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Received: 18 January 2021 | Revised: 29 October 2021 | Accepted: 6 December 2021

DOI: 10.1002/eet.1975

RESEARCH ARTICLE

Environmental Policy and Governance | WILEY

How accurate is citizen science? Evaluating public assessments of coastal water quality

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Funding information
Koneen Säätiö, Grant/Award Number: 201800932; Nordenskiöld-samfundet; Otto A. Malm Lahjoitusrahasto; Societatis pro Fauna et Flora Fennica

Abstract

Citizen science is changing society's contribution to research projects worldwide. Non-experts are no longer just spectators, they are active participants and supporters of scientific work. Using citizen science, that is, data collected by laypeople, the opportunities to collect large-scale data on the environment are increasing. Such community-based and citizen scientific approaches can provide useful tools as local people can be trained to accurately take measurements that can be used in scientific studies. However, little is known about how well volunteer-based non-standard subjective assessments of the environment based on prior experience only and no training compare with scientifically measured estimates of that environment. In this paper, we tested how well measures of coastal water quality assessed by local inhabitants corresponds with objective water quality data collected using scientific instruments. Our results showed that over 70% of the respondents assessed water quality in the right direction and almost 60% were correct in their estimates. We found that socio-demographic factors affect the assessments, but do not markedly improve reliability. We conclude that simple questionnaires can be used to assess general coastal water quality.

KEYWORDS

Baltic Sea, citizen science, community science, environmental degradation, environmental democracy, eutrophication, procedural environmental rights

1 | INTRODUCTION

Citizen science, the 'active public involvement in scientific research' (Irwin, 2018) and collaboration across different disciplines, is becoming increasingly significant, particularly in the natural sciences. The increasing importance of citizen science has many merits. Citizen science builds bridges between society and academic research, and is becoming an important tool for data collection, which ultimately serves decision-making and policy-making (Hollow et al., 2015; Science Communication Unit, 2013; Stilgoe, 2009). From a societal perspective, citizen science raises awareness of society and involves the public in local issues that have significance for many people.

Citizen science can be seen as a tool for promoting environmental democracy (Conrad & Hilchey, 2011) by involving society in procedural environmental rights (PERs) (May & Daly, 2014). In order to realize environmental democracy, PERs aim to provide the right of access to information, participation, and justice in environmental-related issues. Although such rights may not always have a direct environmental impact (Gellers & Jeffords, 2018), PERs affect societal capital through generations. This influence is crucial in achieving

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environmental democracy in the long term. Citizen science could thus play a vital role to achieve this goal by addressing solutions for mitigating climate change and making climate policies more effective through democratic systems (Kythreotis et al., 2019). Yet, citizen science can also be used to increase a society's knowledge of natural resource management, sustainability, and environmental protection (Cooper et al., 2007; McKinley et al., 2017).

From the viewpoint of research, citizen science presents scholars with an exciting opportunity to collect a larger amount of data from a larger area using standardized methods (Havens et al., 2012; Lukyanenko et al., 2014). In particular, citizen science increases researchers' ability to collect data on a local scale (Newman et al., 2017). Moreover, the use of volunteers and activists for data collection can be a cost-effective method (NACEPT, 2016; Pocock et al., 2014) and can often explain why people are willing to contribute to a research project (Danielsen et al., 2005; O'Fallon & Dearry, 2002). This creates mutual benefits since scientists gain data from locals, and simultaneously society gains access to the scientists who can convey the information they deem important (Bonney et al., 2015; Carolan, 2006; Trumbull et al., 2000). For these reasons, citizen science is widely used in biodiversity studies (Danielsen et al., 2008; Pocock et al., 2017), where a large number of amateurs contribute to a project by reporting verifiable observations. The field of ornithology in particular, has a long history of citizen science approaches (Greenwood, 2007; Lehikoinen et al., 2020; Piha et al., 2019) including databases such as eBird, which produces highly credible models of species distributions and habitat use in bird species worldwide (Bonney et al., 2009; Coxen et al., 2017). In some projects, such as water monitoring programs, researchers often require volunteer training for data collection (Capdevila et al., 2020; Zhang et al., 2017) with the aim of ensuring data reliability (Toivanen et al., 2013).

