. Several logistic regression models are tested to identify the most suitable approach for predicting surface water ecological status, and probability maps are produced for alternative SSP-RCP scenarios, highlighting regions where targeted interventions may be most needed to safeguard or improve future ecological conditions.

## 2. Materials and methods

### 2.1. Case study area description

The Italian Peninsula is a diverse landmass extending into the Mediterranean Sea, characterized by varied topography, climate, and land use (Todorovic et al., 2018) (Fig. 1a) and covered an area of 302,073 km<sup>2</sup>. The Alps in the north and the Apennines running from north to south define its geography, influencing both climate and hydrology by directing watersheds toward the Adriatic and Tyrrhenian Seas. Italy's coastline extends for 7375 km, and its freshwater resources (Massarutto, 2005), including major rivers like the Po, Arno, and Tiber, are vital for agriculture, industry, and human settlements (Fig. 1c). Land use in Italy varies across its diverse terrain, from intensive agriculture in



**Fig. 1.** Case Study Area: The map on the left shows Italy as depicted by OpenStreetMap (OSM). The top right panel presents the elevation profile derived from the Digital Elevation Model (DEM). The bottom right panel illustrates the river network of Italy, as sourced from ISPRA.

the Po Valley (Bozzola and Swanson, 2014; Montanari, 2012) to small-scale farming (e.g., vineyards and olive groves, interspersed with forests) (Ferrara et al., 2021). The Apennines and Alps host deciduous and coniferous forests crucial for biodiversity and carbon sequestration, though urbanization and agriculture have fragmented these areas (Ferrara et al., 2017; Romano et al., 2017). The landscape of Italy reflects a long history of human settlement, where urban areas, agriculture, and natural ecosystems coexist, shaping both its biophysical and socio-economic identity within Europe.

The choice of Italy as a case study was motivated by its significant water quality issues, which highlight many of the problems that the EU WFD aim to address by the year 2030. River basins in Italy are under constant pressure from agriculture, urban expansion and infrastructure development. Despite progress in many monitoring sites, a large proportion of Italian rivers still do not achieve good ecological and chemical status, mostly because of the excess nutrients from intensive agriculture and human activities in urban areas (Erba et al., 2022; ISPRA, 2020). Therefore, this makes Italy an ideal case to study to investigate the relationship between land use and water quality in a way that can benefit both science and policy. Moreover, this research was carried out within the national GRINS (Growing Resilient, INclusive and

Sustainable) project (<https://grins.it/>), which means that it is part of a coordinated national effort to better integrate land and water management. By working within this framework, our case study contributes to the broader discussion on how Italy can meet WFD objectives while adapting to ongoing land-use pressures.

## 2.2. Case study data collection

To build a predictive model capable of forecasting SWES across diverse and extensive landscapes, a comprehensive data set was collected to support a detailed spatial analysis of the interactions between various environmental factors. This dataset includes critical information on landscape morphology used to identify and delineate water basins and watersheds, providing insights into the physical structure and boundaries of the terrain. The technical details of the collected data are summarized in Table 1, and an in-depth description of the data is presented in Section B of the Supplementary Material (SM.B). Specifically, hydrography data was gathered, including details on water flow direction, river connectivity, and the intricate network of streams and rivers (see SM.B2). High-resolution WFD-based SWES data were obtained for the entire river network (see SM.B3). This data offers

**Table 1**  
Metadata of collected data.

Dataset	Spatial Domain	Published year	Spatial Resolution	Time Frame	Data Format	Reference/Link
Land Use Data LULC (CORINE Land Cover)	Europe	2020	100 m * 100 m	2018	Raster	<a href="https://land.copernicus.eu/en/products/corine-land-cover">https://land.copernicus.eu/en/products/corine-land-cover</a> (Last access: 09/09/2024)
LULC Projection	Global	2022	1 km * 1 km	(2015), 2050, 2100	Raster	Chen, G., Li, X., & Liu, X. (2022). Global land projection based on plant functional types with a 1-km resolution under socio-climatic scenarios. <i>Scientific Data</i> , 9(1), 125.
Hydrology Data Watershed (GISCO)	Europe	2014	-	-	Shapefile	<a href="https://ec.europa.eu/eurostat/web/gisco/geodata/digital-elevation-model/eu-dem#Hydrography%20(LAEA)">https://ec.europa.eu/eurostat/web/gisco/geodata/digital-elevation-model/eu-dem#Hydrography%20(LAEA)</a> (Last access: 09/09/2024)
Watershed (HydrosHED)	Global	2014	-	-	Shapefile	<a href="https://www.hydrosheds.org/products/hydrobasins">https://www.hydrosheds.org/products/hydrobasins</a> (Last access: 09/09/2024)
River Network (GISCO)	Europe	2014	-	-	Shapefile	<a href="https://ec.europa.eu/eurostat/web/gisco/geodata/digital-elevation-model/eu-dem#Hydrography%20(LAEA)">https://ec.europa.eu/eurostat/web/gisco/geodata/digital-elevation-model/eu-dem#Hydrography%20(LAEA)</a> (Last access: 09/09/2024)
Water Quality Data SWES (ISPRA)	Italy	2016	-	2010–2016	Shapefile	<a href="https://sdi.isprambiente.it/geoserver/web/wicket/bookmarktable/org.geoserver.web.demo.MapPreviewPage?0&amp;filter=false">https://sdi.isprambiente.it/geoserver/web/wicket/bookmarktable/org.geoserver.web.demo.MapPreviewPage?0&amp;filter=false</a> (Last access: 09/09/2024)

crucial insights into SWES current status and variability across different regions. Then, detailed land use data was collected to assess the influence of various human activities and natural landscapes on SWES and the broader hydrological system. Finally, future land use projections under different socioeconomic and climate scenarios were utilized to predict the future state of SWES in Italy (see SM.B1). These scenarios, which represent a range of socio-economic pathways and climate conditions, allowed for an examination of potential changes in land use patterns and their consequent effects on SWES, helping to forecast and plan for future environmental challenges in mid- and long-term timeframes.

### 2.3. Data processing methods

#### 2.3.1. Land use re-classification

When working with LULC data, researchers often use the Corine Land Cover (CLC) nomenclature, focusing on its broad Level 1 categories due to their distinct characteristics (Xu et al., 2019; Zhang et al., 2023). This approach is sensible because the classification at this level follows precise criteria that divide the data into macro-classes with well-defined and distinct structural, ecological, and landscape characteristics. Since the future scenario projections of LULC from Chen et al. (Chen et al., 2022), which uses the ESA Climate Change Initiative Land Cover (CCI-LC) nomenclature, will be utilized for the scenario analysis, it is crucial to harmonize these with the CLC nomenclature of LULC data. To harmonize the CLC and ESA-CCI classifications, the categories need to be aligned from each system based on their structural, ecological, and landscape characteristics. This alignment ensures consistency and comparability across datasets, which is essential for producing reliable and robust analytical outcomes.

CLC and ESA-CCI land cover maps of Europe were examined and compared by Vilar et al. (2019) at regional and local scales from 2010 to 2014. They harmonized the map legends and assessed the similarities and differences through a cross-tabulation process to quantify spatial agreement and disagreement. The overall agreement between the two maps for all of Europe was about 75 %. The highest agreement was found in the forest and agriculture categories, whereas the shrubland and grassland categories had the lowest agreement. In land cover comparison, agreement measures depend on the semantic resolution of the chosen land cover typology, with a lower number of classes resulting in higher agreement/accuracy (Reinhart et al., 2021). Following Chen et al. (2022) approach, land use classes were consolidated into seven macro-groups for both land use change analysis and future projections: Water, Forest, Grassland, Barren, Cropland, Urban, and Permanent Snow and Ice. The specifics of this harmonization are detailed in the SM. A1 while definition and description of the classes are reported in guidelines of the CLC and ESA-CCI (European Space Agency - ESA, 2020; Kosztra et al., 2017).

#### 2.3.2. Selection of landscape metrics

To analyse the composition and spatial arrangement of different land-cover classes in the Italian landscape, a comprehensive patch- and class-based analysis was conducted. This analysis aimed to quantify the number and abundance of land-cover classes, facilitate comparisons among different landscapes, track landscape changes over time in response to disturbances or land-use pressures, and explore the relationship between landscape characteristics and ecological patterns affecting SWES. The selection criteria for various landscape metrics and indicators are based on a review of articles related to land-use change analysis (Chiang et al., 2021; Clément et al., 2017; Zhang et al., 2023). The selected landscape metrics are reported in the SM.A5.

