International Journal of E-Planning Research
Volume 13 • Issue 1 • January-December 2024

Citizen Science for Transition to Sustainability and SDG Monitoring in an Italian River Basin

Venere Stefania Sanna
https://orcid.org/0000-0001-5420-7216
University of Siena, Italy

Francesco Di Grazia
https://orcid.org/0000-0001-8979-6452
University of Siena, Italy

Cristina Capineri
https://orcid.org/0000-0001-5874-9872
University of Siena, Italy

Alessio Polvani
https://orcid.org/0009-0006-2912-1019
University of Siena, Italy

ABSTRACT

The direct involvement of the public in data collection and analysis can be a powerful tool to fill information gaps, while simultaneously improving community influence on urban planning and land management policies. Using a robust case study, this paper shows how Citizen Science (CS) data can support complex sustainability transitions. In a study of the Ombrone River Basin (ORB) in Italy, the paper shows how data produced by a large group of citizen participants was integrated into official datasets on land use and water quality, demonstrating the potential for this method in supporting the monitoring of Sustainable Development Goal (SDG) indicators at the local level. In addition, through scenario analysis including a reforestation hypothesis, the paper offers useful pointers for leveraging and optimising the voluntary participation of non-professional scientists in the various stages of research and innovation activities, in support of data-driven policies and planning that take environmental sustainability into account.

KEYWORDS

Water Quality, Scenario Analysis, Reforestation, Italy, SDGs, Data-Driven Policies, Agenda 2030

INTRODUCTION

In 2015, the United Nations signed the 2030 Agenda for Sustainable Development, which established a powerful strategic framework based on 17 Sustainable Development Goals (SDGs), 169 targets, and an unprecedented set of indicators capable of tracking their level of achievement, revolving around the five Ps (people, planet, prosperity, peace, and partnership). Based on three key principles established in the agenda—to be indivisible, universal, and participatory—SDGs trace a collective path to leave no one behind and require tight collaboration among scientific researchers,

DOI: 10.4018/IJEPR.366585

decision-makers, institutions, and nonstate actors in order to accelerate processes of change in individual, institutional, and collective behavior (Cossu et al., 2023).

To date, many SDGs are still far from being achieved. To assess their progress, a framework and set of indicators were developed through a shared global methodology, but these are viable only when data are available to support them. While national governments have the primary responsibility to measure SDG targets and indicators, parallel monitoring should also take place at subnational and local levels to ensure consistency of the policies and actions undertaken and also to ensure their effectiveness in a territorial context based on a logic of "one size does not fit all."

Official statistics used for the monitoring processes have typically been based on data collected and validated by national governments [e.g., through surveys, censuses, etc. (Fraisl et al., 2020)]. Nevertheless, traditional data sources are not always sufficient for measuring all the targets. This is not only because the data are sometimes not available or costly to obtain, but also because, in some cases, official datasets are lacking in accuracy or geographical coverage and/or are not always produced at the geographical scale suitable for observing the phenomenon being studied. Moreover, official data incur high production costs and long periods for their release, and they can quickly become outdated. Therefore, "new and nontraditional sources of data are required. Citizen science [CS] is an emerging example of a nontraditional data source that is already making a contribution" (Fritz et al., 2019, p. 922).

Although a single definition is yet to be agreed upon, CS broadly "refers to the active engagement of the general public in scientific research tasks…[CS] is a growing practice in which scientists and citizens collaborate to produce new knowledge for science and society" (Vohland et al., 2021, p. 1). Although some studies have shown the potential use of CS data for monitoring SDGs (Fritz et al., 2019), to our knowledge, data collected through CS have been used for reporting on only a very limited number of cases for a specific target at the national or global level (Fraisl et al., 2020, 2023a).

The aim of this article is therefore to shed light on the future role and potential of CS for monitoring SDGs. By means of a practical application of data generated as part of the activities of the Citizen Science for Rivers (CS4RIVERS) project (Citizen Science for Rivers, n.d.) on the Ombrone River Basin (ORB) in Tuscany and through the use of forecasting models (up to the year 2050 and including, among others, a reforestation scenario), we demonstrate how data produced through CS not only are able to contribute to the estimated values of SDG indicators that were previously unmeasured but also can guide useful policy recommendations for taking concrete action, developing sustainable and data-driven policies, and planning activities. The ultimate goal of this research is thus to offer useful approaches for optimizing the voluntary participation of nonprofessional scientists in the various stages of research, innovation activities, and policymaking in support of planning that takes into account environmental sustainability and the participation of local actors and stakeholders.

CS AS A TOOL FOR RESEARCH, INNOVATION, AND POLICYMAKING

CS has existed for a long time. Historically, its application was rooted in the natural sciences—from biodiversity conservation to environmental monitoring and natural resource management (Crain et al., 2014; Hyder et al., 2015; Chandler et al., 2017; Kelly et al., 2019). In 2016, more than 80% of CS practices were devoted to life and natural sciences and 11% to the social sciences and humanities (Hecker et al., 2018a, p. 193).

In recent years, the digital turn (Ash et al., 2018; Westera, 2012), advancements in information technology, and new ways of collecting data such as crowdsourcing, digital sharing, online projects, and social networks (Hecker et al., 2019; Vohland et al., 2021) have enabled the proliferation of CS applications and projects that not only address the environmental sphere but also are increasingly being used to address a wide range of societal challenges (Haklay, 2013).

CS has further expanded through EU funded projects, and it is encouraged by Horizon Europe to "support and promote the involvement of citizens, civil society, and end users in public engagement, CS, and user-led innovation modes of research and innovation" (European Commission, 2021). In this regard, eight pillars have been identified by the European Commission to promote open science, and CS is one of the activities specifically mentioned as being capable of (and aimed at) "promoting public engagement in research and innovation and enhancing public trust in science" (European Commission, n.d.). As a result, CS is increasingly being applied to interdisciplinary research in the social sciences and humanities (Hecker et al., 2018a; Tauginienė et al., 2020; Albert et al., 2021), with prominent examples in urban planning (Karvonen & Van Heur, 2014; Devisch et al., 2016; Butkevičienė, 2021) and sustainable urban development (Albert et al., 2021; Cappa et al., 2022).

CS for Sustainability: Challenges and Advantages

The proliferation of CS programs has stimulated a great deal of curiosity and studies about the effects and impacts of projects and initiatives (Skarlatidou & Haklay, 2021). Successful elements but also disadvantages and challenges can be synthesized according to a framework that traces the three pillars of sustainability: social, economic, and environmental (Millar & Searcy, 2020).

In terms of the social pillar, CS expands the opportunities for public participation in scientific research, builds knowledge, increases the well-being and literacy of citizens, and thus serves social and educational purposes. When interviewed, CS project participants indicated that their involvement increases scientific knowledge and provides information for the greater good (Martin, 2016). In many cases, participation in CS programs creates resilience to key local- to global-scale environmental issues (e.g., CS has supported local communities in terms of geohazard monitoring and disaster resilience) (Lee et al., 2020, p. 615). Existing studies show that CS boosts engagement in urban and environmental management by members of the public and that it increases awareness of the importance of research and monitoring (Crain et al., 2014) in policymaking and urban and regional planning.

By serving causes with and for the population, and by answering the calls for nonscientists' engagement in knowledge production processes (Hecker et al., 2019), CS has increasingly shown its potential for the democratization of science (Irwin, 1995). This is further encouraged by the very nature of CS initiatives that are the result of a cocreation exercise in which different stakeholders—ranging from interested citizens to scientific institutions, local organizations, public authorities, businesses, members of the educational sector, etc.—take part (Carayannis et al., 2012). Due to the participation of a variety of stakeholders, CS initiatives also strengthen local network ties, train stakeholders to participate, and enhance local development processes. As a result, CS research findings are increasingly being used to design more democratic, less research-centric approaches to creating policy-informing science (Mattei, 2023).

However, CS also faces challenges related to accessibility, justice, equity, diversity, and inclusion. In terms of accessibility, one issue is the digital divide and the possibility of using digital tools, mobile applications, platforms, or instrumentation that is expensive or otherwise not accessible to all categories of user (e.g., elderly people). In terms of equity, diversity, and inclusion, CS has been accused of not being "an egalitarian variant of science, open and available to all members of society" (Cooper et al., 2021, p. 1386). Indeed, assessments have shown that CS participants "are overwhelmingly white adults, above median income, with a college degree" (Cooper et al.). Finally, exploitation of free work (citizens/volunteers normally are not paid for their contributions), private data (e.g., from participants), and data collected (that have a value) have been raised as crucial issues that are often overlooked in CS (Tauginienė et al., 2020).

With regard to the economic pillar, CS allows a series of research phases and/or tasks to be conducted more quickly and economically. Contributions from a large number of citizens increase the cost-effectiveness and overall investment of the project (Kieslinger et al., 2018; Bonney et al., 2009). This has a direct effect also on the efficiency of data collection, resulting in a greater temporal extent and finer spatial resolution of the data collected (Ballard et al., 2018). Citizen scientists with longer engagement provide a large amount of valid data, e.g., to document the worldwide presence or absence of birds (Lepczyk, 2005). CS experiments have proven to provide data at finer spatial and temporal scales than would otherwise be possible (Diblíková et al., 2019), as data are often collected at higher frequencies than traditional data sources used as inputs to the SDG indicators, as well as in a spatially disaggregated manner (Diblíková et al., 2019).

Nevertheless, potential economic disadvantages remain, for example, setup costs (Kieslinger et al., 2018). If a project involves the use of a mobile application that does not exist or is not accessible as an open-source product, this may be a barrier to entry. Overall, all preparatory phases of CS projects, such as the training and equipping of citizen scientists, have a per capita cost. CS data collection is labor intensive and often requires much more work than expected to ensure the data quality needed for scientific analysis. Data quality is, in fact, one of the greatest challenges in CS projects (Loiselle et al., 2016; Quinlivan et al., 2020; Stankiewicz et al., 2023), depending mainly on the clarity of data collection protocols, data forms, and the presence of support for participants (Bonney et al., 2009). Nevertheless, "assessing and quantifying the quality of data is still an area of debate" (Fraisl et al., 2020, p. 1747).

Often, the number of participants to be included in a CS project is relatively high, and when technical equipment is needed for evaluations (e.g., in the environmental field) and it is not sufficient merely to observe and report on mobile apps, the costs increase (Kieslinger et al., 2018). Long-term projects require feedback and subsequent training of citizen scientists, so the financial sustainability of projects is in many cases dependent on the availability of funding. Finally, long-term projects require commitment by individual volunteers, while "most contributors participate only once and with little effort" (Sauermann & Franzoni, 2015, p. 679), leaving the top 10% of them responsible for almost 80% of total classifications (Sauermann & Franzoni).

When it comes to the environmental pillar, it is widely acknowledged that CS contributes to the monitoring and reduction of environmental impacts (Cappa et al., 2022, p. 649). According to Chandler et al. (2017), CS makes substantial contributions to national and international biodiversity monitoring and has revealed its full potential to help generate the environmental data needed to understand and address wider challenges such as loss of biodiversity, flooding risks, deforestation, air pollution, etc. Besides stimulating and increasing public interest and engagement, which are essential for societal change (Hecker et al., 2018b), policies and grass-roots activities ideated or boosted in the framework of CS projects (e.g., nature-based solutions) have enhanced human–nature interactions, pro-nature conservation behaviors, and nature connectedness (Bonney et al., 2009).

Clearly, CS is more than just a way to gather environmental data, and despite the wide and well-established use of CS in the field of environmental monitoring, it should be noted that its use is also growing in urban areas for diverse purposes, e.g., to map, monitor, and assess the condition of roads and their walkability, architectural barriers, odors, silenced areas, etc. (Butkevičienė et al., 2021). The use of CS in urban settings can represent a strategy for cities to combine environmental benefits with those of sustainable urban planning, helping to reconcile human life with the environment. The application of CS at the urban scale, as "an essential ally for sustainable cities" (European Commission, 2023), is also strongly promoted by the European Commission within the Horizon 2020 and Horizon Europe programs, as evidenced by the increasing number of EU funded projects tackling a wide array of urban challenges. Examples include the recently funded Urban ReLeaf (European Union Citizen Science, 2023), CitiObs (n.d.), and GREENGAGE projects (Sanz, 2024).