Given both the societal and methodological advantages, it is no surprise that the use of citizen science in various fields of environmental science is rising (Bonney, 2021; Silvertown, 2009; Theobald et al., 2015). The methodology of collecting data in citizen science projects has a wide range of applications (de Sherbinin et al., 2021) and a common characteristic of involving people interested in the project's topic (West & Pateman, 2016). A question of fundamental importance in citizen science is whether we can trust the accuracy of information gathered. In a recent review, Danielsen et al. (2021) convincingly demonstrated that data collected by community members are highly comparable with data collected by trained scientists, independent of techniques used, environments monitored or purposes of the research. Their (Danielsen et al., 2021) conclusion was that accuracy and precision is high between community members and trained scientists.

While it is intuitive that a community member with an interest in the topic (e.g., a birdwatcher who collects data on bird observations) or with specific training prior to participation (e.g., in the use of a technical instrument) should be able to produce as accurate data as a scientist (Aceves-Bueno et al., 2017; Albus et al., 2020), it is less clear if simpler and more cost-efficient subjective or qualitative data are accurate enough to resemble data collected with high-technology instruments. This could be the case if the participants have no prior training, represent different backgrounds and education levels, and have no access to professional scientific equipment, but do have sufficient knowledge and experience to give a qualitative estimate of the environment in question. If such citizen-based information provides useful and accurate data that can be used as proxies in natural resource management, decision-making or large scale environmental monitoring, it will allow rapid and cost-effective data collection. It will also allow the inclusion of the whole society in the data collection process, which has been found to speed up conservation and management actions (Danielsen et al., 2007, 2010). However, when untrained participants are used to collect qualitative data of the environment on their own, the assessments might be affected by the participants' socioeconomic status and experience of the environment (Steinke et al., 2017). Psychological, ecological, social and political factors may affect the reliability of the data collected by volunteers. For instance, education and personal experience may affect the objectivity of the collected data, and preconceived opinions due to political background or social status may affect people's perception of environmental issues. These issues are normally addressed by increasing sample size (Dickinson et al., 2010) or effective training (Kosmala et al., 2016), but formal tests of the impact of such citizen-based environmental data collection are still rare.

Our aim in this paper is to test if non-experts who participate in research by reporting simple qualitative observations are able to provide a reliable assessment of the state of the water environment in their surroundings. Water quality is determined by chemical, physical and biological characteristics of and processes in waterbodies (Usali & Ismail, 2010). Here, we focus on visually identifiable qualities that reflect the ecological status of the target environment in a comprehensive manner, both directly and indirectly. Chlorophyll-*a* (Chl-*a*), fluorescent dissolved organic matter (fDOM) and turbidity belong to the most elemental variables for assessing water quality based on observations from surface waters (Zolfaghari et al., 2020). We utilize a unique research design that matches precise measurement of water quality from a number of specific locations, with citizen assessments of water quality in the same locations. By associating subjective citizen science-based perceptions of water quality in the local environment with simultaneously measured objective water quality data, we hypothesize that (1) people are able to assess water quality in their local environment, (2) the accuracy of the assessments is affected by education, experience and emotional aspects related to the environment and property.

2 | METHODS

2.1 | Study area

The study area, Raseborg, is located along the southwest coast of Finland (Figure 1). In terms of water quality, the area is particularly significant due to the 6400 summer cottages that are located in the municipality. The municipality has a population of almost 28,000 inhabitants. This increases significantly in the summer due to the presence of vacationers (up to 50%). In Raseborg, the population is distributed due to the administrative features of the municipality. The municipality of Raseborg was created in 2009 by merging different