#### 2.3.3. Hydrology and water quality: from rivers to watersheds

Given that surface water ecological status (SWES) is reported at the river segment level, it is necessary to translate this information to the sub-catchment level to allow the aggregation of all variables. Therefore,

the ISPRA's water quality layer was adjusted to match the nearest GISCO river network. The alignment was considered accurate based on the Dice Similarity Coefficient (DSC) of 0.916 and the Jaccard Similarity Index (JSI) of 0.845, considering a buffer of 100 m for each river branch, indicating strong agreement between the datasets (Rizwan I Haque and Neubert, 2020). After refinement, the layers were intersected to assign a single SWES value to each watershed based on WFD classification. If multiple river branches intersected a watershed, the SWES value of the longest river segment was assigned to that watershed. This approach follows the methodology proposed by (Vigiak et al., 2021), where the mainstem is considered the most representative flowline for sub-catchment-level assessments. This simplification may overlook smaller but highly impacted tributaries; however, it ensures consistency across the dataset and transparency in model inputs.

#### 2.3.4. Landscape metrics extraction: cumulative influence of upstream land use on downstream watersheds

The intrinsic connections of headwaters to landscape processes and downstream waters are important, as they influence the supply, transport, and fate of water and solutes within watersheds. The hydrological and biogeochemical dynamic processes in upland streams influence the chemical form, timing, and longitudinal distances of solute transport to downstream waters (Alexander et al., 2007), and thus, its ecological status. To assess the cumulative impact of upstream land use on downstream SWES, all upstream watersheds connected to the downstream ones were traced and identified (see SM.A 6 of the Supplementary Material for the details). Then, the landscape metrics for each catchment are calculated based on the spatial union of all upstream connected regions. This aggregated polygon represents the total upstream area influencing the SWES of a specific downstream watershed (Fig. 2). The 'landscapemetrics' package (v2.1.2, Maximilian et al., 2019; McGarigal and Marks, 1995) was utilized in RStudio to reach this aim, with its output serving as a drop-in replacement for the FRAGSTATS software, offering a streamlined environment for landscape analysis. In addition, Pearson Correlation (PC) and Generalized Linear Model (GLM) were conducted to assess a preliminary relationship between SWES and the

various landscape metrics. While Pearson Correlation Coefficient (PCC) is used to quantify the strength and direction of the linear relationship between two continuous variables (Liu et al., 2021; Pei et al., 2023), GLMs were employed to explore how each specific metric influences ecological outcomes.

#### 2.4. Methodology

The methodology applied in this study consists of three main steps: (1) Production of future LULC maps, which includes the downscaling process to generate high-resolution LULC maps from low-resolution future projections; (2) Source-to-Sink Landscape Metrics Extraction and Principal Component Analysis (PCA), used to analyse the interactions between land use classes and their influence on landscape structure; (3) Regression Analysis, applied to predict the likelihood of achieving good SWES based on the transformed metrics, followed by the production of probability maps for SWES under future SSP-RCP scenarios (Fig. 3).

##### 2.4.1. Future land use rejections

The 1-km resolution of land use projections from Chen et al. (2022) was insufficient for the analytical needs of the research, as it was too coarse to accurately derive the landscape metrics needed for training the predictive models. The hydrological layer used in the study had a very fine resolution (i.e., median size of 15.5 km<sup>2</sup>), resulting in a significant mismatch between the datasets. Aggregating the 100 m data to 1 km would have resulted in an excessive loss of information on the configuration of land-cover patches, leading to an overgeneralization of landscape composition—especially critical given the relatively small size of the watersheds. A clear example of the importance of higher resolution concerns riparian buffer zones, which often form narrow strips of vegetation separating rivers from the surrounding landscape. These zones are essential for maintaining ecological functions such as filtering pollutants, stabilizing riverbanks to prevent erosion, and ensuring habitat connectivity (Gu and Li, 2024). A 100 m riparian buffer zone has been identified as a key spatial scale for capturing the effects of

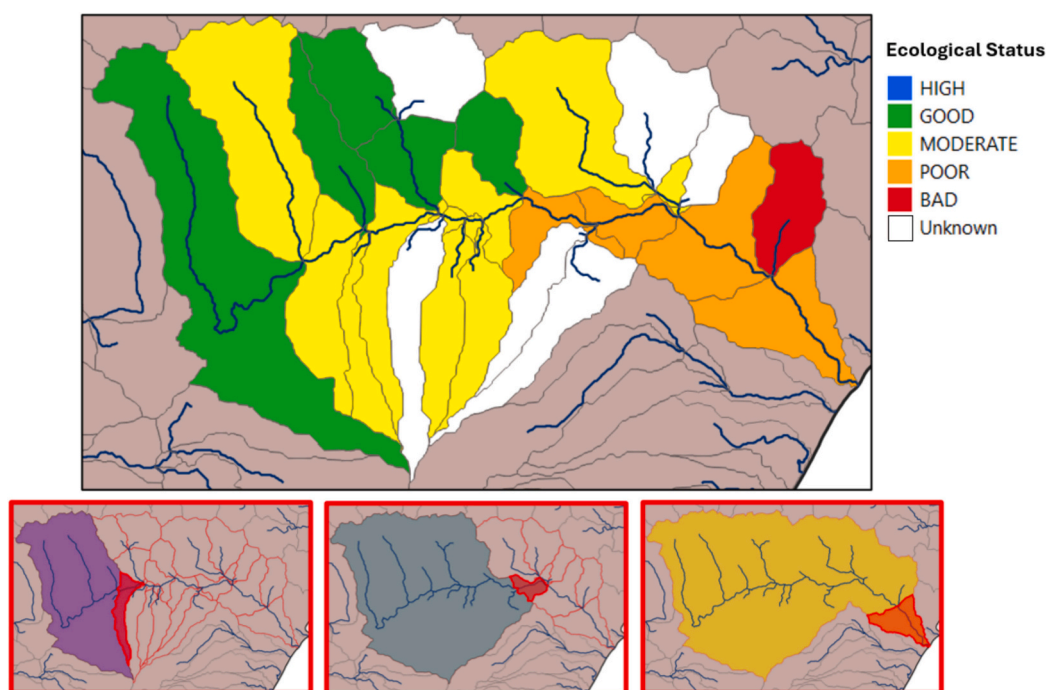


Fig. 2. Criteria for calculating landscape metrics, accounting for the influence of upstream watersheds on downstream ones. The top image illustrates a river network with its associated watersheds and SWES. The bottom images depict the upstream united polygons used for extracting landscape metrics of a specific downstream watershed (e.g., in red), highlighting the upstream connections between river branches.