Finally, environmental disadvantages are not often explored or mentioned in the literature. Limitations exist, and some challenges have been identified by a survey of participants in CS projects (Martin et al., 2016). For example, merely accessing some sensitive sites could harm biodiversity, or revealing the location of rare animal or plant species could risk loss or damage (e.g., making them traceable for illegal activities, poaching, illegal collectors, or general damage). More generally, doubt has been expressed as to how the data (often made open access) may be used to benefit the natural environment.

The Contribution of CS to SDG Monitoring and Achievement

Among the recognized impacts of CS, its actual and potential contribution to the monitoring and achievement of the SDGs is of increasing importance. A growing body of studies addresses this issue; as we will discuss briefly, some contribute more theoretically, while others contribute through specific reviews and case study analyses. The literature examining the contribution of CS to the monitoring of SDGs is very diffuse and is frequently based on specific and goal-related case studies at different territorial scales (often at the local scale and relating to the precise interventions of citizen scientists in specific locations); inferring the potential to scale up these practices to regional or national scales is particularly complex.

West and Pateman (2017) pointed out how CS can contribute to the definition, monitoring, and evaluation of SDGs by identifying 42 of the 169 targets to which CS could potentially contribute. Some studies carried out at the EU level have analyzed CS projects in declarative terms, i.e., whether the project states that it aims to contribute directly to the achievement of one or more SDGs or whether it does so indirectly (Bio Innovation Service, 2018).

Similarly, Liu et al. (2023) analyzed 44 projects active between 2016 and 2027 in more than 100 European cities that, through EU funding, conducted research projects involving the use of CS and that had a link—direct or indirect—with the SDGs. The study revealed that CS practices in cities predominantly relate to SDG 3 (good health and well-being), 11 (sustainable cities and communities), and 13 (climate action). However, there is a difference between what is declared (in the project or by the participants) and what is officially used at the city level for official monitoring.

In a survey of CS projects by Ballerini and Bergh (2021), subjects were asked, “Is your project familiar with the 17 SDGs?” Most participants claimed that their involvement was rather superficial and that the subjects “never explicitly engage with [the SDGs]” (Ballerini & Berg, p. 1956).

Among the most recent initiatives, of particular interest is the creation in 2020 of the Task Group on Data from Participatory Mapping for the SDGs (Committee on Data of the International Science Council [CODATA], n.d.). Aimed at supporting the use of citizen-generated data toward achieving the requirements of the Result Framework proposed by the United Nations 2030 Agenda, the CODATA group amplifies the values and contributions of citizen-generated data and in particular its fitness for use by the United Nations and NGOs to make data work for cross-domain grand challenges.

Nevertheless, to date and to our knowledge, only a few international organizations use CS data for SDG monitoring and reporting—specifically the World Bank, United Nations Environment Programme (UNEP), UN Office for Disaster Risk, International Union for Conservation of Nature, and the World Health Organization (Fraisl et al., 2020, 2023b). The authors undertook a comprehensive systematic review of the SDG indicators by analyzing a wide array of CS projects, determining for each SDG indicator whether “data from at least one CS project” has already been used for monitoring or reporting the SDG indicator at national or global level, could potentially contribute, or is not aligned (Fraisl et al., 2020, p. 1738). In particular, this in-depth study reveals that CS data are already contributing directly to only five indicators, most of which related to an environmental and social issue: 9.1.1, rural access index; 14.1.1, index of coastal eutrophication and floating plastic debris density; 15.1.2, proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type; 15.4.1, coverage by protected areas of important sites for mountain biodiversity; and 15.5.1, red list index.

According to UNEP (2024), in order to improve data coverage, Sierra Leone and Zambia for the first time combined citizen-generated data with national monitoring data to report on ambient water quality (SDG 6) with the launch of the Citizen Scientist 632 Toolbox (UNEP, 2021) for the monitoring of SDG Indicator 6.3.2, the proportion of water bodies with good ambient water quality. The lack of information for this indicator is a widespread problem in many countries, including Italy, because reporting on it requires (among others) *in situ* water quality data to be collected on basic physicochemical parameters from designated monitoring locations on a defined sample collection schedule.

In Italy, our analysis of the national SDGs reports (Italian National Institute of Statistics [Istat], n.d.) for the past 20 years (and related datasets) regarding Indicator 6.3.2 and its components reveals that a proxy (partial) for the statistical measure of coastal bathing waters was produced from 2013 to 2019; percentage of rivers with high or good quality of ecological state and percentage of rivers with good quality of chemical state were estimated at the hydrographic district level in 2015 and 2021. Nevertheless, they are not reported on the country's most recent official Istat report (Istat, 2023). At the regional level, river indicators were estimated only in 2015. For the following years and/or at finer territorial levels, indicators on water bodies (rivers, lakes, and groundwater) are missing.

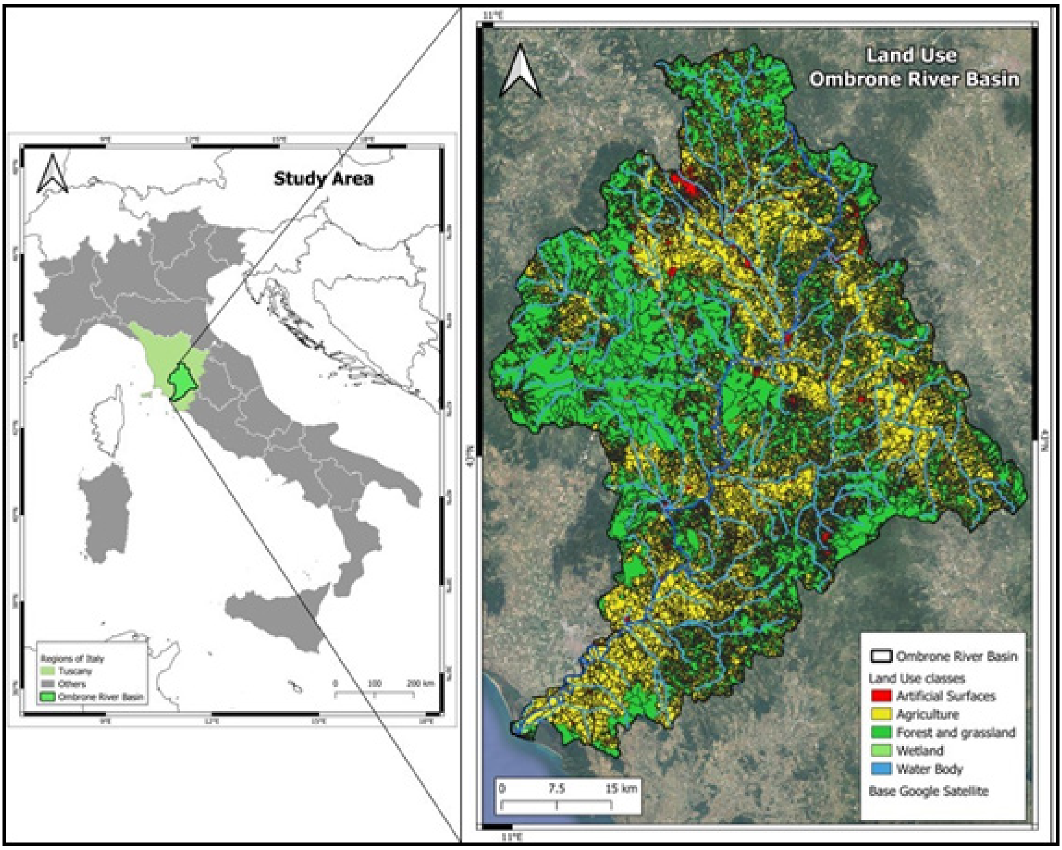
In order to fill this gap and to contribute to this emerging body of studies, in the next sections we offer a concrete example of how CS data can be used to monitor and report on this indicator for an Italian river basin.

CASE STUDY: THE WATER QUALITY OF THE ORB

Study Area

The ORB is located in the part of central Italy facing the Tyrrhenian Sea (Fig. 1). With a length of 161 km, the Ombrone is the second largest river of Tuscany after the Arno (241 km). It flows north to south through the southernmost part of the Tuscan region, reaching as far as the region's central valley, and then turns southwest until it reaches its delta in the municipality of Grosseto (42° 46' N, 11° 06' E). The river has the highest flow of suspended solid sediment among the Tuscan rivers. This is due to the high erodibility of the rocks on which the river has established its course. The surface area of its basin is 3,494 km^2. It has several tributaries, including, on the hydraulic right, the Arbia, which rises on the slopes of the Caballari hill (648 m ASL), near Castellina in Chianti, in the province of Siena, and flows into the Ombrone at Buonconvento; the river Merse, 70 km long, which originates on the Croce di Prata hill and flows into the Ombrone shortly after receiving the Farma (its first tributary) at Piani di Rocca; and the Gretano and Lanzo Rivers. The left-hand tributaries of the Ombrone are the Melacce, the Trasubbie, the Maiano, the Grillese, the Rispescia, and the Orcia. The latter is the most important, with a total basin area of 748 km^2.

Figure 1. The ORB and the 2019 CORINE land cover



Approximately 280,000 inhabitants live in the basin area distributed among 38 municipalities, of which 25 are in the province of Siena and 13 in the province of Grosseto (Istat, 2021). The climate of the ORB is influenced by the Tyrrhenian Sea and its mitigating action, by the overall exposure to the west, and by the protection to the east offered by the Apennine barrier, which contrasts with the infrequent but cold winter currents from the east and northeast. The predominant currents are those from the west and especially those from the northwest, and the wind regime is influenced by the succession of depressions of Mediterranean origin and by orographic depressions during the winter semester: the latter, from October to April, pull in humid currents from the south over Tuscany.

Available Data for SDG Monitoring on the Case Study

Environmental data in Italy are available from various national [e.g., the National Institute for Environmental Protection and Research (ISPRA)], regional (e.g., regional environmental protection agencies), and local (e.g., municipal) sources. Parallel to this, the entity entrusted by the UN Statistics Division with the task of coordinating the production of national indicators for measuring and monitoring SDGs is Istat. Since 2018 (Istat, 2018), Istat has published the SDGs report[1] (Istat, n.d.), which describes, on an annual basis, Italy's position along the path of sustainable development and offers some thematic and analytical insights at different territorial levels, where available.

Regarding water quality in Tuscany, the agency responsible for producing official data is the Regional Agency for Environmental Protection of Tuscany (ARPAT).

As a proxy for Indicator 6.3.2 (percentage of water bodies with good ambient water quality), the European Water Framework Directive (European Union, 2000) established that the quality of water bodies is measured by the assessment of ecological and chemical status[2]. By using the latest ARPAT measures (2023), we can estimate that in 2021, 44% of the ORB water bodies were of good environmental quality, while 56% of the remaining water bodies of the basin did not reach that status.

Although ARPAT carries out a series of sampling and data collection activities on the regional river basins, the first and only useful measure (proxy) for the regional scale (Tuscany) was published in 2015, while no specific SDG river water quality indicator was produced at either the municipal scale (Siena and/or Grosseto) or the local scale (ORB). As discussed above, this information gap is reflected in the Istat annual report, which does not include these indicators.

To fill this gap at the local level, we utilized CS data combined with existing data sources to assess Goal 6, clean water and sanitation, Indicator 6.3.2, proportion of bodies of water with good ambient water quality. Moreover, the CS data are compared with those produced by ARPAT for mutual quality control and are then used to forecast water quality under a series of possible future scenarios to demonstrate how such CS data can also be used for future planning purposes.

The CS4RIVERS Project: Objectives, Methodology, and Data Collection

The sampling campaigns were developed as one step in the CS4RIVERS project, which started in September 2022. This is an initiative led by the National Biodiversity Future Center with the aim of establishing an observatory for river biodiversity in the ORB, including tributaries, through the monitoring and protection of river biodiversity.

Through CS4RIVERS, citizens can take part in one or more types of activities, including the monitoring of the macroinvertebrate community, the monitoring of riparian vegetation, and water quality measurements. For the purposes of this article, only water sampling data will be used.

After a citizen recruitment[3] and training campaign—a standard step in any CS project—in the period September 2023 to July 2024, a group of 21 citizen scientists carried out monthly sampling and data collection activities[4]. Sampling sites were identified in collaboration with the volunteers[5]. The data collection, storage, and validation platform identified by the scientists is FreshWater Watch (FWW), a global CS project developed by the environmental charity Earthwatch Europe (2022). The one-day training events included initial theoretical training and field activities in which citizens carried out practical exercises together with the scientists[6].