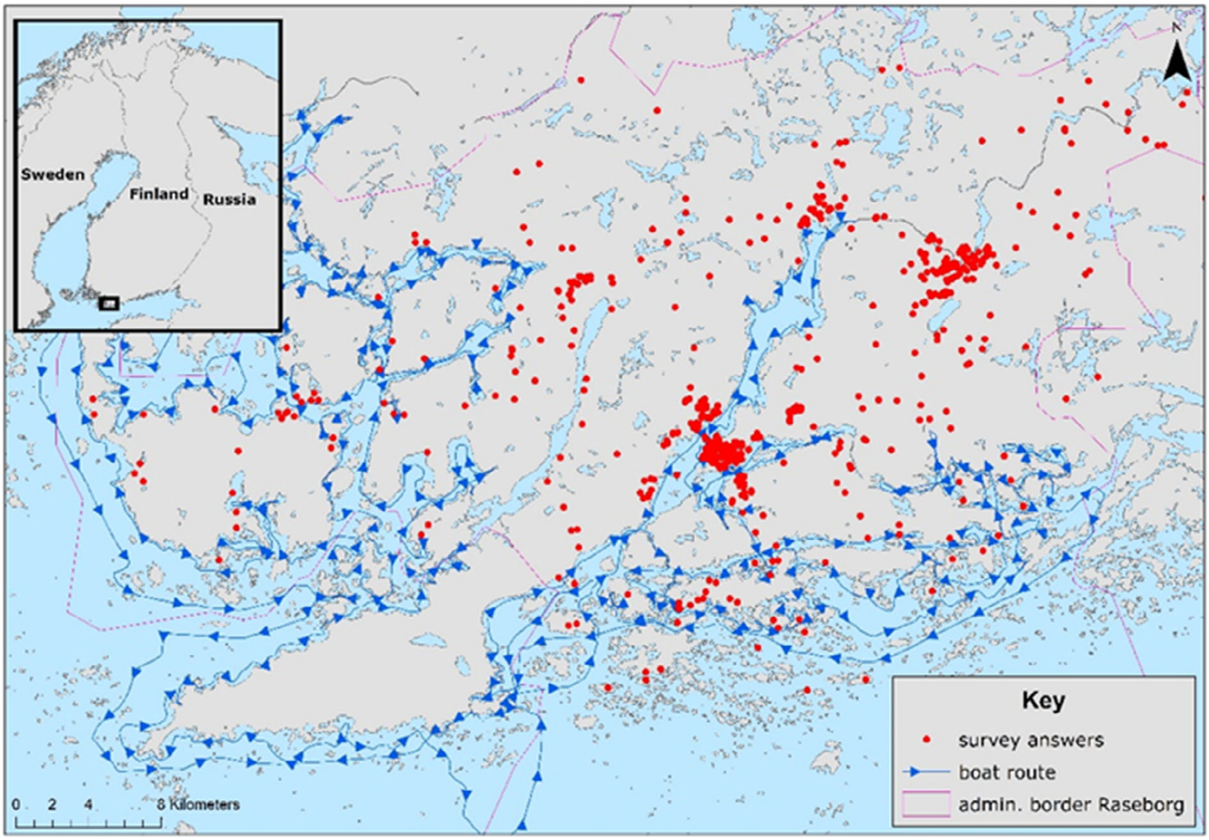

FIGURE 1 Study area with mapped data collection hotspots: subjective (survey answers) and objective environmental data (boat route) [Color figure can be viewed at wileyonlinelibrary.com]

municipalities. Thus, it has urban areas with a higher population density and administrative centers (Ekenäs, Karis and, Pojo), and areas closer to nature with small villages and houses far apart from each other.

2.2 | Objective water quality data

Spatially detailed and extensive in situ data on surface water salinity, Chl-*a*, fDOM and turbidity were collected by an automated underway measurement system equipped with optical sensors along a coastal transect of approximately 300 nautical miles (550 km) covering the Raseborg archipelago. Data were collected during four consecutive days in mid-October 2019. The system was installed in a rigid inflatable boat (Brig N610H) with 0.4 m draft and water intake at 0.5 m depth, enabling the system to operate even in very shallow environments. Data were constantly recorded together with geospatial referencing information at 5 s intervals by an EXO2 multiparameter sonde and an associated Handheld Unit (Xylem Inc.). As the typical traveling speed of the boat was 22.3 knots (12 m/s), the vast majority of the data were logged at 60 m intervals, resulting in a total of 14,484 observations. Data collection, calibration and handling are described in detail in Scheinin and Asmala (2020).