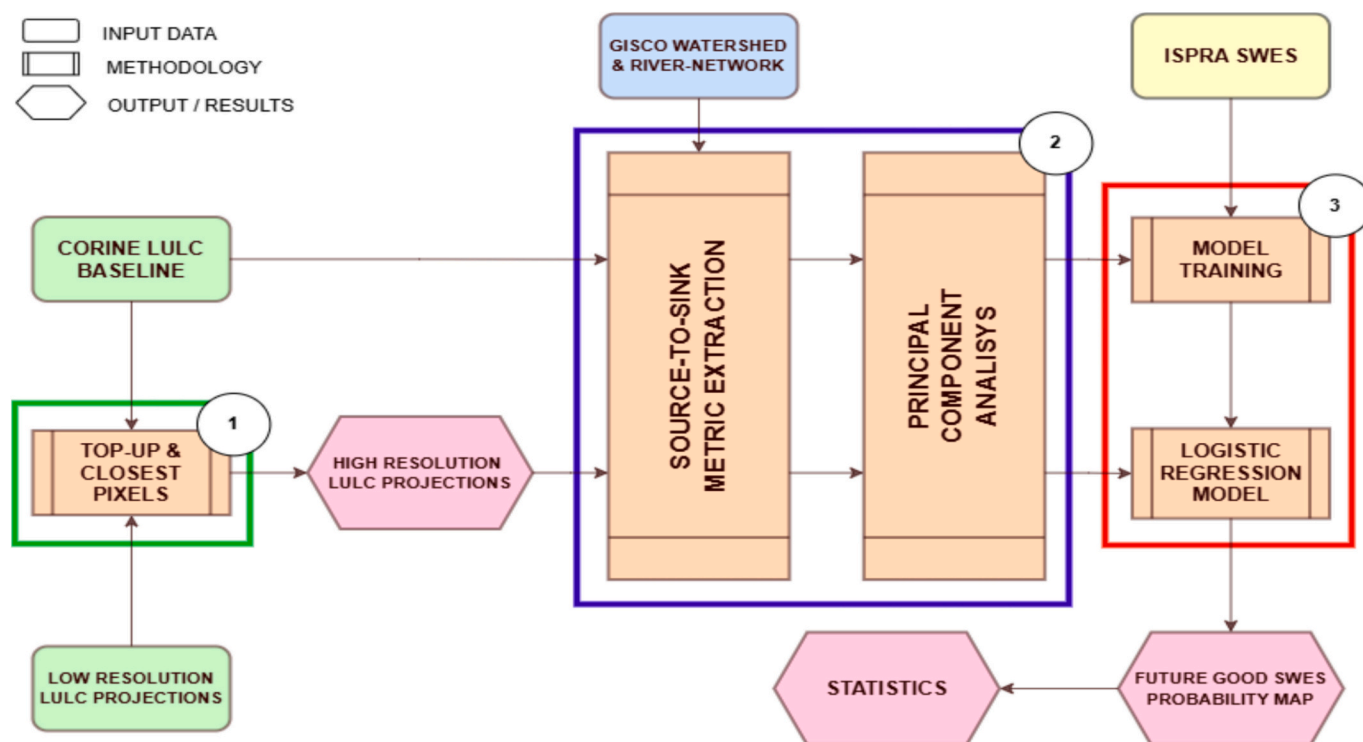


Fig. 3. Methodology framework of the study. It combines high-resolution LULC map production (green box, 1), landscape metric extraction through the source-to-sink analysis and PCA (blue box, 2), and logistic regression modelling (red box, 3) to assess the impact of LULC dynamics on SWES.

landscape patterns on river water quality (Gu et al., 2025). At a 1 km resolution, these features would almost entirely disappear from the maps, despite their crucial role in determining the ecological status of rivers. Another example of the importance of higher resolution concerns small-scale land-use mosaics, such as fragmented croplands or small urban settlements alternating with natural or semi-natural green areas. These mosaics strongly influence nutrient runoff and hydrological connectivity (Wu et al., 2025) but would be largely invisible or misrepresented at a 1-km resolution, which tends to merge them into dominant land-cover classes.

A refined methodology was developed to address this mismatch and generate high-resolution future land use maps from the low-resolution projections. First, the “Top-up” approach was utilized to calculate the changes in land use and LULCC information between future projections and the baseline in the coarse dataset. Then, the nouvelle “Closest Pixels” method was adopted to translate these changes accurately to the higher resolution map (i.e., CLC). Finally, the Similarity Index (SI), calculated as the ratio of matching pixels to the total pixels, was utilized to quantify consistency between the raw 1-km land use by Chen et al., 2022 and the new one of 100-m from the CLC (see SM.C of the Supplementary Material for more details).

Importantly, given the complex topography and land use of the study area, the HydroSHED layer at level 08 was used to subdivide the Italian peninsula into smaller units based on distinct hydrological regions, enabling the assessment of land use change dynamics within each specific region. This method enabled the creation of a high-resolution future land use map that maintained the same rates and patterns of change as those proposed by Chen et al. (2022), ensuring consistency while enhancing spatial resolution for more detailed analysis (see SM.A7 and SM8 of the Supplementary Material for the comparison).

#### 2.4.2. Principal component analysis

The landscape analysis produced 95 distinct metrics concerning over 15,000 observations, making it difficult to interpret individual contributions. Therefore, PCA was applied to reduce dimensionality while

retaining the most significant variability in the data (Holland, 2019; Ioele et al., 2020; Umwali et al., 2021). PCA simplifies complex datasets by identifying principal components (PCs). Each PC is a linear combination of the original variables, meaning the computation of a weighted sum of these variables in a way that maximizes the variance captured by that component. Each weight, or loading, represents how much each original variable contributes to the principal component. This method enhances data interpretation by revealing underlying patterns that might be obscured in high-dimensional data, with each principal component capturing a unique aspect of the data’s variance. PCA was performed on landscape metrics that showed a moderate-to-significant correlation with SWES (PCC threshold of  $\pm 0.2$ ), transforming the metrics into PCs for dimensionality reduction and to address multicollinearity. While a PCC of  $\pm 0.3$  is typically considered a moderate effect size (Cohen, 1988), opting for a more inclusive threshold of  $\pm 0.2$  may avoid the exclusion of variables that might still carry relevant information. This approach allowed the retention of metrics that, while exhibiting weaker individual correlations with SWES, could collectively reveal meaningful patterns when analysed through PCA, as metrics with lower individual correlations may still contribute to the dominant axes of variance when interacting with other variables in the dataset. The analysis retained the most important PCs, based on a 5 % variance threshold, ensuring that the reduced dataset still captured critical information.

#### 2.4.3. Regression models and predictions

This study evaluated different logistic regression models and compared their performances to select the best one for the final application. Tested models include Binary Logistic Regression (BLR), Multinomial Logistic Regression (MLR), and Ordinal Logistic Regression (OLR). To assess the accuracy of models predicting SWES and select the most effective one, Monte Carlo Cross-Validation (MC-CV) was employed. A detailed description of the different logistic regression models and their accuracy testing is provided in the SM.D2 of the Supplementary Materials.

By testing different models, the best model was identified to provide the accurate and suitable analysis for linking LULC with SWES. In these models, the SWES was treated as the dependent variable, with all watersheds classified as having 'Unknown' status excluded from the training dataset, while the predictors were the principal components derived from the PCA, based on the landscape metrics calculated for each watershed through the analysis of upstream connections, thereby enhancing the predictive power of the logistic models (Zhu et al., 2019). This approach efficiently models the probability of different outcomes, ranging from binary classifications to more complex ordinal and multinomial scenarios, enabling the prediction of the likelihood of achieving good ecological status. Finally, the methodology was applied to different SSP-RCP future scenarios, that were carried out by re-mapping land use data from (Chen et al., 2022) (see SM.B and SM.C of the supplementary material) and used to extract landscape metrics as inputs for the models, in order to assess the potential impacts of future land use changes on freshwater resources.

Once the best model was validated and selected, probability predictions of achieving good ecological status were generated for the various SSP-RCP scenarios. These predictions were then compared to the 2018 baseline to evaluate changes in probability for 2050 and 2100. This comparative analysis allowed us to quantify whether future conditions are expected to increase or decrease the likelihood of achieving good ecological status. The calculated differences are expressed as:

$$\text{Var} = P_{\text{good SWES}}^{2018} - P_{\text{good SWES}}^{\text{SSP\_RCP}} \quad (1)$$

where *Var* is the variation or difference in probability, and *P* is the probability.

Negative *Var* indicate that the probability of achieving good ecological status in 2018 was lower than the projected for future scenarios, suggesting improvements in SWES, while positive *Var* indicate a potential decline in SWES.

### 3. Results

#### 3.1. Accuracy of future land use projections

The SI between Chen 2015 baseline and the upscaled 2018 CLC map was 77 %. For the SSP2-RCP4.5 scenario, the SI reached 80 % in 2050 and 79 % in 2100, while for SSP5-RCP8.5, it was 78 % in 2050 and 77 % in 2100. The average similarity rate is 78 %, indicating a relatively high level of agreement between the maps. Moreover, the differences observed between the baseline scenarios are consistent and propagate in the same ratio across the projections. This consistency implies that the overall variations between each pair of raster maps are largely attributable to differences in the baseline scenarios used to derive the various projections. Such results highlight the effectiveness of the Top-Up and Closest Pixels methodologies in creating high-resolution maps, as they preserve spatial and categorical integrity despite the differences in the baseline data. The consistency across scenarios further supports the reliability of these methods in accurately reflecting expected land use changes and maintaining coherence in high-resolution projections.