As recognized in other similar CS projects, the level of training of citizen scientists can influence the accuracy of monitoring data (Fore et al., 2001). To guarantee the highest level of data accuracy, each participant was instructed on key ecosystem concepts and freshwater issues, and during the practical sessions they were provided with all the equipment and sampling kits (as discussed below and shown in Fig. 2) and instructed on the project's sampling protocol and on the FWW methodology and mobile app. Citizens were given time to practice using the sampling kits during field activities along the river under the supervision of the scientists, who were able to provide feedback, answer questions, and verify the accuracy of the operations carried out by the citizens.

Figure 2. FreshWater Watch kit

Note. The kit includes a reusable Secchi tube, a sample cup, color charts, 15 nitrate tests, 15 phosphate tests, an instruction sheet, and a pair of compostable gloves.

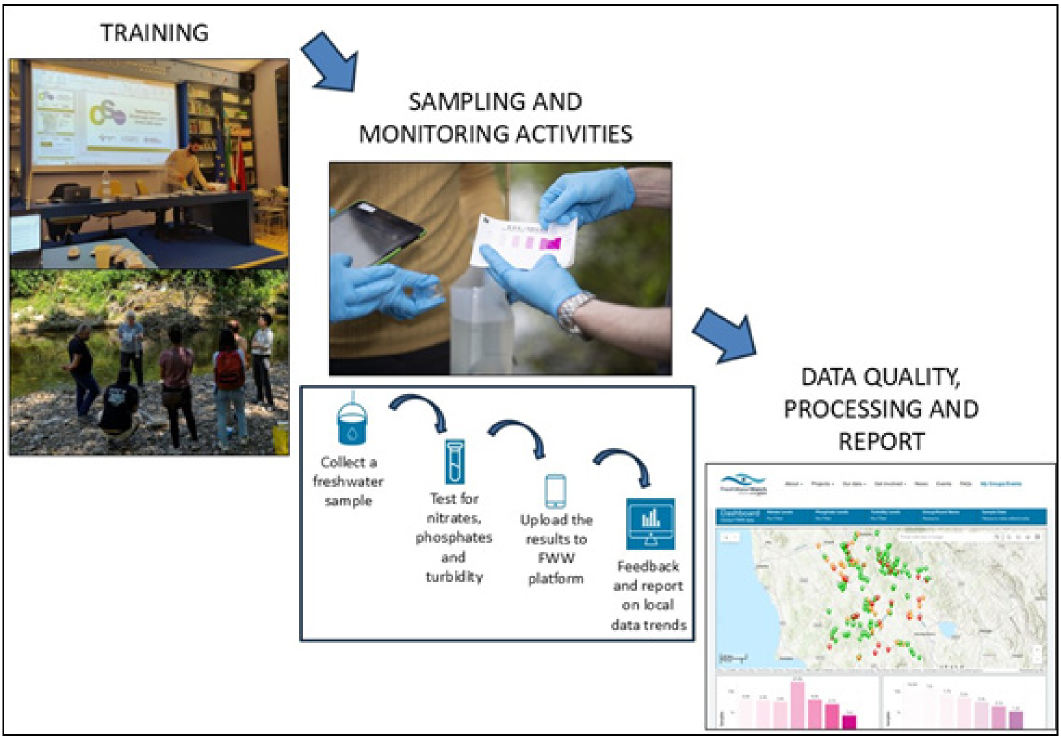
To validate the model, trained citizens used the FWW method and mobile app to determine and report on water quality at 50 sites in the Ombrone catchment. More precisely, participants collected both observation data (color, presence of algae, etc.) and semiquantitative measurements of nitrate, phosphate, and nephelometric turbidity.

Traditional scientific methods employ standardized protocols to ensure that the data collected meet specific standards, and it is largely because of the lower accuracy of equipment and simpler data quality control procedures used in CS projects that the scientific community and official monitoring agencies often question or distrust data from CS projects (Hoyer & Canfield, 2021). With this in mind, the colorimetric method—also employed in this CS project—is low cost and easy to use for almost everyone and provides ranges or classes of concentrations (Win et al., 2019; Quinlivan et al., 2020). The large amount of data collected by the colorimetric method reduces this difference, and the data are useful for providing a baseline of water quality conditions or for identifying pollution hotspots, as demonstrated in other studies following the FWW methodology (e.g., Thornhill et al., 2017; Zhang et al., 2017; Ulloa et al., 2020).

In terms of specific semiquantitative measurements, while nitrate (NO_3) is a primary form of nitrogen (N) in lakes and streams, phosphate (PO_4) is the most common form of phosphorus (P) in natural waters. Nitrate-nitrogen (NO_3–N) and phosphate-phosphorus (PO_4–P) levels were therefore measured in closed plastic tubes, which are designed to mix a fixed volume of water with reagents to produce increasing color values (peak absorption at 540 nm) with increasing concentration[7]. The median values for each classification were used for quantitative analysis.

During the measurements, geolocation and time were recorded automatically using the FWW app and transferred to the online database. As summarized in Fig. 3, according to the FWW methodology the final stage concerns the validation of the data performed by both the platform and project scientists. Once entered, all data underwent quality control by project leaders and citizen scientists. Data were checked by experts against samples from similar areas and from the ORB.

Figure 3. FreshWater Watch methodology

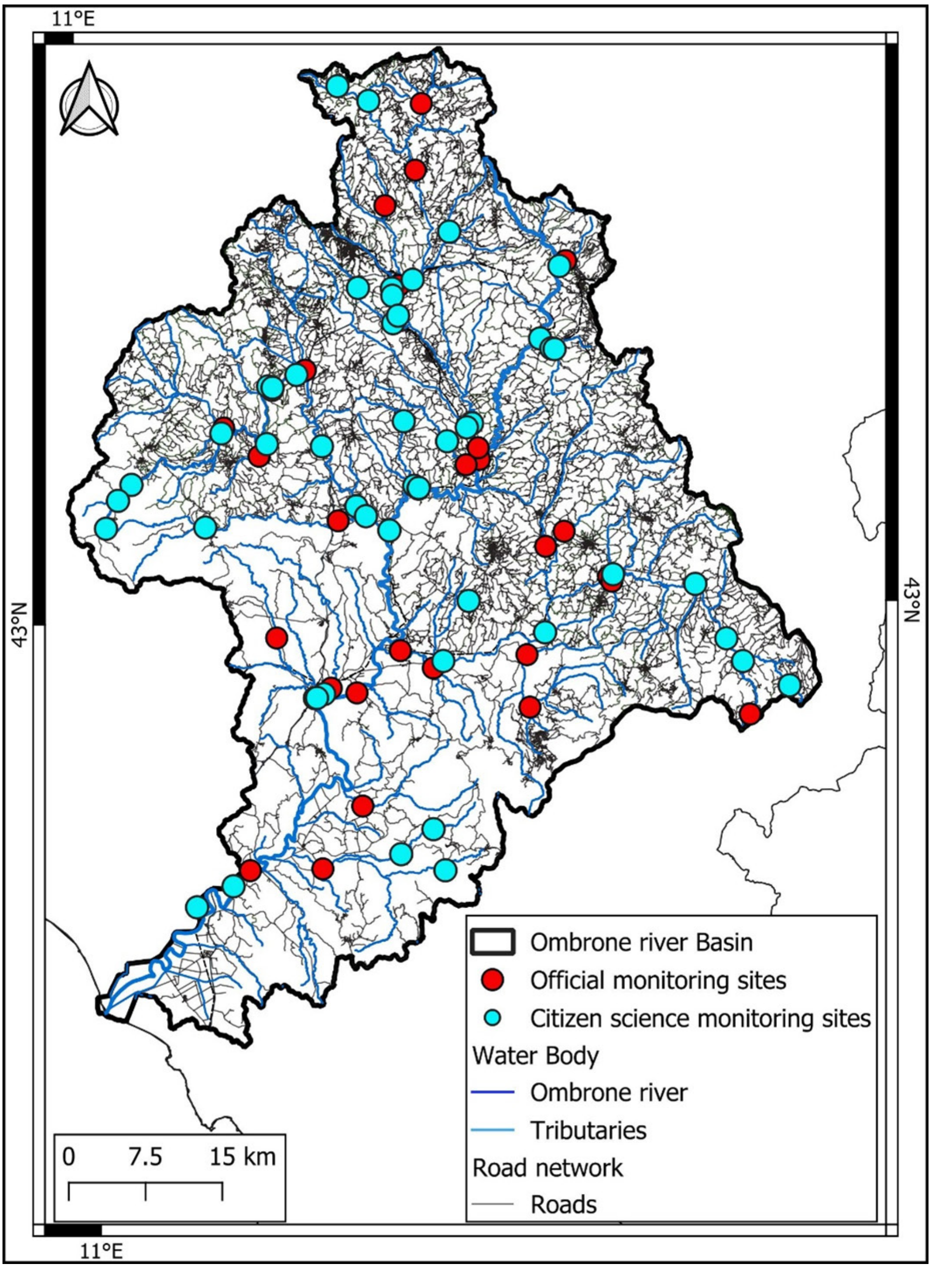


Note. From left to right, the pictures show classroom and field training sessions; sampling activities conducted by the trained citizens; and data quality verification, processing, and reporting by the FWW platform and local project experts.

Of particular interest are the data collection points along the course of the rivers. In several cases, the coordinates provided by citizen scientists were incorrect, as they did not correspond to the location of a water body, most likely due to uncalibrated GPS devices or poor network coverage. As instructed in the FWW protocol, participants must provide a brief site description and/or a photograph of the collection point. These allowed the incorrect coordinates to be relocated correctly during the validation phase by the project scientists.

Thanks to the local and experiential knowledge of those who habitually frequent the basin context (such as fishermen, trekkers, teachers, and citizens), the network of data collection points has been expanded compared to the monitoring points used by ARPAT. Ten selected sites were defined by project members in correspondence with or near ARPAT monitoring sites. This reinforces data quality and not only is useful for the validation of the CS data against official data by the project experts but also allows verification of the accuracy of the official data released by ARPAT. Other sites were selected directly by citizens considering accessibility to the site (e.g., the road network in Fig. 4), interest in monitoring a specific area, or proximity to their home. As can be seen from Fig. 4, the network of CS monitoring points is more widespread and capillary than the official one: there are more than 50 CS monitoring sites (blue dots) on a monthly basis in the CS4RIVERS project, compared to the 32 official ones of ARPAT (red dots), which carries out only four data collection campaigns per year.

Figure 4. CS4RIVERS project and ARPAT monitoring sites (2024)



Consistent with the benefits produced by CS, it was agreed among local governments, academia, citizens, and environmental agencies—and formalized with an official agreement between the University of Siena and ISPRA—that data on biodiversity and water quality will flow into the repository of ISPRA's National Biodiversity Network. ISPRA will then use this data to develop the National Strategy for Biodiversity Protection. Data collection standards were then defined to make them interoperable and integrable with other data (e.g. "Open Toscana", an open data repository for Tuscany).

MODEL DEVELOPMENT: WORKFLOW

Model development and validation were performed using information from different regional, national, and global datasets and through *in situ* monitoring from both ARPAT (2024) and CS4RIVERS citizen scientists. The geographic and temporal dynamics of the nutrient export and retention in the ORB were modeled following the mass balance approach of the InVEST software kit nutrient delivery ratio model (Version 3.14.2) (Stanford University, n.d.). This model is based on mapping nutrient sources and their potential for transport to the river to identify the spatial variation in nutrient retention across the watershed with respect to different land use/land cover (LULC) conditions (e.g., vegetative areas) and catchment morphology (Di Grazia et al., 2021).

Catchment nutrient dynamics were based on nutrient loads across the landscape and the nutrient retention capacity of the landscape. Nutrients loads per LULC were identified from data acquired in collaboration with ARPAT and available empirical data by Istat. Nutrient flows were divided into sediment-bound (transported via surface flow) or dissolved (and transported via subsurface flow). A nutrient delivery ratio index was simulated for each pixel (10 m resolution) of the catchment based on the nutrient loads, LULC, and a digital elevation model. At the watershed outlet, the P and N export to the river was calculated based on the weighted aggregation of pixel-level contributions: site-specific information related to the maximum retention efficiency, a runoff proxy (i.e., annual precipitation) representing the spatial variability in runoff potential, and an estimate of the proportion of nutrients delivered via subsurface and surface flows. The subsurface flow was considered for N only and was estimated from NO_3 concentrations in the ground and surface waters.