In coastal waters, visually identifiable variables used in our study Chl-*a*, fDOM and turbidity are strongly correlated with surface water salinity through the level of freshwater input and the degree of mixing with saline seawater (Asmala et al., 2014) Chl-*a* is a central photosynthetic pigment found in plants, algae and cyanobacteria. Chl-*a* causes water to appear green, since the pigment mainly absorbs energy from violet-blue and orange-red light. As a proxy for phytoplankton biomass, Chl-*a* concentration is the prime indicator for eutrophication, and thus, for nutrient (N and P) pollution (Carlson, 1977). Dissolved organic matter consists of naturally occurring, water-soluble, biogenic, heterogeneous organic substances that vary in color from yellow to brown (Aiken et al., 1985). In addition to reflecting the level of organic matter loading, fDOM is a surrogate parameter for dissolved organic carbon, an important driver of ecosystem function (Niu et al., 2014). Unlike Chl-*a* and fDOM, turbidity scatters rather than absorbs light, thus mainly affects water clarity rather than its color. As the level of turbidity completely depends on the quantity of suspended particles in the water, turbidity is a direct measure of particle loading. Additionally, turbidity is strongly associated with particle-bound nutrients and carbon in coastal waters (Myint & Walker, 2002). In addition to being visible, water quality indicators which can be associated with vision-based subjective water quality assessment, (Chl-*a*, fDOM and turbidity), are involved, through multiple biogeochemical processes, in several topical and concrete concerns (e.g., eutrophication, acidification, reduction of the photic zone, oxygen depletion and increased sedimentation). These processes influence the living conditions of all aquatic organisms in the coastal zone (Gholizadeh et al., 2016).

Since salinity relates the observations on the target variables to the physical characteristics of the environment, we corrected each variable in the statistical analysis using salinity. By using salinity as a constant control variable, the natural tendency for a negative correlation between the target variables and salinity could be taken into account.

2.3 | Subjective water quality data

We collected subjective water quality data by surveying people who live and/or own property in Raseborg. The data were collected in two rounds, the first in October–December 2018 and the second in July–September 2019. The survey had 16 questions, including items asking people to assess water quality and the state of the environment in the vicinity of their property or home. In the questionnaire, people were also asked to evaluate the importance of this location for them personally and how emotionally attached they felt to the location (or property). The answers were given on a scale ranging between 0 and 10, where 0 means bad/not important and 10 means good/very important. Simultaneously, we collected data on socio-demographic parameters, such as age, gender, education level, level of income, health situation, how long they had lived in/owned the property, type of property and what type of relationship they had with it (owning or renting). The full questionnaire is available in Appendix. Each respondent had to give a reference point (an address) for the location, which he/she referred to, in the survey when assessing water quality. Surveys were delivered in three languages, Swedish, Finnish, and English. We recruited respondents by approaching them with the questionnaire in paper format during recreational events in the municipality. We also offered the option to fill out the form online. We advertised the online questionnaire via mass media (local newspaper), and an invitation to participate in the survey was sent by post across the municipality. We also used Facebook advertising. To maximize the number of answers, the respondents were told that they would be entered in a lottery with a small monetary prize. In total, we received 859 answers (706 in Swedish, 129 in Finnish and 24 in English). All answers were sorted and unclear responses (e.g., incomplete surveys, missing address data, age of respondent under 16, etc.) were excluded. We had 779 answers available for the analysis.

We corrected the data for age and gender by applying a post-survey weight based on the population age structure in Raseborg (OSF, 2020) using the formula

$$\omega_{\mathrm{i}} = \frac{NK_i}{n_i},$$

where N is the number of respondents, K_i is desired distribution in the age group and n_i is the number of respondents from the following age-gender group. In this way, we corrected the data and made them representative of the population structure.

2.4 | Data preparation and statistical analyses

We used ArcGIS 10.5 (ESRI, 2017) to convert water quality data into rasters using the interpolation tool Geostatistical Analyst (Diffusion Kernel method with the land as a barrier). We split the study area into watersheds using a 10 m Digital Elevation Model (NLS, 2016). We created a 100 m offshore buffer for each watershed and calculated the mean value of water quality parameters for the corresponding watershed. Thus, each watershed had a water quality measure package (Chl-*a*, fDOM, turbidity and salinity measures). All survey answers were coupled with a corresponding watershed (in total 79 watersheds) and with the water quality parameters using the address information from the surveys.