#### 3.2. Principal component analysis

Out of the initial 95 landscape metrics, 30 were selected for further analysis based on their significant influence on SWES, reflected by their PCCs which were either lower than  $-0.2$  or higher than  $0.2$  (SM.A 9). The key selected metrics, namely those with the highest absolute correlation coefficient, included Edge Density (ED), Largest Patch Index (LPI), Percentage of Landscape (PLAND), Mean Patch Area (AREA\_MN), Landscape Division Index (DIVISION), Interspersion and Juxtaposition Index (IJI), Patch Density (PD), and Aggregation Index (AI). The analysis of variance demonstrated that the first five PCs collectively explain over 70 % of the total variability in the dataset (SM.A 11) and were therefore

retained for the regression. The loadings of the selected landscape metrics on the first five PCs are reported in Table 2, while the complete set of loadings is provided in SM.A10.

#### 3.3. Regression model and predictions

Following the PCA analysis, the 30 selected landscape metrics were reduced and projected onto the principal component space in order to eliminate redundancy and collinearity. These transformed components were then used as predictors to train the different logistic regression models, in order to predict SWES status for the baseline (2018) and future (2050, 2100) under different socio-economic and land use scenarios. The BLR model achieved a high average accuracy of approximately 90 % in predicting whether SWES meets "good" ecological status, validated by a Hosmer and Lemeshow test showing a chi-squared statistic of 41.6 and a p-value of 0.4, indicating a good fit. In contrast, the MLR model achieved an overall accuracy of about 52 %. Precision scores varied among classes: 0.60 for Class 2, 0.45 for Class 3, 0.31 for Class 4, and 0.19 for Class 5. Class 2 had the highest recall at 0.72, while other classes displayed lower recall values. Finally, the OLR model had an accuracy of approximately 51 % and a Congdon Weighted Kappa statistic of about 0.43, indicating moderate agreement between predicted and actual categories, with room for improvement. Comparing the AIC values, the BLR model has the lowest AIC of 10,765, suggesting the best fit for binary outcomes. The MLR's AIC is 22,333, and the OLR's is 22,507, reflecting their greater complexity without a proportional improvement in fit. The MLR and OLR models show limited ability to accurately predict the extreme SWES classes (levels 1 and 5) due to their low representation within the dataset, with class 1 accounting for only 3.4 % of observations and class 5 for 4.2 %, which reduces the models' capacity to learn patterns associated with these categories. Ultimately, the BLR model was selected as the final model for its optimal balance of fit and simplicity, with a high accuracy. Although the BLR model's simplicity is a potential limitation in predicting the five levels of SWES status with precision and independently, it aligns well with the goal of the WFD, which focuses on distinguishing between "good" and "non-good" ecological statuses, resulting consistent with the methodology applied by Vigiak et al. (2021).

##### 3.3.1. Regression model for baseline scenario

The BLR model assesses how various PCs impact the SWES, classified as either good (1) or non-good (0). The intercept of  $-0.42$  indicates that when the effects of the principal components are not accounted for (i.e., when their values are zero), the log odds of a water body being classified as "good" are negative, suggesting a lower probability for the baseline scenario to achieve good ecological status in the absence of these predictors. In 2018, according to data from ISPRA, 28.3 % of watersheds achieved "good" SWES, 38.9 % failed to meet this standard, while the status of 32.8 % remained unknown. However, model predictions for the same year suggested that 62.1 % of watersheds were expected to fall short of achieving "good" SWES, leaving only 37.9 % projected to reach this target. Fig. 4a illustrates the BLR model predicted probability of achieving a good SWES, as indicated by merging levels 1 and 2 of the WFD. Fig. 4b is the predicted binary SWES for the year 2018, while Fig. 4c presents the observed SWES recoded into a binary format: 1 and 2 indicate "good" status (green), and 3, 4, and 5 indicate "non-good status" (red).

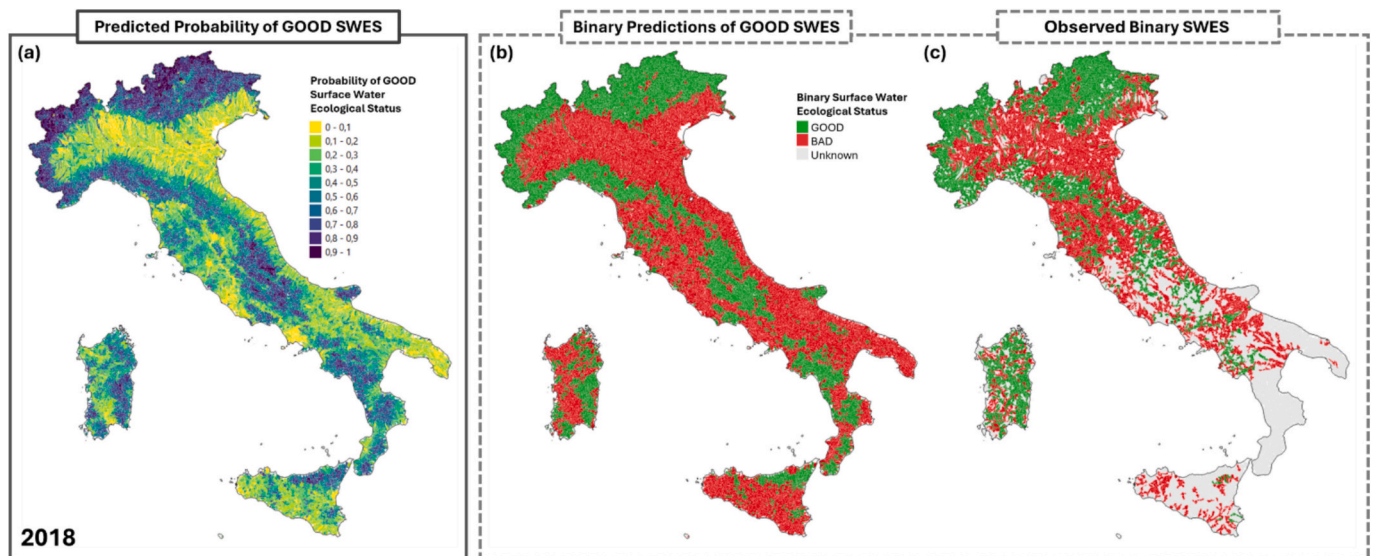
PC1 has an estimate of 0.4 and a highly significant p-value ( $<2e-16$ ), indicating a strong positive association with the likelihood of achieving good ecological status. PC2, with an estimate of  $-0.2$  and a similarly significant p-value ( $<2e-16$ ), shows a notable negative relationship with ecological status. In contrast, PC3, with an estimate of  $-0.002$  and a p-value of 0.879, is not significant in predicting ecological status. PC4, with an estimate of  $-0.19$  and a p-value  $<2e-16$ , reflects a significant negative effect on SWES, while PC5, with an estimate of 0.03 and a p-value of 0.05, shows a marginally significant positive effect.

**Table 2**  
Loadings of the selected landscape metrics on the first five Principal Components (PC). Blue colours signify negative contributions to the PC, whereas green colours denote positive contributions.

	ED				LPI				PLAND				AREA MN				Proportion of variance	
PC1	0,14	0,2	0,21	-0,2	0,22	0,15	-0,3	-0,1	0,24	0,17	0,18	-0,3	-0,2	0,17	0,13	-0,1		-0,1
PC2	0,04	0,07	-0	0,29	-0	-0,1	-0,1	0,27	0,02	0,06	-0,1	-0	0,31	0,08	-0	-0	0,33	0,13
PC3	-0,3	0,07	0,3	0,1	-0,3	0,43	0,06	0,11	-0,3	0,07	0,43	0,03	0,13	-0,1	0,36	0,09	0,08	0,10
PC4	0,01	0,14	-0	-0,2	-0,2	-0,1	0,26	-0,3	-0,2	0,14	-0,1	0,25	-0,3	-0,1	-0	0,3	-0,1	0,09
PC5	-0,1	0,45	-0,1	0,11	-0,1	-0,1	0,02	0,14	-0,1	0,44	-0,1	0,01	0,14	-0,2	-0,2	-0	-0	0,07

	DIVISION				IJI		PD		AI				Legend	
PC1	0,22	0,21	0,2	-0,1	0,21	-0,1	0,17	-0,2	0,2	0,22	0,23	-0,1		-0,1
PC2	0,18	0,16	0,23	0,35	0,21	0,25	0,03	0,15	0,1	0,18	0,13	0,18	0,38	
PC3	0,03	0,04	-0,2	-0	0,05	0,03	-0	0,08	-0,2	0,05	0,15	-0,1	-0	
PC4	0,24	0,17	-0,1	0,19	0	0,17	0,08	-0,2	0,02	0,25	0,14	0,26	0,15	
PC5	0,09	-0,1	-0,1	-0,2	0,09	-0,1	0,44	0,12	-0,2	0,11	-0,1	-0,1	-0,2	



**Fig. 4.** Results of the BLR model for the baseline 2018. Panel (a): the predicted probability of achieving good SWES; Panel (b): predicted binary classification of achieving good SWES; Panel (c): observed SWES values in binary classification.