Data Sources for Model Development and Validation

In addition to the data collected by the citizen scientists, data required to develop and validate the nutrient N and P models were obtained from multiple sources. Some of these are as follows:

- A digital elevation model, of 10 m resolution, obtained from the Italian National Institute of Geophysics and Volcanology (Tarquini et al., 2023), which was corrected to fill hydrological sinks and checked with the digital watercourse network to ensure routing along the specific watercourse using QGIS 3.46.
- LULC raster data (2019) were obtained from Tuscany Region geoservices (Open Toscana, 2021) based on CORINE LULC Level 4 for Italy at a 100 m resolution.
- Nutrient runoff proxies were based on raster precipitation data from 2012 to 2023 at a 10 m resolution (Regione Toscana Servizio Idrologico Regionale, 2024). These raster data were interpolated using an inverse distance weighting of information from 59 ARPAT stations.
- Future nutrient runoff proxies were based on precipitation estimates for 2050 by Dezsi et al. (2018) with high-resolution gridded surfaces (1 km cell size) developed in an Albers equal-area conic projection for Europe.
- Vector delineation of the watershed was obtained from the geoportal of the Basin Authority of the Northern Apennines relative to the Water Protection Plan 2015–2021 (Autorità di bacino distrettuale dell'Appennino Settentrionale, 2015).

- The threshold value for flow accumulation, the number of upriver cells that flow into a cell before it is considered part of a river, was set to 1,000 after several tests to compare the river layer output of the model to the measured river network data.
- Borselli's *k* for the connection of the surrounding land to the river with respect to the ratio of nutrients reaching the river was set to 2 (Borselli et al., 2008).
- The nutrient (P and N) sources associated with each LULC class (kg ha^{-1} $year^{-1}$) were based on the estimation of N and P loads resulting from the resident population, industrial activities, agricultural and uncultivated land use, and livestock activities (ARPAT, 2001). For CORINE LULC Classes 111–142 (artificial surfaces), data were obtained from the Italian population census (Istat, 2021) and the enterprises census (Istat, 2011). The CORINE LULC Classes 210–244 (agricultural areas) for each municipality were scaled for the quantities of N and P present in fertilizers reported in the Istat lists of fertilizers by province (Istat, 2022). For CORINE LULC Classes 311–523 (forest and seminatural areas and water bodies), nutrient load data for 2019–2023 were obtained from ARPAT (2024).
- Retention efficiencies for N and P, as the maximum nutrient retention expected from each LULC type, were calculated following Pärn et al. (2012), Mayer et al. (2007), and Zhang et al. (2010).
- Retention lengths for N and P for each LULC class, as the typical distance necessary to reach the maximum retention efficiency, were based on previous studies of riparian buffers and ranged from 10 to 300 m. In the absence of data, the retention length was set to the pixel size.
- Subsurface critical length, the distance after which the soil retains N at its maximum capacity, was set to 200 m following Mayer et al. (2007). Maximum retention of N reached through subsurface flow was set to 0.8.
- NO_3 and PO_4 concentrations were obtained through regulatory (ARPAT, 2023) and CS measurements. Quarterly ARPAT monitoring of total N and total P in ten stations in the ORB was used for model development.

The complete biophysical table is available in the Supplementary Materials (STab 1)

Scenarios

In order to inform local policymakers about possible impacts on water quality related to land management and data-driven planning policies, we developed a multiple-scenario analysis, including a forecast analysis based on a future reforestation setting. Scenario analysis is a process of examining and evaluating possible events and policy options that could take place in the future by considering various feasible outcomes. The development of several scenarios helps to understand what actions are needed to achieve better (good) water quality in the river as required by the European Water Framework Directive and what actions are needed to achieve SDG 6.3.2.

The overall period considered for the scenario analyses is 2019–2050. Below are the proposed scenarios and a discussion of the methodological reasons for this choice:

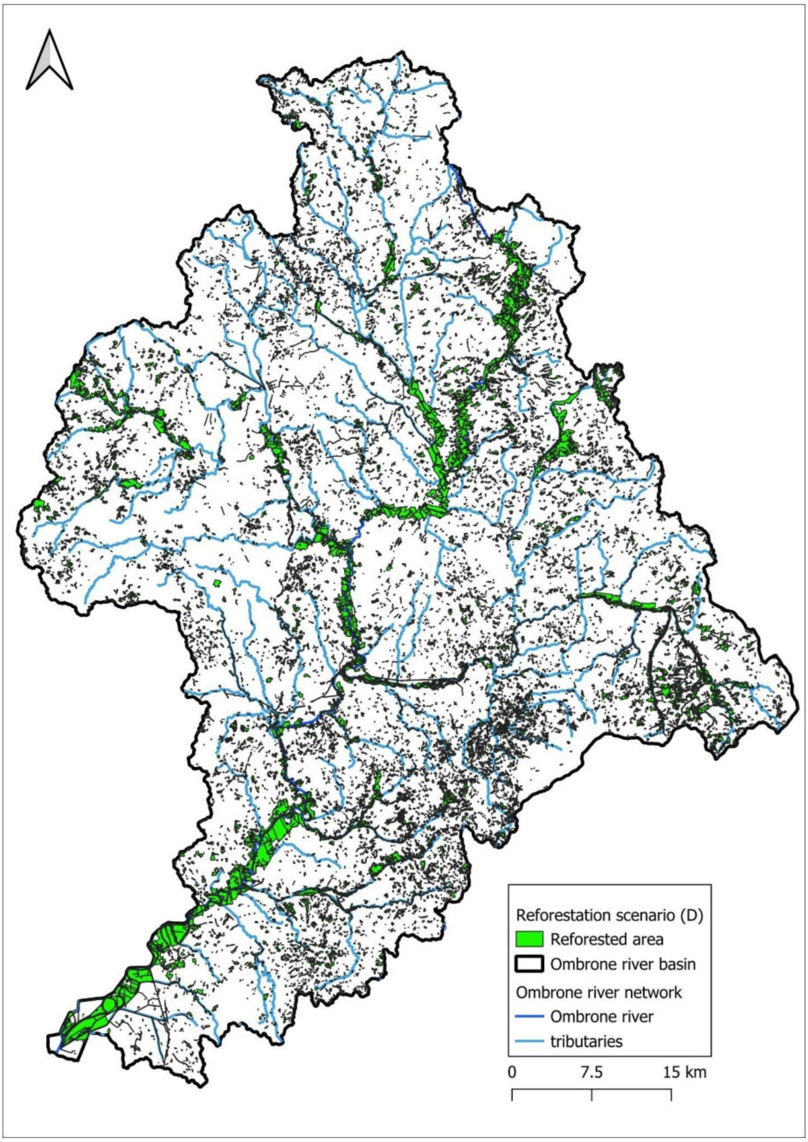
A. Baseline scenario (2019)
B. Medium-term (business as usual) (2030)
C. Long-term (including climate change) (2050)
D. Reforestation scenario (2050)

CORINE Land Cover was used to conduct the analysis for the current scenario (2019), with a spatial resolution of 100 m. The future land cover scenario was developed based on an analysis of land-use change trends (from 1990 to 2023), including photometric and satellite-based images.

The scenarios are outlined in more detail below. CS data produced by the project is used in Scenarios B, C, and D:

A. The 2019 baseline scenario[8] is the situation that has been used to compare, calibrate, and validate the future model predictions. This model considered the 2019 nutrients, river flow, and precipitation data by the regional environmental monitoring agency (ARPAT).
B. The medium-term scenario analysis focuses on predicting the future in the medium term (5–10 years, up to 2030)[9] based on available and existing past and present data, including CS data, e.g., using current trend analysis methods (a continuation of present business as usual) extrapolated into the future.
C. The long-term scenario analysis focuses on making projections in the long term (up to 2050) based on what might happen under a specific set of assumptions, which at the time of making the projections was judged plausible. In this case, the assumptions are based on the climate changes (temperature and precipitation) modeled by the Intergovernmental Panel on Climate Change (IPCC)[10], which globally predicts a +1.5°C (±0.5) increase in temperature and a reduction in precipitation by 2050.
D. The reforestation scenario is a long-term backcasting model that focuses on planning in the medium (5–15 years) or long term (>15 years). Backcasting is a method that starts with defining a desirable future and then works backward to identify policies and programs that will connect that specified future to the present (Bibri, 2018). In this case, the climate assumptions are the same as in Scenario C, but these are compounded by the assumption of reforestation (see Fig. 5) based on 10% reforestation[11] of selected agricultural areas of the ORB. The reforested areas were identified mainly along the river network to promote the buffering function (nutrient removal) of riparian forests (Gumiero & Boz, 2017).

Figure 5. Reforestation scenario (D) with mixed forest (LU class 313)



As already tested by other scholars, introducing scenarios allows policymakers to estimate the consequences of actions or inactions over time. In the case of Scenario C, as already applied by Dezsi et al. (2018), who estimated a reduction in water availability across Europe—with a more pronounced decrease in southern Europe—the scenario analysis allows the estimation of the quantity and quality of water available in the future, considering the effects of climate change already estimated by the IPCC. Scenario D goes a step further with the introduction of a possible action (reforestation) that has been shown to improve water quality in this and other rivers (Gumiero & Boz, 2017; Di Grazia et al., 2021).

RESULTS AND DISCUSSION

In reference to SDG Indicator 6.3.2, knowing that the ecological status of surface waters is an expression of the quality of the structure and functioning of aquatic ecosystems and that according to the 2020 European Water Framework Directive, a quality rating of good is given by the assessment of ecological status and chemical status. By using the data collected by the CS4RIVERS project, we can estimate that in 2024, 46% of the ORB water bodies are of good quality (versus 44% in 2021, estimated using only ARPAT data), while 54% do not reach good status (versus 56% in 2021).

In order to boost water quality and achieve good levels throughout the entire ORB, actions should be taken. We suggest, for example, reforestation. This measure would lower the pollutant load of NO_3 and PO_4 in the ORB and would therefore contribute to the achievement of SDG 6.3.2.

As shown below, the changes in nutrient retention in the Ombrone catchment, in the medium and long term up to 2050, show the relative impact of different land-use scenarios and the impact of climate change, in particular increased temperature and decreased precipitation as estimated by the IPCC.

In order to validate the modeled N and P load exported to the river, the ARPAT and CS data were used, considering monthly average nutrient concentrations, minimum and maximum values, and river water flow for 2019 due to data availability. The monthly average flow rate in the ORB was 22 m^3/s.

ARPAT samples (see Table 1) show high concentrations of total N in the winter of 3.1 mg L^{-1} and lower concentrations in the summer of 0.5 mg L^{-1}. Total P concentrations were high in the spring (2.5 mg L^{-1}) and low in the autumn (0.025 mg L^{-1}).

Table 1. Annual concentrations of total N and P from ARPAT monitoring in the ORB in 2019 and estimated export per year

Nutrient (ARPAT)	Mean	Min.	Max.	SD	Export (ARPAT) (tonne year^{-1})
Total N (mg L^{-1})	1.99	0.5	9	±1.97	7.63 x 10^{+3}
Total P (mg L^{-1})	0.14	0.025	2.5	±0.35	5.34 x 10^{+2}

Note. Standard deviation (SD) is a measure of the amount of variation of the values of a variable about its mean. A low SD indicates that the values tend to be close to the mean, also called the expected value.

Trained citizen scientists collected more than 120 samples along the entire ORB (see Table 2), where the number of ARPAT monitoring stations is limited (as discussed above in Fig. 2). NO_3–N concentrations were high in the winter and spring (1.5 mg L^{-1}) and low in the summer (0.35 mg L^{-1}). The PO_4–P concentrations were low in the summer (0.035 mg L^{-1}) and high in the winter (0.15 mg L^{-1}).

Table 2. Annual concentrations of NO_3–N and PO_4–P from CS monitoring in the ORB in 2024 and estimated export per year

Nutrient (CS)	Min.	Max.	Mean	SD	Export (CS) (tonne year^{-1})
NO_3–N (mg L^{-1})	0.1	7.5	0.8	±1	2.25 x 10^{+3}
PO_4–P (mg L^{-1})	0.01	0.35	0.06	±0.07	1.65 x 10^{+2}

Note. SD, see Table 1.