To get simple accuracy estimates, we calculated the extracted residuals from a linear regression of the relationship between fDOM and salinity (objective water quality) and gave them group values (0–10) so they could be compared with survey assessments (subjective water quality). Both values (regrouped residuals and subjective water quality) were compared by simple subtraction, and proportion of values 0 (exact evaluation) and 2, 1, -2, -1 (close to exact values) defined as the accuracy score. We chose to include values ±2 units to the accuracy score due to the size of the ranking system. Additionally, we calculated a direction accuracy score by dividing regrouped residuals and subjective water quality into two categories each: lower mid-ranking value (from 0 to 5) and higher mid-ranking value (from 6 to 10) with given values 0 and 1, respectively. Next, regrouped values were summarized and judged using the following approach: values 0 and 2 represent the right direction (people assessed water quality as close to the reality by giving lower estimates of objective water quality below the mid value, and higher estimates of water quality above the mid value) and 1, the false direction. The proportion of right direction values was defined as the direction accuracy score.

We then used linear mixed models with normal errors to test whether objective water quality estimates (corrected for salinity) can predict the subjective water quality estimated by the respondents. Watershed was entered as a random effect since several survey answers could be related to the same watershed and each survey answer was thus not independent. The subjective water quality represented respondents' water quality assessment in the survey. To estimate the objective water quality, we used chlorophyll-*a*, fDOM and turbidity. Salinity was always entered as a covariate as it correlates naturally with the objective water quality variables. We proceeded stepwise, adding variables related to the respondent's relationship with the property (living/owning period, rent/own property, resident housing/secondary housing, and level of emotional attachment to the property), as well as their level of education, gender and age. We also tested the effect of distance to the sea on the accuracy of assessment. Additionally, we tested a backward stepwise approach and verified our final model. We used $\alpha = 0.05$ for significance testing with F-tests in the stepwise modeling approaches. All models were run in R statistical software v.3.6.1. (R Core Team, 2014).

3 | RESULTS

According to the direction accuracy score, the large majority of assessments (72.4%) corresponded very well with the measured water quality. However, an independent look at each answer in comparison to the objective water quality showed that 59.1% of respondents were correct within a two-point deviation in either direction in their estimates. The latter, a more stringent estimation, nevertheless demonstrates a reasonably high level of accuracy.

We tested the association between subjective water quality estimate and three different measures of objective water quality corrected for salinity using linear mixed models. The respondents' assessments were not associated with chlorophyll-*a* (Chl-*a*: $F = 0.523$, df $= 29.987$, $p = 0.475$, salinity: F $= 1.226$, df $= 18.983$, $p = 0.282$) nor turbidity (F $= 1.002$, df $= 20.173$, $p = 0.329$, salinity: F $= 2.223$, df $= 29.212$, $p = 0.147$)). On the contrary, the linear mixed model with fDOM as the explanatory variable showed a strong negative relationship ($b = -0.06 \pm 0.03$, $F = 4.159$, df $= 43.887$, $p < .05$, salinity: $F = 1.838$, df $= 30.568$, $p = .185$; Figure 2).

By adding additional parameters to our model in a stepwise forward modeling approach (Crawley, 2005), we tried to improve the assessment with the respondents' local expertise and related factors. We did not find any effect on the assessment related to the respondent's distance to seawater (distance: $F = 0.025$, df $= 51.585$, $p = 0.874$). Similarly, the period of living in/owning the property (period of living: $F = 2.038$, df $= 750.99$, $p = 0.154$) and whether the property was rented or owned (rent/own: $F = 1.589$, df $= 749.69$, $p = 0.205$) did not have an effect on the assessment accuracy. The factor indicating property type tended to have a weak but non-significant effect on the respondent's assessment (type of property: $F = 2.455$, df $= 568.85$, $p = .087$). Thus, we did not include these parameters in our final model. On the other hand, the level of education had a strong effect on water quality assessment; people with higher education showed a tendency to underestimate water quality (Table 1: education). We found no interaction between education and objective water quality, which suggests that subjective water quality was not differently assessed by respondents representing different levels of education (fDOM by education: F $= 0.303$, df $= 746.947$, $p = 0.582$). We found a strong effect of emotional attachment to the place on water quality assessment; people who were more attached to the property overestimated the water quality (Table 1: emotional attachment). However, emotional attachment did not have a different effect depending on the objective water quality (fDOM by emotional attachment: F $= 0.185$, df $= 745.59$, $p = 0.667$). We found that males gave higher scores than females in their evaluation (Table 1: gender). At the same time, there was no interaction between gender and objective water quality, which indicated that neither gender was more accurate than the other in their assessment, but that the evaluation differed between them. Nevertheless, emotional attachment affected the assessment of males; the more emotionally attached they were, the more they underestimated water quality (Table 1: gender by emotional attachment). The age of the respondent had no effect on their assessment (age: $F = 1.006$, df $= 746.478$, $p = 0.316$). The random effect (respondents belonging to watersheds) and fixed factors explained 48.3% ($R^2_{conditional}$) of the variance in the model, while fixed factors separately explained 45.1% of the variance ($R^2_{marginal}$). The fixed factors of the final model are summarized in Table 1.