Model performance is highlighted by a null deviance of 13,909, reduced to a residual deviance of 10,753, indicating an improved fit. Convergence was achieved after four Fisher Scoring iterations.

**3.3.2. Scenario analysis related to future land use**

This section presents statistical and spatial projections of SWES probabilities under future land use scenarios, focusing on SSP2-RCP4.5 and SSP5-RCP8.5 for the years 2050 and 2100. These two scenarios were selected as they represent contrasting socio-economic and climate pathways: SSP2-RCP4.5 reflects moderate population and economic growth combined with climate mitigation measures, while SSP5-RCP8.5 depicts a high-emission, fossil fuel-intensive future with rapid economic expansion. By analysing both the mid-term (2050) and long-term (2100) horizons, we capture a range of plausible future conditions and assess how land use change may affect SWES, offering insights for sustainable water management and long-term planning.

These projections are vital for understanding the potential impacts of future land use on SWES and for informing long-term water

management strategies. Significant regional disparities are highlighted in the projected likelihood of achieving good SWES under the SSP2-RCP4.5 scenario (SM.A 12), with 62.7 % of the 15,205 watersheds predicted to fail to achieve good SWES by 2050, slightly decreasing to 62.2 % by 2100. With similar percentages, the SSP5-RCP8.5 scenario (SM.A 13) shows that 62.6 % of 2050 and 62.7 % of 2100 of the watersheds are predicted to fail to achieve good SWES. The Po Valley shows low probabilities of achieving good SWES, primarily in the 0–0.2 range, indicating significant challenges in this densely populated agricultural region. Coastal areas, particularly around the Adriatic and Tyrrhenian Seas, and the islands of Sardinia and Sicily also exhibit low probabilities, with Sardinia’s west coast showing greater susceptibility to SWES decline than the east. In contrast, mountainous regions like the Alps and the central Apennines show significantly higher probabilities of achieving good SWES, predominantly in the 0.6–1 range.

This analysis highlights hotspot at risk of declining SWES and those expected to improve. Fig. 5 and Fig. 6 illustrate the spatial variations in probabilities of achieving good SWES by comparing the 2018 baseline

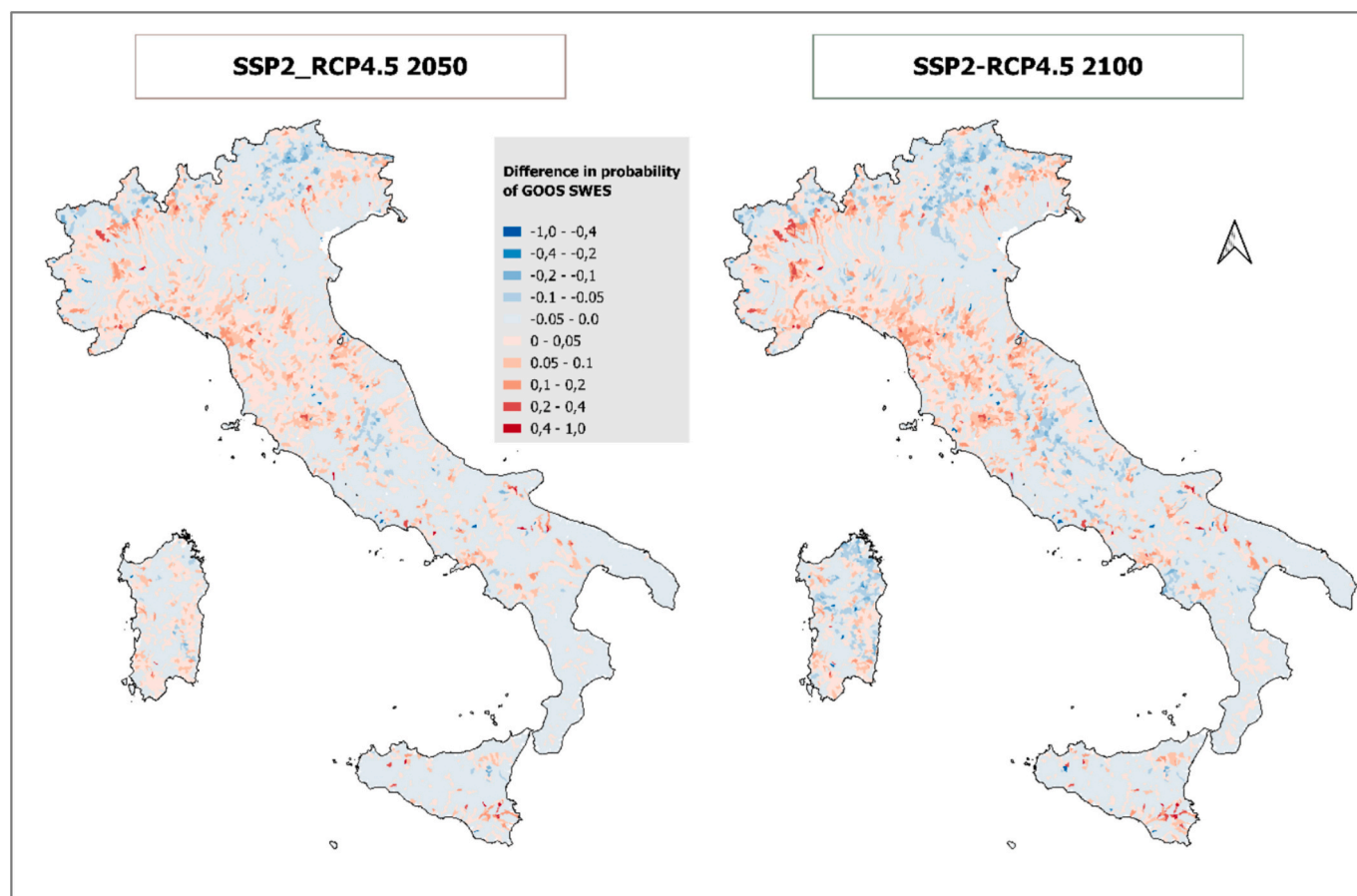


Fig. 5. Differences in the probability of achieving good SWES between the baseline scenario (2018) and the SSP2-RCP4.5 scenario in 2050 (left) and 2100 (right).

with projections for SSP2-RCP4.5 and SSP5-RCP8.5 for 2050 (left) and 2100 (right).

Projections for both the SSP2-RCP4.5 and SSP5-RCP8.5 scenarios revealed that substantial changes in SWES, defined by probability differences exceeding  $\pm 0.1$ , were relatively limited. For the SSP2-RCP4.5 scenario, approximately 2.2 % of watersheds (330 watersheds) were projected to experience a significant decline in the probability of achieving good SWES by 2050, with an increase to 3.4 % (518 watersheds) by 2100. Meanwhile, only 0.8 % (116 watersheds) and 1.4 % (218 watersheds) were expected to show significant improvements in 2050 and 2100, respectively (SM.A14). Under the SSP5-RCP8.5 scenario, 2.8 % of watersheds (430 watersheds) were projected to experience a notable decline by 2050, increasing to 4.2 % (642 watersheds) by 2100. The proportion of watersheds with significant improvements remained low, at 0.8 % (128 watersheds) for 2050 and 1.4 % (212 watersheds) for 2100 (SM.A15). Watersheds with probability differences between  $-0.1$  and  $0.1$  were considered statistically and environmentally insignificant and were not included in the analysis. Fig. 7 illustrates SWES changes under the SSP5-RCP8.5 scenario for 2100 in the area nearby lake Como, showing an example where urban expansion replacing forest cover (panels f, g) leads to declines in SWES, whereas areas where cropland is replaced by forests (panels d, e) experience improvements.