The nutrient delivery ratio index model outputs showed a total N and P export of nearly 4,500 tonnes per year of N and 600 tonnes of P (see Table 3).

Table 3. Nutrient delivery model results of the baseline scenario A (2019)

Model nutrients	Surface load (tonne year^{-1})	Surface export (tonne year^{-1})	Total export (tonne year^{-1})
Total N	2.99 x 10^{+4}	7.12 x 10^{+3}	1.02 x 10^{+3}
Total P	7.17 x 10^{+3}	1.24 x 10^{+2}	-

Note. Surface load: total P and N loads (sources) in the watershed. Surface export: total P and N export from the watershed by surface flow. Total export: total N export from the watershed by surface and subsurface flow.

By using the precipitation scenario raster for 2050, changes in nutrient export were explored. By applying the baseline land cover in 2050, P export is expected to increase by 2.2% and N export is expected to increase 1.5% (Table 4). A decrease in the delivery and retention of total N and total P reflects the precipitation reduction for the 2050 projection.

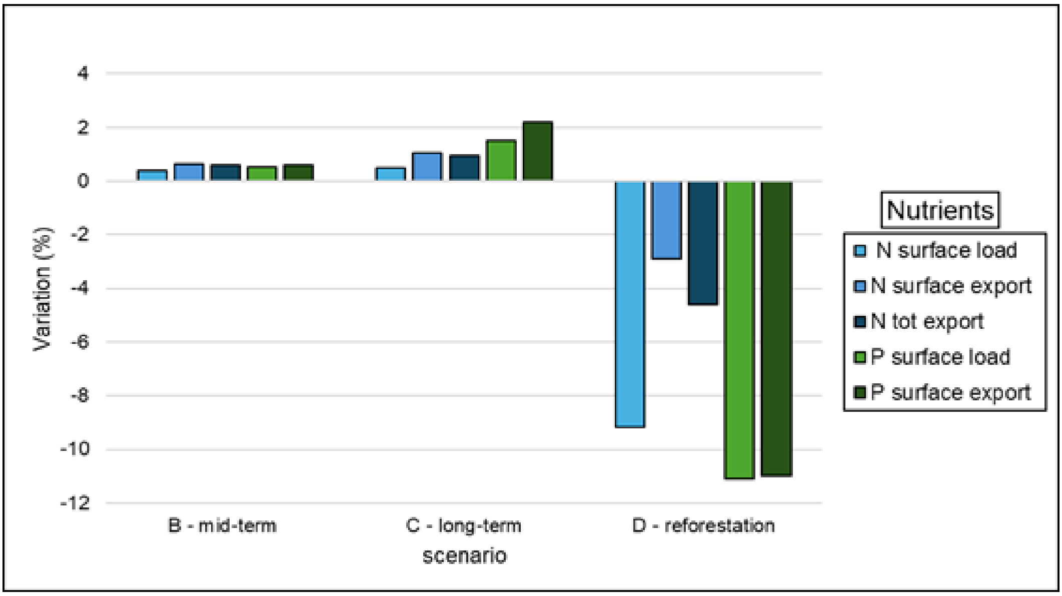
Table 4. Nutrient delivery model results comparing the scenario estimations of nutrient loads and exports

Scenario	P surface load (tonne year^{-1})	P surface export (tonne year^{-1})	N surface load (tonne year^{-1})	N surface export (tonne year^{-1})	N total export (tonne year^{-1})
A. Baseline (2019)	7.17 x 10^{+3}	1.24 x 10^{+2}	2.99 x 10^{+4}	7.12 x 10^{+3}	1.02 x 10^{+3}
B. Mid-term trend (2030)	7.21 x 10^{+3}	1.25 x 10^{+2}	3.00 x 10^{+4}	7.17 x 10^{+3}	1.03 x 10^{+3}
C. Long-term trend (2050)	7.28 x 10^{+3}	1.27 x 10^{+2}	3.00 x 10^{+4}	7.20 x 10^{+3}	1.03 x 10^{+3}
D. Reforestation (2050)	6.41 x 10^{+3}	1.11 x 10^{+2}	2.72 x 10^{+4}	6.92 x 10^{+3}	9.73 x 10^{+2}

Note. Surface load: total P and N loads (sources) in the watershed. Surface export: total P and N export from the watershed by surface flow. Total export: total N export from the watershed by surface and subsurface flow.

The reforestation scenario results in a reduction in both the N and the P load and export (see Table 4). The P export decreases by 11%, corresponding to a reduction of 459 tonnes per year, while the N export reduction is relatively lower (5%), with a reduction of 129 tonnes per year (see Fig. 6).

Figure 6. Percentage reduction in N and P load (input) and export (output) in different scenarios along the ORB



The results of the simulated nutrient conditions in three different scenarios (B, C, and D) suggest that the nutrient load and export in the ORB catchment are sensitive both to climate change and to an increase in wooded areas, particularly in agricultural areas where there is a trend in agricultural land abandonment (Vergari et al., 2013; Debolini et al., 2015).

Similar to what has been demonstrated in previous research on other river basins in Italy (e.g., Di Grazia et al., 2021), reforestation presents multiple benefits, promoting biodiversity (Wade et al., 2006) as well as reducing surface water runoff and soil erosion, improving water quality (Tasser et al., 2007), controlling sediment loss, and improving soil properties (Seeber & Seeber, 2005).

The overall impact of the mid- and long-term scenarios is clear in the reduced export of both P and N, with the largest reduction occurring in the reforestation scenario (D). The values support results from other studies that show that increased forest cover and decreased agricultural areas decrease sediment, N, and P exports (De Mello et al., 2017).

Through the use of spatially explicit models, it was possible to identify the locations within the catchment with the greatest sensitivity to climate change and reforestation actions, in this case with respect to nutrient loads and nutrient export. The costs of natural reforestation are limited, and the benefits for the watershed and the receiving waters (the Tyrrhenian Sea) could be translated into support for farmers to manage these lands as productive forests.

It is expected that the new European common agricultural policy (CAP) (Regulation 2021/2115) and the Nature Restoration Law (Regulation 2024/1991) will incentivize this land-use transformation. The Italian CAP Plan (Goal 2.2 greener CAP) (European Commission, 2024) focuses on the green transition of the agricultural, food, and forestry sectors. To this end, more than 80% of the agricultural area will comply with good agricultural and environmental conditions, such as establishing buffer strips between rivers and agricultural crops to reduce the water pollution[12] (Gumiero & Boz, 2017; Lampkin et al., 2020). On the other hand, N and P loads from urban wastewater represent a significant source (Cozzi et al., 2019). Recent studies on lowland rivers that have created riparian buffer strips have demonstrated a high NO_3 removal efficiency (Gumiero & Boz).

The unit cost for P removal in different treatment alternatives ranges from 80 EUR/kg of P to 120 EUR/kg of P (Bashar et al., 2018). Jabłonska et al. (2020) estimated the costs of a hypothetical establishment of wetland buffer zones to reduce the nonpoint source of N and P to be EUR 9 M ± 107 M to remove 11–82% of the N load and 14–87% of the P load from the catchment. This translates into a cost that is saved due to the lack of eutrophication and the problems associated with poor water quality (Nie et al., 2018).

The above exercise indicates the way in which complex analysis and recommendation can be achieved by boosting traditionally derived institutional data with the inevitably far more volumetric and comprehensive data produced by active citizen scientists, the latter group of data being verified for validity by expert comparison with both historical and like-for-like data.

CONCLUSION

The purpose of this paper was twofold. The overall objective was to reflect on the future role and potential of CS for transitions toward sustainability, while the empirical goal was to demonstrate how data produced through CS can contribute to the estimation of SDG indicators that were previously unmeasured. Moreover, through forecast analysis, we aimed to provide examples of the possible use of CS data to forecast water quality under future scenarios and therefore reveal how CS data can also be used for future planning purposes. This exercise allowed us to confirm the validity and importance of CS approaches and their contribution to open science by offering useful pointers for optimizing the voluntary participation of nonprofessional scientists in the various stages of research and innovation activities.

Referring to Indicator 6.3.2, proportion of bodies of water with good ambient water quality, with observations collected by the CS4RIVERS project over the course of 11 months (using the FWW method), we assessed that 46% of the water bodies of the ORB are of good quality, while 54% do not reach good status.

In order to comply with the national and European water regulations and to achieve a good level of water quality (thus achieving and advancing SDG 6.3.2), interventions need to be made. What we have suggested in this paper is reforestation.

Starting from a baseline scenario (2019) derived using existing official statistics through the integration into a forecast model of water quality data collected from citizen scientists on the ORB, we made assumptions by deriving possible future scenarios: medium term (to the year 2030) business as usual, calibrating the model as a continuation of current trends in water quality and land use; long term (to the year 2050) introducing a climate change assumption with increased temperatures and decreased precipitation as estimated by the IPCC; and a future scenario to the year 2050 that, leaving the previous assumptions unchanged, introduced an intervention: reforestation.

Through these forecasts, we provided an example of how existing information can be used to predict water quality trends in a future business-as-usual scenario and compare it with a future situation involving climate change and activities to restore environmental quality. The results of our forecasts suggest that the water quality of the ORB is sensitive to climate change but also to restoration actions (e.g., reforestation).

As discussed by Di Grazia et al. (2021), decreasing trends in P export by rivers in Europe have resulted mainly from environmental and agricultural policies leading to reduced nutrient inputs to river catchments. The IPCC's Climate Change Report (IPCC, 2022) and the European Union's Nature Restoration Law (Regulation 2024/1991) emphasize the need to explore the mitigation potential of restoration actions and the improved management of forests. The scenario analyses may therefore be able to inspire and guide data-driven policies and more conscious spatial planning practices that will not only contribute to the goals of the 2030 Agenda but also meet urgent regulatory pressures.

Our research demonstrated that CS contributes to the three pillars of sustainability for a number of reasons. It allows socially and environmentally oriented research projects to be conducted and data to be collected quickly and economically in accordance with the Sustainability Development Goals' economic pillar.

Our experiment confirmed that not only can CS data complement the data production of official statistics in real time (in terms of both increased frequency and spatial resolution), but it also has the potential to have its accuracy confirmed during validation by professional scientists. In addition, the current production of a historical CS dataset will soon allow the monitoring of changes in water quality in the ORB during the next project year and therefore continuation of the monitoring of SDG 6.3.2.

In remote areas (as in the case of the project), input from citizen scientists may even prove to be invaluable, since it can lead to the production of information that otherwise would not be collected at all. Indeed, citizens engaged in the CS4RIVERS project have even begun to collect and contribute data on FWW about smaller rivers in the areas where they live. This means that in the future, the project might be able to use additional information to assess and monitor water quality in other rivers of the region.

The active participation of citizen scientists in the CS4RIVERS project is already producing a variety of social effects—fulfilling the social pillar—that will be discussed in future outputs of this research, and, in line with the environmental pillar, it actively contributes to the monitoring and reduction of environmental risks in the study area.

Another important outcome is the collaboration and partnership established as part of the project with ISPRA that will enable not only the pooling of resources (the data will feed both into the Open Data Tuscany Region and into the National Strategy for Biodiversity Protection) but also has the potential to enhance local development processes and data-driven policies and support regional planning. This will enable positive long-term results and the systematization of CS efforts.

We also intend to highlight how the formalization and institutionalization of bottom-up coproduction processes are leading, at least in the Italian case, to the acceptance of the dataset produced within the CS project in Tuscany by the bodies in charge of producing official government statistics.

In conclusion, we argue that greater participation in the management and monitoring of our river environments is necessary to further improve their status. CS has proven to be an additional tool for supplementing available official data and validating models in this study and others. Involving citizens directly in monitoring activities can be a powerful tool to supplement missing information and to improve the influence of local communities on their land management policies.

FUNDING STATEMENT

This article is an output of the CS4RIVERS project, funded under the National Recovery and Resilience Plan, Mission 4 Component 2 Investment 1.4, Call for Tender No. 3138 of December 16, 2021, rectified by Decree No. 3175 of December 18, 2021, of Italian Ministry of University and Research funded by the European Union—NextGenerationEU. This research was supported by Project Code CN_00000033, Concession Decree No. 1034 of June 17, 2022, adopted by the Italian Ministry of University and Research, CUP B63C22000650007, project title National Biodiversity Future Center - NBFC.