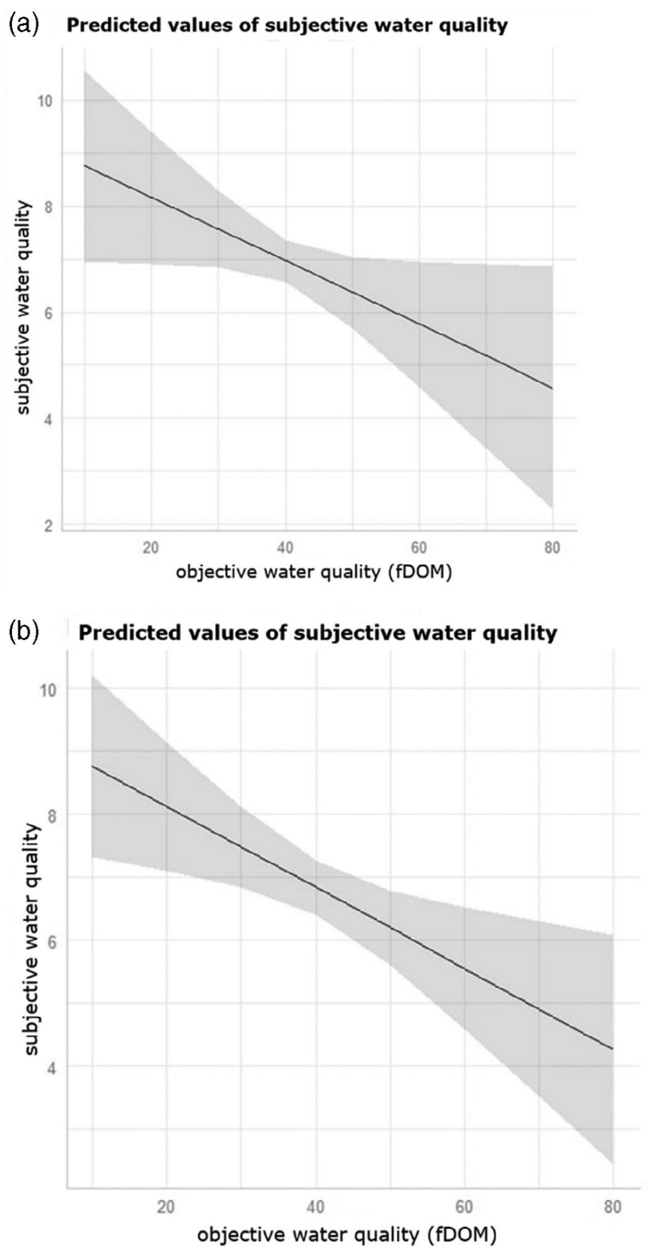

FIGURE 2 The relationship between water qualities assessed by the respondents and objectively assessed water quality (corrected for salinity). The slopes are derived from linear mixed models (see material and methods for model structure). In (a) the model includes no covariates relating to the respondents and in (b) the model takes into account emotional attachment, gender and education of the respondents (see Table 1 for statistics)