Fig. 8 compares probability differences in achieving good SWES between SSP2-RCP4.5 and SSP5-RCP8.5 for 2050 and 2100, excluding probability changes between  $-0.1$  and  $0.1$  to emphasize significant deviations. In all scenarios, a skew toward positive values indicates more watersheds are expected to experience deteriorating SWES over time. SSP5-RCP8.5 predicts more frequent and severe declines in SWES probability (positive values), particularly between  $0.1$  and  $0.25$ , as seen

in the higher histogram bars compared to SSP2-RCP4.5. At higher thresholds of probability differences (e.g.,  $>0.5$ ), trends converge, with fewer differences between the scenarios. For probability increases (negative values), SSP5-RCP8.5 shows higher frequencies between  $-0.4$  and  $-0.1$ , while SSP2-RCP4.5 forecasts more substantial improvements by 2100. Overall, SSP5-RCP8.5 suggests a more adverse outlook for SWES in both 2050 and 2100.

## 4. Discussion

### 4.1. Comparison of baseline scenarios and future land use projections

A comparison between the baseline scenario of 2018 and future projections suggests that forests are likely to expand in mountainous regions, with a more significant increase under SSP2-RCP4.5 compared to SSP5-RCP8.5, potentially due to natural processes of forest recovery in abandoned agricultural areas. Grasslands are expected to remain largely stable, with slight losses in SSP2-RCP4.5 and modest gains in SSP5-RCP8.5. Both barren areas and cropland are projected to decrease in both scenarios, with cropland potentially being replaced by forests and urban areas, particularly under SSP5-RCP8.5, where the losses may be more pronounced. Urban areas are projected to experience substantial growth, especially under SSP5-RCP8.5, likely driven by factors such as population growth, economic development, and migration from mountainous regions. Wetlands and perpetual snow and ice areas were not included in Chen's model for a changing scenario, and as a result, no variations are expected in their areas.

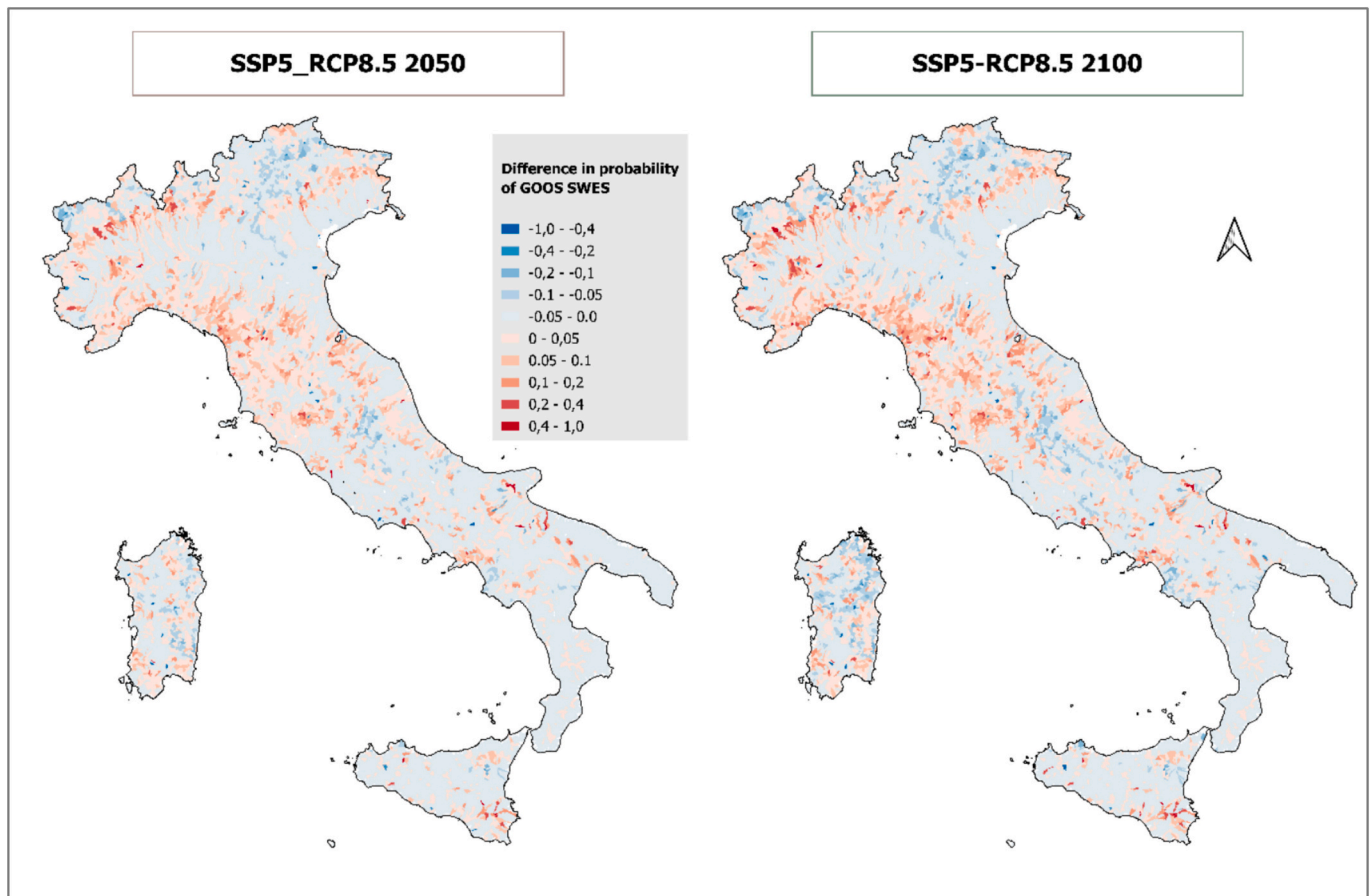


Fig. 6. Differences in the probability of achieving good SWES between the baseline scenario (2018) and the SSP5-RCP8.5 scenario in 2050 (left) and 2100 (right).