COMPETING INTERESTS

The authors of this publication declare there are no competing interests.

CORRESPONDENCE

Venere Stefania Sanna, venere.sanna@unisi.it; Francesco Di Grazia, francesco.digrazia2@unisi.it; Cristina Capineri, cristina.capineri@unisi.it; Alessio Polvani, alessio.polvani@student.unisi.it

PROCESSING DATES

12, 2024

This manuscript was initially received for consideration for the journal on 09/20/2024, revisions were received for the manuscript following the double-anonymized peer review on 11/21/2024, the manuscript was formally accepted on 12/07/2024, and the manuscript was finalized for publication on 12/20/2024

ACKNOWLEDGMENTS

Our thanks go to the cooperation partners of CS4RIVERS and to the entire research team. We particularly express our immense gratitude to all the stakeholders involved, especially to the citizen scientists for their valuable continuing participation, without whom this project would not be possible.

REFERENCES

Agenzia Regionale per la Protezione dell'Ambiente Toscana. ARPAT. (2001). *Rapporto sullo stato delle acque dei principali fiumi in Toscana 2001*. Regione Toscana. https://www.arpat.toscana.it/documentazione/catalogo-pubblicazioni-arpat/rapporto-2001-sullo-stato-delle-acque-dei-principali-fiumi-in-toscana/?searchterm=None

Agenzia Regionale per la Protezione dell'Ambiente Toscana. ARPAT. (2023). *Banca dati MAS - Acque superficiali in Toscana* [Data set]. https://www.arpat.toscana.it/datiemappe/banche-dati/banca-dati-mas-acque-superficiali-in-toscana

Albert, A., Balázs, B., Butkevičienė, E., Mayer, K., & Perelló, J. (2021). Citizen social science: New and established approaches to participation in social research. In Vohland, K., Land-Zandstra, A., Ceccaroni, L., Lemmens, R., Perelló, J., Ponti, M., Samson, R., & Wagenknecht, K. (Eds.), *The science of citizen science* (pp. 119–138). Springer., DOI: 10.1007/978-3-030-58278-4_7

Ash, J., Kitchin, R., & Leszczynski, A. (2018). Digital turn, digital geographies? *Progress in Human Geography*, *42*(1), 25–43. DOI: 10.1177/0309132516664800

Autorità di bacino distrettuale dell'Appennino Settentrionale. (2015). *Piano di gestione delle acque (PGA) 2015-2021*. https://www.appenninosettentrionale.it/itc/?page_id=2906

Ballard, H. L., Phillips, T. B., & Robinson, L. (2018). Conservation outcomes of citizen science. In S. Hecker, M. Haklay, A. Bowser, Z. Makuch, J. Vogel, & A. Bonn (Eds.), *Citizen science: Innovation in open science, society and policy* (pp. 254–268). UCL Press. DOI: 10.2307/j.ctv550cf2.25

Ballerini, L., & Bergh, S. I. (2021). Using citizen science data to monitor the Sustainable Development Goals: A bottom-up analysis. *Sustainability Science*, *16*(6), 1945–1962. DOI: 10.1007/s11625-021-01001-1 PMID: 34316319

Bashar, R., Gungor, K., Karthikeyan, K. G., & Barak, P. (2018). Cost effectiveness of phosphorus removal processes in municipal wastewater treatment. *Chemosphere*, *197*, 280–290. DOI: 10.1016/j.chemosphere.2017.12.169 PMID: 29353678

Bibri, S. E. (2018). Backcasting in futures studies: A synthesized scholarly and planning approach to strategic smart sustainable city development. *European Journal of Futures Research, 6*, 13. DOI: 10.1186/s40309-018-0142-z

Bio Innovation Service. (2018). *Citizen science for environmental policy: Development of an EU-wide inventory and analysis of selected practices*. Final report for the European Commission, DG Environment under the contract 070203/2017/768879/ETU/ENV.A.3, in collaboration with Fundacion Ibercivis and The National History Museum. DOI: 10.2779/961304

Bonney, R., Cooper, C. B., Dickinson, J., Kelling, S., Phillips, T., Rosenberg, K. V., & Shirk, J. (2009). Citizen science: A developing tool for expanding science knowledge and scientific literacy. *Bioscience*, *59*(11), 977–984. DOI: 10.1525/bio.2009.59.11.9

Borselli, L., Cassi, P., & Torri, D. (2008). Prolegomena to sediment and flow connectivity in the landscape: A GIS and field numerical assessment. *Catena*, *75*(3), 268–277. DOI: 10.1016/j.catena.2008.07.006

Butkevičienė, E., Skarlatidou, A., Balázs, B., Duží, B., Massetti, L., Tsampoulatidis, I., & Tauginienė, L. (2021). Citizen science case studies and their impacts on social innovation. In Vohland, K., Land-Zandstra, A., Ceccaroni, L., Lemmens, R., Perelló, J., Ponti, M., Samson, R., & Wagenknecht, K. (Eds.), *The science of citizen science* (pp. 309–329). Springer., DOI: 10.1007/978-3-030-58278-4_16

Cappa, F., Franco, S., & Rosso, F. (2022). Citizens and cities: Leveraging citizen science and big data for sustainable urban development. *Business Strategy and the Environment*, *31*(2), 599–683. DOI: 10.1002/bse.2942

Carayannis, E. G., Barth, T. D., & Campbell, D. F. J. (2012). The Quintuple Helix innovation model: Global warming as a challenge and driver for innovation. *Journal of Innovation and Entrepreneurship*, *1*(1), 2. DOI: 10.1186/2192-5372-1-2

Chandler, M., See, L., Copas, K., Bonde, A. M. Z., López, B. C., Danielsen, F., Legind, J. K., Masinde, S., Miller-Rushing, A. J., Newman, G., Rosemartin, A., & Turak, E. (2017). Contribution of citizen science towards international biodiversity monitoring. *Biological Conservation, 213*(B), 280–294. DOI: 10.1016/j.biocon.2016.09.004

CitiObs. (n.d.). *Enhancing citizen observatories for healthy, sustainable, resilient and inclusive cities.* https://citiobs.eu/

Citizen Science for Rivers. (n.d.). *Biodiversity, citizen science and local contexts.* https://www.cs4rivers.unisi.it/

Committee on Data of the International Science Council. (n.d.). *CODATA-WDS TG on citizen-generated data for the SDGs.* https://codata.org/initiatives/task-groups/citizen-science-for-the-sustainable-development-goals/

Cooper, C. B., Hawn, C. L., Larson, L. R., Parrish, J. K., Bowser, G., Cavalier, D., Dunn, R. R., Haklay, M., Gupta, K. K., Jelks, N. O., Johnson, V. A., Katti, M., Leggett, Z., Wilson, O. R., & Wilson, S. (2021). Inclusion in citizen science: The conundrum of rebranding. *Science*, *372*(6549), 1386–1388. DOI: 10.1126/science.abi6487

Cossu, M., Occhino, T., Sanna, V. S., & Coronato, M. (2023). Invertire la narrazione: Il potenziale del sistema di attuazione della Strategia Nazionale per lo Sviluppo Sostenibile. In Albanese, V. E., & Muti, G. (Eds.), *Narrazioni/narratives: XII giornata di studio "Oltre la globalizzazione," memorie geografiche* (pp. 741–747). Società di Studi Geografici., http://www.dista.uninsubria.it/MemorieGeografiche2023/Memorie_Geografiche_2023.pdf

Cozzi, S., Ibáñez, C., Lazar, L., Raimbault, P., & Giani, M. (2019). Flow regime and nutrient-loading trends from the largest south European watersheds: Implications for the productivity of Mediterranean and Black Sea's coastal areas. *Water (Basel)*, *11*(1), 1. DOI: 10.3390/w11010001

Crain, R., Cooper, C., & Dickinson, J. L. (2014). Citizen science: A tool for integrating studies of human and natural systems. *Annual Review of Environment and Resources*, *39*(1), 641–665. DOI: 10.1146/annurev-environ-030713-154609

De Mello, K., Randhir, T. O., Valente, R. A., & Vettorazzi, C. A. (2017). Riparian restoration for protecting water quality in tropical agricultural watersheds. *Ecological Engineering, 108*(B), 514–524. https://doi.org/ DOI: 10.1016/j.ecoleng.2017.06.049

Debolini, M., Schoorl, J. M., Temme, A., Galli, M., & Bonari, E. (2015). Changes in agricultural land use affecting future soil redistribution patterns: A case study in southern Tuscany (Italy). *Land Degradation & Development*, *26*(6), 574–586. DOI: 10.1002/ldr.2217

Devisch, O., Poplin, A., & Sofronie, S. (2016). The gamification of civic participation: Two experiments in improving the skills of citizens to reflect collectively on spatial issues. *Journal of Urban Technology*, *23*(2), 81–102. DOI: 10.1080/10630732.2015.1102419

Dezsi, ¸. S., Mîndrescu, M., Petrea, D., Rai, P. K., Hamann, A., & Nistor, M.-M. (2018). High-resolution projections of evapotranspiration and water availability for Europe under climate change. *International Journal of Climatology*, *38*(10), 3832–3841. DOI: 10.1002/joc.5537

Di Grazia, F., Gumiero, B., Galgani, L., Troiani, E., Ferri, M., & Loiselle, S. A. (2021). Ecosystem services evaluation of nature-based solutions with the help of citizen scientists. *Sustainability (Basel)*, *13*(19), 10629. DOI: 10.3390/su131910629

Diblíková, L., Pipek, P., Petrusek, A., Svoboda, J., Bílková, J., Vermouzek, Z., Procházka, P., & Petrusková, T. (2019). Detailed large-scale mapping of geographical variation of Yellowhammer *Emberiza citrinella* song dialects in a citizen science project. *The Ibis*, *161*(2), 401–414. DOI: 10.1111/ibi.12621

E., Walde, J., Tappeiner, U., Teutsch, A., & Noggler, W. (2007). Land-use changes and natural reforestation in the eastern central Alps. *Agriculture, Ecosystems & Environment, 118*(1–4), 115–129. https://doi.org/DOI: 10.1016/j.agee.2006.05.004

Earthwatch Europe. (2022). *FreshWater Watch*. https://www.freshwaterwatch.org/

European Commission. (2020). *Citizen science—Elevating research and innovation through societal engagement*. Directorate-General for Research and Innovation, Publications Office of the European Union. https://data.europa.eu/doi/10.2777/624713

European Commission. (2021). *Horizon Europe: Strategic plan 2021–2024.* DOI: 10.2777/083753

European Commission. (2023, October 27). *Citizen science—An essential ally for sustainable cities.* https://rea.ec.europa.eu/news/citizen-science-essential-ally-sustainable-cities-2023-10-27_en

European Commission. (2024). *Italy – CAP Strategic Plan*. https://agriculture.ec.europa.eu/cap-my-country/cap-strategic-plans/italy_en

European Commission. (n.d.). *Open science*. https://research-and-innovation.ec.europa.eu/strategy/strategy-research-and-innovation/our-digital-future/open-science_en

European Union. (2000). *Directive 2000/60/EC of the European Parliament and of the council establishing a framework for community action in the field of water policy.* https://faolex.fao.org/docs/pdf/eur23005.pdf

European Union Citizen Science. (2023). *Urban ReLeaf*. https://eu-citizen.science/project/486

Fore, L. S., Paulsen, K., & O'Laughlin, K. (2001). Assessing the performance of volunteers in monitoring streams. *Freshwater Biology*, *46*(1), 109–123. DOI: 10.1111/j.1365-2427.2001.00640.x

Fraisl, D., Campbell, J., See, L., Wehn, U., Wardlaw, J., Gold, M., Moorthy, I., Arias, R., Piera, J., Oliver, J. L., Masó, J., Penker, M., & Fritz, S. (2020). Mapping citizen science contributions to the UN Sustainable Development Goals. *Sustainability Science*, *15*(6), 1735–1751. DOI: 10.1007/s11625-020-00833-7