Variable	Estimate ± SE	df	*F*	*p*
fDOM	−0.065 ± 0.023	34.414	7.991	<.01
Salinity	−0.700 ± 0.213	26.209	10.77	<.01
Level of education	−0.591 ± 0.196	745.756	−2.644	<.01
Emotional attachment	0.688 ± 0.036	747.756	455.243	<.001
Gender	3.406 ± 0.445	739.653	58.632	<.001
G by E.A.	−0.276 ± 0.051	746.529	30.852	<.001

TABLE 1 Final linear mixed model of the relationship between subjective and objective water quality. In the model: level of education presented by two groups (1—lower education level, 2—higher education level) and gender presented by two groups (1—females, 2—males). G by E.A. refers to the interaction 'gender by emotional attachment'

4 | DISCUSSION

Citizen science, that is, the involvement of the public in scientific research, and particularly the use of volunteers to collect data about the environment, is becoming an important tool for decision-making and data collection for scientific studies (Hecker et al., 2018). Citizen science enables large amounts of data to be collected from large areas using standardized methods. Nevertheless, in many cases, the reliability of using citizen science data collected by untrained people with a varying range of motivation and interest in the subject has been questioned and more research is needed to critically address this caveat. The objective of our study was to investigate whether ordinary citizens are able to provide assessments that can be reliably used in environmental research. Our empirical focus was water quality. In the analysis, we measured whether the perceptions of water quality among ordinary citizens is reliable, and if it is affected by individual-level factors such as gender, emotions or education level.

Our results confirmed our expectations by showing that citizen science can be a reliable source for researchers. The respondents gave lower water quality scores in places where the objectively measured water quality (as indicated by fDOM) was poor, and they gave higher scores where water quality was higher. Moreover, 72% of respondents provided a water quality assessment, which was at least 'in the ballpark', and approximately 60% were within ±2 scale points from the correct estimation. This indicates that the majority of the respondents were able to provide good assessments of water quality. It is important to bear in mind that the non-experts who we surveyed were not in any way prepared for the task. They were asked to fill out the survey and provide an accuracy score without prior warning or training. Consequently, we consider our analysis as a rather rigorous test on the accuracy of citizen science and speculate that accuracy might be considerably higher with some training and preparation.

We further tested whether accuracy was affected by emotional and socio-demographic factors. We found that including the respondent's emotional attachment to the site, education level and gender helped to explain variation in the assessments (Figure 2). Interestingly, these covariates did not explain much of the variation in accuracy of assessing water quality (no interaction effects) among respondents. Therefore, our findings suggest that the accuracy of citizen science does not necessarily depend on the socio-demographic profile of the participants and therefore we conclude that simple questionnaires can be used to assess the general water quality in coastal areas. One notable exception was that people with a higher education underestimated water quality. Potentially, this could be due to informed awareness and knowledge about environmental problems. Thus, people with university and polytechnic university degrees could be more concerned about the state of the environment, which could lead to a tendency to give lower quality values.

Although we did not have access to a random sample of the population in Raseborg, we feel confident that our sample provides a reasonably reliable picture. Self-selection is a potential caveat for any survey, because responding is always voluntary. This is potentially an even greater concern when sampling is not genuinely random. Since respondent motivation varies across time and context, for example, people are interested to spend more time in nature (O'Brien et al., 2011), have unique experience (Pegg et al., 2012) or have personal, social and community motivations (Asah & Blahna, 2013), it would be useful to know exactly what leads an individual to agree to contribute to citizen science. This could further advance our understanding of how to increase the sample size for citizen science projects and indicate what leads people to opt in or out. For future research, we suggest including an open-answer question about respondent motivation to participate in citizen science projects that utilize surveys. Moreover, asking respondents to self-assess their ability, for example, to evaluate water quality, could shed further light on the quality of data in citizen science projects. In general, do people feel confident about their evaluations or the measurements they contribute, or do they feel unsure?

In terms of sample size, some studies suggest that an increase in sample size improves the reliability of the data (Brown & Williams, 2018; Crall et al., 2020; Stelle, 2017). The sample used for the analysis in our research is equal to 2.8% of the population in Raseborg and in terms of key demographic variables, it corresponds well with the entire population. However, despite sufficient socio-demographic representation, it is difficult to assess how representative the sample is in terms of knowledge about water quality and environmental issues, that is, competence to evaluate water quality. It is possible, at least in theory, that competence in water quality assessment is unrelated to socio-demographic factors, in which case there is a risk that our sample does not capture all relevant individual-level variation. However, we consider this risk to be relatively small.