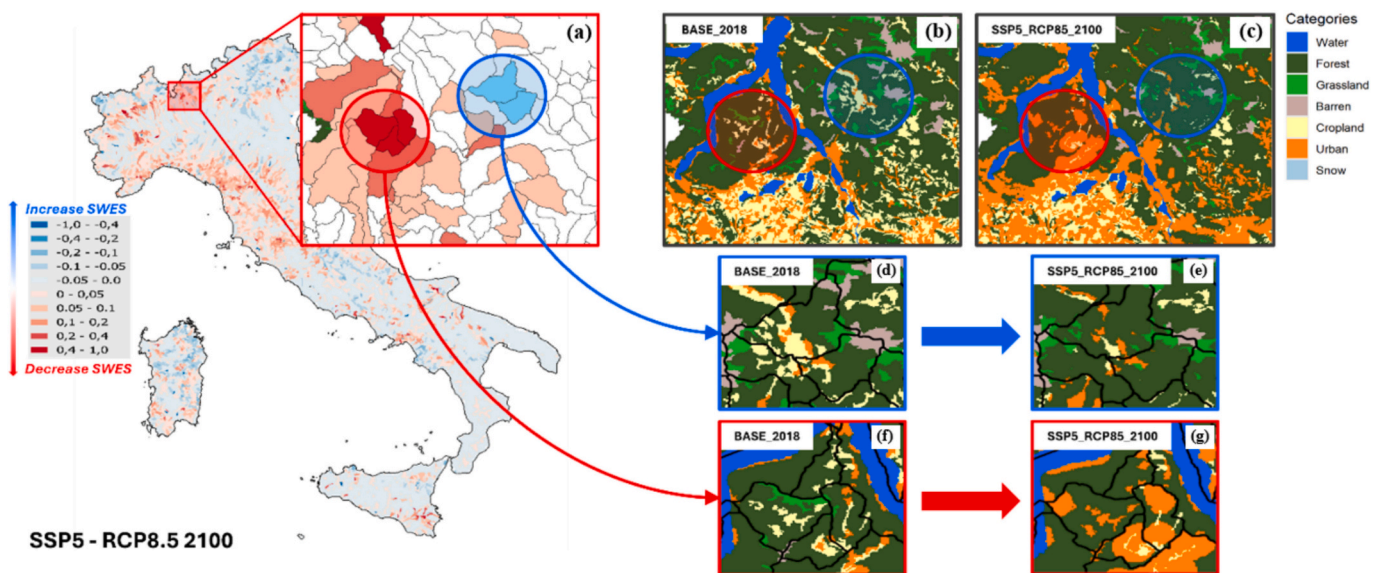
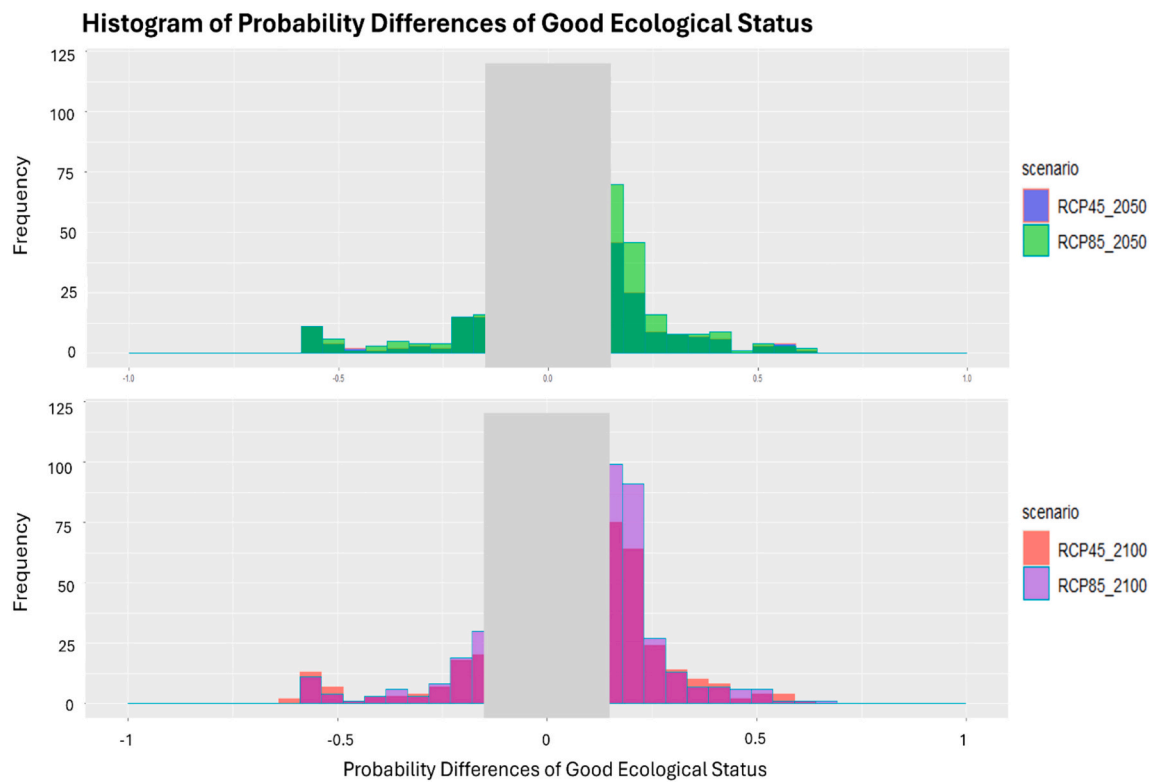


Fig. 7. Variations in good SWES probability between the baseline year (2018) and 2100 under SSP5-RCP8.5 scenario in the area close to the lake Como. Panel (a): hotspot of probability change; Panels (b) and (c): LULC maps for interest regions, in 2018 and under SSP5-RCP8.5 in 2100; Panels (d, e, f, g): detailed LULC changes for the baseline and future. The red arrows and circles recall a decline in SWES, while the blue ones highlight projected improvements.

#### 4.2. LULC interactions and their implications for SWES

A key difference of this study compared to previous literature is that we evaluated the influence of interacting land-use classes on SWES using

PCA, rather than analysing the effects of individual classes separately. This approach captures how combinations of land uses—such as forests co-occurring with cropland or urban areas—jointly influence water quality, highlighting synergies and trade-offs that single-metric analyses



**Fig. 8.** Frequency histograms comparing probability differences in achieving good SWES between different SSP-RCP scenarios for the same year. The y-axis represents the number of watersheds undergoing probability changes, while the x-axis displays the probability differences between the baseline and each scenario. When columns overlap, the visual output blends the original colours of both bars.

would overlook. Moreover, by employing the WFD ecological status as an integrated measure of water quality, rather than relying on individual physicochemical or biogeochemical parameters as is common in many studies (Ross and Randhir, 2022; Shree and Kumar, 2023; Zhu et al., 2023), we provide a more holistic perspective on ecological conditions. By focusing on landscape-level interactions at a fine spatial resolution, our findings offer a nuanced understanding of how landscape composition and configuration drive SWES across small watersheds.

PCA was applied to crucial landscape metrics influencing SWES, summarizing most of the variance in landscape configuration into five principal components among 30 PCs, capturing the dynamics of land cover interactions and landscape structure. The principal components were then used as inputs for a logistic regression model to assess their influence on SWES. This approach clarified how different LULC patterns impact the likelihood of achieving good ecological status in surface waters.

First, a significant distinction between natural and human-influenced land covers in shaping landscape structure is highlighted by PC1, effectively capturing the relationship between natural and anthropic landscapes (SM.A 11). It demonstrates how natural land covers, such as forests, grasslands, and barren land, are strongly interconnected and associated with maintaining the cohesion and continuity of natural landscapes, while human land uses tend to introduce variability and disruption, highlighting their contrasting impacts on landscape structure. Positive loadings of landscape metrics, such as PLAND, LPI, AREA\_MN, and AI, for natural landcover (i.e., forest, grassland, and barren) mutually reinforce themselves and the cohesive structure of the environment, while negative loading for the same metrics of human-influenced landcover tends to have the opposite effect. Forests, grasslands, and barren lands play crucial roles in maintaining the integrity of ecosystems and their associated SWES. This dynamic is confirmed and reinforced by the existing literature. Forests help regulate water flow, reduce runoff, and enhance soil retention (Locke, 2024). This regulation

minimizes sedimentation and nutrient loading into water bodies, thereby improving water quality. Grasslands similarly contribute to SWES through their ability to absorb and filter water, reducing surface runoff and supporting biodiversity that contributes to ecosystem health (Botter et al., 2021). Barren lands, while less directly beneficial, might affect water flow and sediment dynamics in ways that seem to also indirectly influence SWES. Considering the regression model results, the positive loading of PC1 suggests that landscapes dominated by these natural land covers are generally associated with higher probabilities of good SWES. It has been seen that croplands contribute to water quality degradation through increased runoff, erosion, and the introduction of pollutants from agricultural practices (Bijay-Singh and Craswell, 2021). Urban areas exacerbate these issues by introducing impervious surfaces that increase runoff, leading to higher pollution levels and habitat fragmentation (Locke, 2024). The strong positive relationship observed in PC1 emphasizes the importance of maintaining and enhancing natural landscapes to preserve SWES. As natural land covers are shown to support good ecological conditions, efforts to conserve and restore forests, grasslands, and other natural areas are essential for sustaining SWES and overall ecological health. This finding aligns with broader environmental management strategies that prioritize the protection of natural landscapes as a means to achieve and maintain high standards of SWES and ecological status.

Second, the influence of anthropic surfaces, particularly urban areas, and cropland (SM.A 11), on landscape structure and their negative impact on SWES are highlighted by PC2 and PC4. PC2 is predominantly driven by urbanization, known for introducing significant heterogeneity and landscape fragmentation, most probably due to the extensive development of impervious surfaces such as roads and buildings (Bai et al., 2024; Li et al., 2017; Mu et al., 2024). This disrupts natural hydrological processes, increases runoff and pollution, and leads to habitat fragmentation, ultimately degrading ecological conditions and water quality (Locke, 2024; Romano et al., 2017). Cropland also contributes to

PC2, though to a lesser extent than urban areas. PC4, on the other hand, emphasizes the interplay between cropland and urban land use, particularly in large agricultural regions like the Po Valley. Cropland shapes the landscape by creating agricultural uniformity, while urban areas disrupt this continuity, adding fragmentation and variability and aligning with previous studies relating to urbanization processes in the Po Valley (Romano et al., 2017). Both components reflect how urban and agricultural land use negatively affect SWES, with urbanization and cropland exerting pressure on ecosystems. Effective land use management, incorporating sustainable urban planning and conservation strategies, is essential to mitigate these impacts and improve ecological conditions.