Fraisl, D., See, L., Bowers, R., Seidu, O., Boakye Fredua, K., Bowser, A., Meloche, M., Weller, S., Amaglo-Kobla, T., Ghafari, D., Laso Bayas, J. C., Campbell, J., Cameron, G., Fritz, S., & McCallum, I. (2023a). The contributions of citizen science to SDG monitoring and reporting on marine plastics. *Sustainability Science*, *18*(6), 2629–2647. DOI: 10.1007/s11625-023-01402-4

Fraisl, D., See, L., Estevez, D., Tomaska, N., & MacFeely, S. (2023b). Citizen science for monitoring the health and well-being related Sustainable Development Goals and the World Health Organization's Triple Billion Targets. *Frontiers in Public Health*, *11*, 1202188. DOI: 10.3389/fpubh.2023.1202188 PMID: 37637808

Fraisl, D., See, L., Sturn, T., MacFeely, S., Bowser, A., Campbell, J., Moorthy, I., Danylo, O., McCallum, I., & Fritz, S. (2022). Demonstrating the potential of Picture Pile as a citizen science tool for SDG monitoring. *Environmental Science & Policy*, *128*, 81–93. DOI: 10.1016/j.envsci.2021.10.034

Fritz, S., et al. (2019). Citizen science and the United Nations Sustainable Development Goals. *Nature Sustainability*, *2*(10), 922–930. DOI: 10.1038/s41893-019-0390-3

Gumiero, B., & Boz, B. (2017). How to stop nitrogen leaking from a Cross compliant buffer strip? *Ecological Engineering, 103*(B), 446–454. DOI: 10.1016/j.ecoleng.2016.05.031

Haklay, M. (2013). Citizen science and volunteered geographic information—Overview and typology of participation. In Sui, D., Elwood, S., & Goodchild, M. (Eds.), *Crowdsourcing geographic knowledge* (pp. 105–122). Springer., DOI: 10.1007/978-94-007-4587-2_7

Hecker, S., Garbe, L., & Bonn, A. (2018a). The European citizen science landscape—A snapshot. In S. Hecker, M. Haklay, A. Bowser, Z. Makuch, J. Vogel, & A. Bonn (Eds.), *Citizen science: Innovation in open science, society and policy* (pp. 190–200). UCL Press. DOI: 10.2307/j.ctv550cf2.20

Hecker, S., Haklay, M., Bowser, A., Makuch, Z., Vogel, J., & Bonn, A. (2018b) (Eds.). *Citizen science: Innovation in open science, society and policy*. UCL Press. DOI: 10.14324/111.9781787352339

Hecker, S., Wicke, N., Haklay, M., & Bonn, A. (2019). How does policy conceptualise citizen science? A qualitative content analysis of international policy documents. *Citizen Science: Theory and Practice*, *4*(1), 32. DOI: 10.5334/cstp.230

Hoyer, M. V., & Canfield, D. E.Jr. (2021). Volunteer-collected water quality data can be used for science and management. *Lake and Reservoir Management*, *37*(3), 235–245. DOI: 10.1080/10402381.2021.1876190

Hyder, K., Townhill, B., Anderson, L. G., Delany, J., & Pinnegar, J. K. (2015). Can citizen science contribute to the evidence-base that underpins marine policy? *Marine Policy*, *59*, 112–120. DOI: 10.1016/j.marpol.2015.04.022

Intergovernmental Panel on Climate Change. (IPCC). (2022). *IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems.* Cambridge University Press. DOI: 10.1017/9781009157988

Irwin, A. (1995). *Citizen science: A study of people, expertise, and sustainable development*. Routledge.

Italian National Institute of Statistics. (2011). *9° Censimento industria e servizi 2011*. https://www.istat.it/statistiche-per-temi/censimenti/censimenti-storici/industria-e-servizi/imprese-2011/

Italian National Institute of Statistics. (2018). *SDGs report 2018*. https://www.istat.it/it/files/2018/07/SDGs.pdf

Italian National Institute of Statistics. (2021). *Risultati del Censimento permanente della popolazione*. https://www.istat.it/statistiche-per-temi/censimenti/popolazione-e-abitazioni/risultati/

Italian National Institute of Statistics. (2022). *Fertilizzanti distribuiti a livello provinciale (Siena, Grosseto)*. https://esploradati.istat.it/databrowser/#/it/dw/categories/IT1,Z1000AGR,1.0/AGR_MEANS/DCSP_FERTILIZZANTI/IT1,104_466_DF_DCSP_FERTILIZZANTI_4,1.0

Italian National Institute of Statistics. (2023). *2023 SDGs report.* https://www.istat.it/wp-content/uploads/2024/05/SDGs-2023-English-version-Ebook.pdf

Italian National Institute of Statistics. (n.d.). *SDGs report.* https://www.istat.it/en/tag/sdgs-report/

Jabłonska, E., Wiśniewska, M., Marcinkowski, P., Grygoruk, M., Walton, C. R., Zak, D., Hoffmann, C. C., Larsen, S. E., Trepel, M., & Kotowski, W. (2020). Catchment-scale analysis reveals high cost-effectiveness of wetland buffer zones as a remedy to non-point nutrient pollution in north-eastern Poland. *Water (Basel)*, *12*(3), 629. DOI: 10.3390/w12030629

Karvonen, A., & Van Heur, B. (2014). Urban laboratories: Experiments in reworking cities. *International Journal of Urban and Regional Research*, *38*(2), 379–392. DOI: 10.1111/1468-2427.12075

Kelly, R., Fleming, A., Pecl, G. T., Richter, A., & Bonn, A. (2019). Social license through citizen science: A tool for marine conservation. *Ecology and Society*, *24*(1), 16. DOI: 10.5751/ES-10704-240116

Kieslinger, B., Schäfer, T., Heigl, F., Dörler, D., Richter, A., & Bonn, A. (2018). Evaluating citizen science—Towards an open framework. In S. Hecker, M. Haklay, A. Bowser, Z. Makuch, J. Vogel, & A. Bonn (Eds.), *Citizen science: Innovation in open science, society and policy* (pp. 81–95). UCL Press. DOI: 10.14324/111.9781787352339

Lampkin, N., Stolze, M., Meredith, S., de Porras, M., Haller, L., & Mészáros, D. (2020). *Using Eco-schemes in the new CAP: A guide for managing authorities*. IFOAM EU, FIBL, and IEEP. https://organicseurope.bio/content/uploads/2020/06/ifoam-eco-schemes-web_compressed-1.pdf?dd

Lee, K. A., Lee, J. R., & Bell, P. (2020). A review of citizen science within the earth sciences: Potential benefits and obstacles. *Proceedings of the Geologists' Association, 131*(6), 605–617. DOI: 10.1016/j.pgeola.2020.07.010

Lepczyk, C. A. (2005). Integrating published data and citizen science to describe bird diversity across a landscape. *Journal of Applied Ecology*, *42*(4), 672–677. DOI: 10.1111/j.1365-2664.2005.01059.x

Liu, H.-Y., Ahmed, S., Passani, A., & Bartonova, A. (2023). Understanding the role of cities and citizen science in advancing sustainable development goals across Europe: Insights from European research framework projects. *Frontiers in Sustainable Cities*, *5*, 1219768. DOI: 10.3389/frsc.2023.1219768

Loiselle, S., Thornhill, I., & Bailey, N. (2016). Citizen science: Advantages of shallow versus deep participation. *Frontiers in Environmental Science*, *4*. Advance online publication. DOI: 10.3389/conf.FENVS.2016.01.00001

Martin, V., Christidis, L., Lloyd, D., & Pecl, G. (2016). Understanding drivers, barriers and information sources for public participation in marine citizen science. *JCOM, Journal of Science Communication*, *15*(02), A02. DOI: 10.22323/2.15020202

Mattei, P. (2023). *Democratizing science: The political roots of the public engagement agenda*. Bristol University Press., DOI: 10.51952/9781529223972

Mayer, P. M., Reynolds, S. K.Jr, McCutchen, M. D., & Canfield, T. J. (2007). Meta-analysis of nitrogen removal in riparian buffers. *Journal of Environmental Quality*, *36*(4), 1172–1180. DOI: 10.2134/jeq2006.0462 PMID: 17596626

Millar, E., & Searcy, C. (2020). The presence of citizen science in sustainability reporting. *Sustainability Accounting*. *Management and Policy Journal*, *11*(1), 31–64. DOI: 10.1108/SAMPJ-01-2019-0006

Nie, J., Feng, H., Witherell, B. B., Alebus, M., Mahajan, M. D., Zhang, W., & Yu, L. (2018). Causes, assessment, and treatment of nutrient (N and P) pollution in rivers, estuaries, and coastal waters. *Current Pollution Reports*, *4*(2), 154–161. DOI: 10.1007/s40726-018-0083-y

Open Toscana. (2021). *Uso e Copertura del Suolo - Intera regione* [Data set]. https://dati.toscana.it/dataset/ucs

Pärn, J., Pinay, G., & Mander, Ü. (2012). Indicators of nutrients transport from agricultural catchments under temperate climate: A review. *Ecological Indicators*, *22*, 4–15. DOI: 10.1016/j.ecolind.2011.10.002

Quinlivan, L., Chapman, D. V., & Sullivan, T. (2020). Validating citizen science monitoring of ambient water quality for the United Nations Sustainable Development Goals. *The Science of the Total Environment*, *669*, 134255. DOI: 10.1016/j.scitotenv.2019.134255 PMID: 31683215

Regione Toscana Servizio Idrologico Regionale. (2024). *Precipitazioni giornaliere* [Data set]. https://www.sir.toscana.it/consistenza-rete

Regulation 2021/2115. *Regulation (EU) 2021/2115 of the European Parliament and of the Council of 2 December 2021 establishing rules on support for strategic plans to be drawn up by Member States under the common agricultural policy (CAP Strategic Plans) and financed by the European Agricultural Guarantee Fund (EAGF) and by the European Agricultural Fund for Rural Development (EAFRD) and repealing Regulations (EU) No 1305/2013 and (EU) No 1307/2013.* https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32021R2115

Regulation 2024/1991. *Regulation (EU) 2024/1991 of the European Parliament and of the Council of 24 June 2024 on nature restoration and amending Regulation (EU) 2022/869 (Text with EEA relevance).* https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32024R1991&qid=

Sanz, F. (2024, August 11). *Citizen science for local government*. https://www.greengage-project.eu/academy/citizen-science-for-local-government/

Sauermann, H., & Franzoni, C. (2015). Crowd science user contribution patterns and their implications. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(3), 679–684. DOI: 10.1073/pnas.1408907112 PMID: 25561529

Seeber, J., & Seeber, G. U. H. (2005). Effects of land-use changes on humus forms on alpine pastureland (Central Alps, Tyrol). *Geoderma*, *124*(3–4), 215–222. DOI: 10.1016/j.geoderma.2004.05.002

Skarlatidou, A., & Haklay, M. (2021). Citizen science impact pathways for a positive contribution to public participation in science. *JCOM, Journal of Science Communication*, *20*(06), A02. DOI: 10.22323/2.20060202

Stanford University. (n.d.). *InVEST*. https://naturalcapitalproject.stanford.edu/software/invest

Stankiewicz, J., König, A., Pickar, K., & Weiss, S. (2023). How certain is good enough? Managing data quality and uncertainty in ordinal citizen science data sets for evidence-based policies on fresh water. *Citizen Science: Theory and Practice*, *8*(1), 39. DOI: 10.5334/cstp.592

Tarquini, S., Isola, I., Favalli, M., Battistini, A., & Dotta, G. (2023). *TINITALY, a digital elevation model of Italy with a 10 meters cell size (Version 1.1)*. Istituto Nazionale di Geofisica e Vulcanologia (INGV). https://doi.org/DOI: 10.13127/tinitaly/1.1Tasser

Tauginienė, L., Butkevičienė, E., Vohland, K., Heinisch, B., Daskolia, M., Suškevičs, M., Portela, M., Balázs, B., & Prūse, B. (2020). Citizen science in the social sciences and humanities: The power of interdisciplinarity. *Palgrave Communications*, *6*(1), 89. DOI: 10.1057/s41599-020-0471-y

Thornhill, I., Ho, J. G., Zhang, Y., Li, H., Ho, K. C., Miguel-Chinchilla, L., & Loiselle, S. A. (2017). Prioritising local action for water quality improvement using citizen science: A study across three major metropolitan areas of China. *The Science of the Total Environment*, *584–585*, 1268–1281. DOI: 10.1016/j.scitotenv.2017.01.200 PMID: 28190572