We found an effect of emotional attachment to the site/property on the water quality assessment. Overestimation of water quality among people who are highly emotionally attached to a specific location can be explained by a cautious and possibly critical approach caused by the desire to see their favorite place in a better condition. Our findings support the conclusion of Gosling and Williams (2010) that emotionally attached people have a higher level of environmental concern. Intriguingly, we did not find any relationship between emotional attachment to the property and renting or owning this property, the type of property (resident, summerhouse or other facility), or the period the person has lived in/owned the property. Our results, therefore, do not follow the theory of the 'Concorde fallacy' (Arkes & Ayton, 1999) where people are thought to defend their investment (property) by rating its environmental quality higher. Instead, it suggests that people are truly attached to the properties without prior financial investments and that they are led by real emotions. Kelly and Hosking (2008) found similar patterns with low importance of the temporal living (rent/own) for how attached people were to their home. However, many studies indicate that attachment depends on how long the person has lived there (Corcoran, 2002; Gustafson, 2001; Wiles et al., 2009), which is contrary to our findings above. Finally, our results demonstrated a gender difference in evaluations. Our findings indicate a more critical approach in evaluation by females, as they gave consistently lower values in water quality assessment. This supports previous studies, where researchers concluded that females are more concerned about the environment than males (McStay & Dunlap, 1983; Sundström & McCright, 2014). Nevertheless, it does not mean that one gender is better than the other in evaluation, it merely suggests that males tend to give higher scores than females.

Despite the visible benefit of using citizen science in data collection, one of the outcomes of this method is the democratization of science and the empowerment of society (Strasser & Haklay, 2018). The support in the usage of the procedural environmental rights and delegating more power to the community enforce the decision-makers to listen to people (Gellers & Jeffords, 2018; Mason, 2010). Involving citizens in the research project strengthens PERs on a local level and increases the role of environmental democracy (Conrad & Hilchey, 2011; Eitzel et al., 2017). However, the use of citizen science as a democratic instrument for environmental decisions requires reforming of the environmental governance and a new innovative view from the local actors (Ferrari et al., 2021). We believe that our findings about the accuracy of citizen science can be used to support an acceleration of these processes. The hallmark of our research is a provision of access to the environmental judgment for people without the prior training or stimulation of motivation to participate. Thus, we are convinced that our approach can promote the development of environmental democracy on a local level (see also Conrad & Hilchey, 2011; Strasser & Haklay, 2018).

Overall, our findings offer encouragement to researchers who are involved in citizen science. In our assessment, at least in terms of accuracy, citizen science can be applied to various assessments of biodiversity or the state of the environment in general. Surveying the general public about the environment seems to result in data that are reasonably accurate, at least for preliminary or general assessments of the environment. People are able to indicate 'environmental hotspots' in their local municipalities and aid scientists in identifying areas of particular interest, either good or bad. However, citizen science will not become a substitute for professional researchers. In terms of accuracy, expert measurement will, of course, always remain more accurate and thus of higher quality for the purposes of scientific research. However, citizen science will raise awareness of environmental problems and build bridges between science, society, and policymakers. Based on the findings presented here, the quality of data gathered through citizen science is high enough to be useful for research.

5 | CONCLUSIONS

Our findings suggest that involvement of citizens in data collection does not necessarily require prior training or motivation from the participants. Our findings support previous documentation of the accuracy of citizen science (Bonney, 2021; Danielsen et al., 2008; Pocock et al., 2017) and demonstrate that data collected about water quality without complicated tools has a high level of accuracy and can be used, for example, in environmental management on a local level. This approach can be an effective measure for the preliminary assessment and identification of "hot spots" that require additional attention from professional scientists. Therefore, the active involvement of people in environmental governance through citizen science has a true potential to raise environmental democracy and empower the role of the community in evidence-based decision-making.

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How to cite this article: Gunko, R., Rapeli, L., Scheinin, M., Vuorisalo, T., & Karell, P. (2022). How accurate is citizen science? Evaluating public assessments of coastal water quality. *Environmental Policy and Governance*, 1–9. https://doi.org/10.1002/eet.1975