Finally, the influence of natural land use classes (i.e., forest, barren land, and grasslands) on landscape structure is focused on by PC3 and PC5, though their independent impact on SWES is minimal compared to anthropogenic influences (SM.A 11). PC3 highlights the contrasting roles of barren land and forests: barren land leads to a more fragmented, exposed landscape, while forests contribute to landscape cohesion and complexity by increasing vegetation cover. Despite this contrast, their spatial interplay does not significantly affect water quality, which tends to maintain stable ecological conditions. PC5 emphasizes grasslands' role in shaping landscape patterns, where their presence contributes to ecological balance and continuity but marginally improves the likelihood of achieving good SWES. However, the overall influence of these natural land covers, singularly taken, remains limited in predicting variations in SWES, especially when compared to the more pronounced impacts of human-altered landscapes or the contrasting effects between natural and anthropogenic land uses.

#### 4.3. Future SWES projections under different socio-economic and climate scenarios

The projections highlight regional disparities in future SWES under the SSP2-RCP4.5 and SSP5-RCP8.5 scenarios, revealing both opportunities and challenges for SWES management in Italy. Improvements are projected in the northern mountainous regions of the eastern Alps, particularly the Retiche and Atesine ranges, as well as in the central Apennines and northeastern Sardinia. These areas are expected to benefit from increased natural cover and reduced anthropogenic disturbances, enhancing ecological conditions. Scenario analysis from other case studies also revealed that the increase in forest areas could potentially improve water quality (Locke, 2024). Conversely, declines are anticipated in lower montane areas and transitional zones, including Piemonte, northern Lombardy, Veneto, parts of Friuli Venezia Giulia, and the northern Apennines in Tuscany, driven by pressures from urbanization and agriculture, which result in the loss of natural land cover and SWES degradation. The Po Valley, dominated by agriculture, remains relatively stable with only minor reductions in the already low probability of achieving good SWES. Other case studies in literature revealed a similar trend, i.e., the expansion of raid-fed farms and residential areas contributes to future declines in water quality (Santy et al., 2020; Torabi Haghighi et al., 2020). This stability in non-good SWES probabilities reflects persistent cropland cover and ongoing urbanization, underscoring the need for effective land use planning and water management. Southern Italy presents a mixed pattern, with regions like eastern Sardinia and southern Campania showing improvements, while western Sardinia and southern Sicily experience significant declines, influenced by local land use practices and environmental factors (Figs. 5 and 6).

Comparing the two scenarios, the overall differences in probability trends are modest. Both scenarios indicate a similar proportion of watersheds experiencing improvements or declines, with SSP5-RCP8.5 predicting an increase in significant deterioration by 2100 compared to the other scenario. Significant improvements in SWES are unlikely without proactive measures to address landscape degradation. These slight modifications are because the analysis carried out aim at

emphasizing land use metric scenarios as the explanatory variables rather than encompassing a complete range of variables like climate change indices. Some other studies revealed that the impacts of climate change on water quality are more significant than those of land use (Torabi Haghighi et al., 2020), especially after the 21th century. Nevertheless, the SSP2-RCP4.5 scenario demonstrated a higher frequency of negative probability differences (e.g., increased probability of good SWES) between the two timeframes in the significant variations (e.g., 30 %–40 %) (see 8). This outcome indicates that this stabilization scenario has a higher potential to improve SWES in the long run.

A key takeaway message is the need for targeted attention to watersheds with probability differences exceeding  $\pm 10$  %. While these areas represent a minority, they are critical for intervention. Regions projected to face significant declines in SWES require focused management strategies (e.g., proper fertilization, crop rotation, vegetation corridor) to mitigate urban and agricultural impacts. Conversely, areas like the eastern Alps and central Apennines offer opportunities for conservation, providing valuable insights into effective land management strategies that could enhance ecological status.

#### 4.4. Limitations and future work

The results indicated a strong ability to analyse land use changes, their interactions, and potential impacts on future SWES. Nonetheless, some limitations in the methodological approach remain, allowing room for further application. Firstly, the reliance on SWES data from 2010/2016 presents a constraint, as this limited temporal scope may not fully capture recent trends or variations, potentially impacting the accuracy and relevance of the projections. Currently, the only available monitoring data provided by ISPRA refer to these years and follow the WFD guidelines, while the dataset for 2022 has not yet been released. Incorporating updated SWES data once released would enhance the temporal resolution and improve the accuracy of future projections. Second, by design, this study exclusively focuses on landscape metrics to specifically examine the influence of landscape structure on SWES. However, other variables such as elevation, slope, soil type, hydrological conditions, precipitation patterns, temperature, nutrient concentrations, and specific pollutants also influence water quality independently of LULC. These additional factors could provide a more comprehensive understanding of SWES determinants. Third, the approach used to enhance the resolution of future LULC maps, remains relatively rudimentary. While it allows resampling from 1 km to 100 m, it inevitably introduces uncertainties. In particular, the method assumes that land-use classes expand in a uniform manner, whereas in reality their spatial dynamics often follow preferred directions shaped by environmental, climatic, or topographic constraints. This simplification may lead to unrealistic patterns of land-use change in certain areas, reducing the reliability of fine-scale projections. Future work should therefore focus on improving downscaling techniques to better reflect the spatial heterogeneity of land-use dynamics. Moreover, the future land use of this study relies on land use projections from the previous study, i.e., Chen et al. (2022), which are based on CMIP6 scenarios. While some limitations and biases from CMIP6 may be inherited, the projections used as input for the further downscaling process described in Section 2.4.1 have a finer resolution of  $1 \text{ km} \times 1 \text{ km}$ . Finally, employing more complex models such as Bayesian Networks or Machine Learning and AI techniques could enhance the analysis by capturing intricate patterns and relationships in the data, leading to more accurate and actionable insights. Overall, despite limitations inherent in the data available and simplification in the construction of the regression model, the results show high promise in the prediction of the probability of achieving good ecological status and insight into the contributing land use classes. This will provide valuable support for policy- and decision-makers who can use the results of this study to prioritize land management policies and contribute to the preservation of water quality in Italy.

## 5. Conclusions

This work develops a novel and integrated approach to understanding the interactions among land use classes and their impacts on SWES, providing a baseline model for predicting the probability of achieving good ecological status for each watershed under different Shared Socioeconomic Pathways (i.e., SSP2 and SSP5) and Representative Concentration Pathway (i.e., RCP4.5 and RCP8.5) for mid- and long-term timeframe (i.e., 2050 and 2100). This work focuses on capturing the upstream-to-downstream influence within river catchments, developing a method to enhance the resolution of freely available land use projections, and utilizing these refined projections to predict future freshwater ecological status. To achieve these goals, this study integrates Principal Component Analysis, and different Logistic Regression Models to explore the influence of various landscape metrics on the ecological status of each watershed, taking into account the effect of changes in land use from upstream watersheds to downstream ones. The outcomes reveal that the interplay between natural landscapes (i.e., forests, grasslands, and barren land) and anthropogenic areas (i.e., cropland and urban areas) is complex and multifaceted. Natural landscapes support biodiversity and enhance ecological functions contributing to SWES, such as filtration, erosion control, and carbon sequestration. In contrast, anthropogenic areas often disrupt these natural processes, negatively impacting SWES. Moreover, the dynamics of land use change reflect the competition between preservation and development. Future projections of SWES indicate that over 60 % of Italian watersheds are expected to fail in achieving 'good' SWES by 2050 and 2100 under both moderate socioeconomic and technological progress scenarios (SSP2-RCP4.5) and rapid economic growth with high emissions scenarios (SSP5-RCP8.5). These alarming predictions underscore the urgent need for more focused strategies to mitigate land use changes and manage their impacts on SWES. Comprehensive land management policies must be developed to prioritize sustainable practices, enhance ecological resilience, and safeguard water resources, ensuring a balance between development and environmental conservation. Addressing these challenges will be crucial for promoting better water quality and ecological health under ongoing environmental pressures.

## CRedit authorship contribution statement

**Samuele Casagrande:** Writing – original draft, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hung Vuong Pham:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Investigation, Data curation, Conceptualization. **Olinda Rufo:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Andrea Critto:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization.

## Declaration of competing interest

All of the reported work in the attached manuscript is original and the manuscript has not been previously published in whole or in part. I also have read and abided by the statement of ethical standards for manuscripts submitted to this journal. All authors have seen the manuscript and approved its submission to the *Science of The Total Environment* journal.

Moreover, all the authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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National Recovery and Resilience Plan (NRRP) - PE9 - Mission 4, C2, Intervention 1.3. The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2025.181003>.

## Data availability

Data will be made available on request.

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