Ulloa, A., Godfrid, J., Damonte, G., Quiroga, C., & López, A. P. (2020). Monitoreos hídricos comunitarios: Conocimientos locales como defensa territorial y ambiental en Argentina, Perú y Colombia. *Íconos (Quito)*, *69*(69), 77–97. DOI: 10.17141/iconos.69.2021.4489

United Nations Environment Programme. (2021). *Progress on ambient water quality. Tracking SDG 6 series: Global Indicator 6.3.2 updates and acceleration needs*. https://www.unwater.org/sites/default/files/app/uploads/2021/09/SDG6_Indicator_Report_632_Progress-on-Ambient-Water-Quality_2021_EN.pdf

United Nations Environment Programme. (2024). *Progress on ambient water quality: Mid-term status of SDG Indicator 6.3.2 and acceleration needs, with a special focus on health.* https://www.unwater.org/sites/default/files/2024-08/SDG6_Indicator_Report_632_Progress-on-Ambient-Water-Quality_2024_EN.pdf

Vergari, F., Della Seta, M., Del Monte, M., Fredi, P., & Palmieri, E. L. (2013). Long- and short-term evolution of several Mediterranean denudation hot spots: The role of rainfall variations and human impact. *Geomorphology*, *183*, 14–27. DOI: 10.1016/j.geomorph.2012.08.002

Vohland, K., Land-Zandstra, A., Ceccaroni, L., Lemmens, R., Perelló, J., Ponti, M., Samson, R., & Wagenknecht, K. (Eds.). (2021). *The science of citizen science*. Springer., DOI: 10.1007/978-3-030-58278-4

Wade, A. J., Butterfield, D., & Whitehead, P. G. (2006). Towards an improved understanding of the nitrate dynamics in lowland, permeable river-systems: Applications of INCA-N. *Journal of Hydrology (Amsterdam)*, *330*(1–2), 185–203. DOI: 10.1016/j.jhydrol.2006.04.023

West, S., & Pateman, R. (2017). *How could citizen science support the Sustainable Development Goals?* Stockholm Environment Institute. https://www.sei.org/publications/citizen-science-sustainable-development-goals/

Westera, W. (2012). *The digital turn: How the internet transforms our existence*. AuthorHouse.

Win, T. T. N., Bogaard, T., & van de Giesen, N. (2019). A low-cost water quality monitoring system for the Ayeyarwady River in Myanmar using a participatory approach. *Water (Basel)*, *11*(10), 1984. DOI: 10.3390/w11101984

Zhang, X., Liu, X., Zhang, M., Dahlgren, R. A., & Eitzel, M. (2010). A review of vegetated buffers and a meta-analysis of their mitigation efficacy in reducing nonpoint source pollution. *Journal of Environmental Quality*, *39*(1), 76–84. DOI: 10.2134/jeq2008.0496 PMID: 20048295

Zhang, Y., Ma, R., Hu, M., Luo, J., Li, J., & Liang, Q. (2017). Combining citizen science and land use data to identify drivers of eutrophication in the Huangpu River system. *The Science of the Total Environment*, *584–585*, 651–664. DOI: 10.1016/j.scitotenv.2017.01.093 PMID: 28132775

ENDNOTES

1 Istat publishes data and metadata, with specific note, target by target, of the indicators used for each goal and indicator, and the geographical scale at which these are made available (or for which a proxy is provided).

2 "Good" indicates an ambient water quality that damages neither ecosystem functions nor humans. For the purpose of global reporting (level 1 of the indicator), overall water quality is estimated based on an index that incorporates data on five core parameter groups and informs on major water quality impairments present in many parts of the world: oxygen (surface water), salinity (surface water and groundwater), nitrogen (surface water and groundwater), phosphorus (surface water), and acidification (surface water and groundwater).

3 The recruitment of volunteers started in 2023 using different dissemination channels from both the university and the various project partners (municipalities, associations, etc.). Meetings for the public presentation of the project were held, as well as stakeholder-engagement activities such as forum discussions.

4 For the purposes of this article, we are therefore using data collected over the course of 11 months. Nevertheless, the sampling campaign continues, so it will also be possible to add new information to these analyses in future project years.

5 Scientists and volunteers visited the river and decided together which sites were most suitable for the data collection considering, for example, accessibility of the banks.

6 Field training sessions for the chemical water quality took place in Paganico (September 24, 2023), Buonconvento (March 7, 2024), and Grosseto (March 28, 2024). Participants received the sampling kits (Fig. 2), printed manuals, and all the information needed for the data collection.

7 PO_4–P concentrations were estimated colorimetrically using inosine enzymatic reactions in seven specific ranges from 0.02 mg L^{-1} to 1.0 mg L^{-1} PO_4–P (<0.02, 0.02–0.05, 0.05–0.1, 0.1–0.2, 0.2–0.5, 0.5–1.0, >1.0 mg L^{-1}). NO_3–N concentrations were estimated colorimetrically using N-(1-naphthyl)ethylenediamine in seven specific ranges from 0.2 mg L^{-1} to 10 mg L^{-1} NO_3–N (<0.2, 0.2–0.5, 0.5–1.0, 1.0–2.0, 2.0–5.0, 5–10, >10 mg L^{-1}).

8 The year 2019 was chosen because is the most recent year where complete data is available for the ORB and all its tributaries.

9 The years 2030 (B) and 2050 (C) were chosen due to the deadlines to achieve the SDGs and the Green New Deal targets. Moreover, the UN-IPCC forecast scenarios are also based on these years.

10 Representative Concentration Pathways 4.5 intermediate scenario.

11 Conversion of CLC Classes 211, 213, 231, 241, 242, 243, 324, 333, and 334 to Class 313, mixed forest.

12 In Italy, Standard 5.2, establishment of buffer strips along water courses (M.D. 27417, December 22, 2011) establishes that any strip of land, minimum 5 m wide, adjacent to all water courses (with some exceptions) where no farming is carried out, can be considered a buffer strip (Gumiero & Boz, 2017, p. 446).

APPENDIX

Supplementary Materials

The table shows, for each Land Use (LU) class (kg/ha/year), the biophysical properties related to nutrient load and retention. Nitrogen (N) and phosphorus (P) loading to land and retention coefficients were derived from existing literature, and data acquired from Italian National Institute of Statistics (ISTAT), and the Regional Environmental Agency (ARPAT).

The nutrient retention capacity is expressed as a proportion of the amount of nutrient from upslope. High values such as 0.6 to 0.8, are assigned to forests, and indicate that 60-80% of nutrients are retained. The critical length is the distance after which the LU class is assumed to retain nutrients at its maximum capacity.

Table 5. Basin nutrient dynamics were based on nutrient loads across the landscape and the nutrient retention capacity of the landscape

LU class code	Load N (kg/ha/ year)	Retention N	Critical length N	Load P (kg/ha/ year)	Retention P	Critical length P	Land use class description
111	164.43	0.6	100	24.48	0.7	100	Continuous urban fabric (IM.D. ≥ 80%)
112	164.43	0.6	100	24.48	0.7	100	Dense urban fabric (IM.D ≥ 30-80%)
1121	164.43	0.6	100	24.48	0.7	100	Low density fabric (IM.D ≤ 30%)
121	97.1	0.6	100	2.36	0.7	100	Industrial, commercial and military units
1211	164.43	0.6	100	2.36	0.7	100	Purifiers
1212	97.1	0.6	100	2.36	0.7	100	Photovoltaic plants
122	164.43	0.6	100	2.36	0.7	100	Railroad networks and technical infrastructure
1221	164.43	0.5	100	2.36	0.7	100	Roads in wooded areas
124	164.43	0.5	100	24.48	0.7	100	Airports
131	164.43	0.5	100	24.48	0.7	100	Mining areas
132	164.43	0.5	100	2.36	0.7	100	Dumps
133	164.43	0.5	100	2.36	0.7	100	Construction sites
141	164.43	0.5	100	2.36	0.7	100	Urban green areas
1411	164.43	0.5	100	2.36	0.7	100	Cemeteries
142	164.43	0.5	100	2.36	0.7	100	Recreational and sports areas
210	169.28	0.3	100	41.2	0.5	100	Irrigated and non-irrigated agriculture land
2101	169.28	0.4	100	41.2	0.5	100	Greenhouses
2102	169.28	0.4	100	41.2	0.5	100	Plant nurseries
213	169.28	0.4	100	41.2	0.5	100	Rice paddies
221	169.28	0.4	100	41.2	0.5	100	Vineyards
222	169.28	0.4	100	41.2	0.5	100	Orchards
2221	169.28	0.4	100	41.2	0.5	100	Arboriculture
223	169.28	0.4	30	41.2	0.5	30	Olive groves
231	169.28	0.4	30	41.2	0.5	30	Permanent grassland
241	169.28	0.4	30	41.2	0.5	30	Temporary crops combined with permanent crops
242	169.28	0.4	30	41.2	0.5	30	Complex cultivation patterns

continued on following page

Table 5. Continued

LU class code	Load N (kg/ha/ year)	Retention N	Critical length N	Load P (kg/ha/ year)	Retention P	Critical length P	Land use class description
244	169.28	0.4	30	41.2	0.5	30	Agroforestry areas
311	23.7	0.6	30	0.05	0.8	30	Broadleaved forests
312	23.7	0.6	30	0.05	0.8	30	Coniferous forests
313	23.7	0.6	30	0.05	0.8	30	Mixed coniferous and deciduous forests
321	46.37	0.8	30	0.05	0.8	30	Natural pastures and grasslands
322	46.37	0.8	30	2.32	0.8	30	Heaths and shrublands
323	46.37	0.8	30	2.32	0.8	30	Sclerophyll vegetation
331	46.37	0.5	100	2.32	0.5	100	Beaches, dunes and sands
332	46.37	0.5	100	2.32	0.5	100	Bare rocks and outcropping cliffs
333	46.37	0.5	30	2.32	0.5	30	Sparse vegetation
3331	46.37	0.5	30	2.32	0.5	30	Firebreaks
334	46.37	0.5	30	2.32	0.5	30	Damaged forest
411	0.48	0.2	100	0.02	0.2	100	Inland marshes
421	0.48	0.2	100	0.02	0.2	100	Salt marshes
511	0.48	0.2	100	0.02	0.2	100	Canals and watercourses
512	0.48	0.2	100	0.02	0.2	100	Water bodies
521	0.48	0.2	100	0.02	0.2	100	Lagoons
523	0.48	0.2	100	0.02	0.2	100	Sea

Venere Stefania Sanna is a Researcher in Economic Geography, currently working for the Department of Social, Political and Cognitive sciences (DISPOC) of the University of Siena. Dr Sanna has been involved in many national and international projects, and her research interests include regional economic development, European policies, sustainability issues, the sharing and collaborative economy, Citizen Science and community-driven participatory research, and quantitative and qualitative research techniques in geography. Her research method is based on a strongly interdisciplinary approach that incorporates policy and practice impacts, and her eclectic publication record reflects her diversity in fields of knowledge and study.

Francesco Di Grazia is a post-doc research fellow in the Department of Social Political and Cognitive Sciences (DISPOC) of the University of Siena. His research focuses on integrating information from multiple sources, remote sensing and citizen science, in new modeling and forecasting approaches to identify pollution sources and propose targeted mitigation and management strategies. His research interests cover citizen science and participatory monitoring, spatial analysis, remote sensing, freshwater ecology and quality, ecosystem services, environmental modelling, biogeochemistry, biodiversity, climate change and sustainability issues.

Cristina Capineri is Full Professor of Geography in the Department of Social, Political and Cognitive Sciences (DISPOC) of the University of Siena, where she teaches human and economic geography and directs the Ladest Lab. She co-founded the Vespucci Initiative for the Advancement of Geographic Information Science, and chaired the COST Action ENERGIC on crowdsourced data and Citizen Science (CS). Her research interests concern broadly transport and telecommunication networks, Giscience, Volunteered Geographic Information (VGI) and Citizen Science, local development and sustainable development, environmental indicators and landscape.

Alessio Polvani is a doctoral student in the Department of Biotechnology, Chemistry, and Pharmacy at the University of Siena. His research primarily focuses on Citizen Science monitoring projects related to freshwater quality. This includes the spatial and temporal analysis of species potentially harmful to water quality, as well as the development of low-cost sensors for future applications in community-based initiatives.