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# Analysing the value of environmental citizen-generated data: Complementarity and cost per observation

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ABSTRACT

The proliferation of Citizen Science initiatives has increased the expectations of practitioners who need data for design, analysis, management and research in environmental applications. Many Citizen Science experiences have reported tangible societal benefits related to improved governance of natural resources due to the involvement of citizens and communities. However, from the perspective of data generation, most of the literature on Citizen Science tends to regard it as a *potentially* cost-effective source of data, with major concerns about the quality of data. The Ground Truth 2.0 project brought the opportunity to examine the scope of this potential by analysing the value of citizen-generated data. We propose a methodology to account for the value of citizen observations as a function of their complementarity to existing environmental observations and the evolution of their costs in time. The application of the proposed methodology in the chosen case studies that were all established using a co-design approach shows that the cost of obtaining Citizen Science data is not as low as frequently stated in literature. This is because the costs associated with co-design events for creating a Citizen Science community, as well as the functional and technical design of the tools, are much higher than the costs of rolling out the actual observation campaigns. In none of the considered cases did an increment in the number of preparatory events translate into an immediate increase in the collected observations. Nevertheless, Citizen Science appears to have the greatest value in places where in-situ environmental monitoring is not implemented.

## 1. Introduction

Although Citizen Science is a difficult concept to define because of the variety of actors, activities and goals it can describe (Eitzel et al., 2017), it generally refers to the involvement of members of the public in some aspect of scientific research. This implies the presence of activities such as data collection, interpretation, analysis and communication. From this perspective, a long history of citizens contributing to observation and knowledge generation in ecology and astronomy can be recognised. In the last 15 years, a number of initiatives in other fields, such as health (Wiggins and Wilbanks, 2019), mapping (Ellul et al., 2013), hydrology (Jonoski et al., 2012; Alfonso et al., 2015; Davids et al., 2019), flood modelling (Alfonso et al., 2010; Mazzoleni et al., 2017; Assumpção et al., 2018), air quality (Beven and Alcock, 2012; Ripoll et al., 2019), water quality (Farnham et al., 2017; Jollymore et al., 2017), education (Newman, 2010), natural history (Everett and Geoghegan, 2016; Turnhout et al., 2016; Ballard et al., 2017; Sforzi et al., 2018) among others, have proliferated. A possible reason for this proliferation of Citizen Science projects is the rapid diffusion of smartphone technologies in society (Tipaldo and Allamano, 2017), which have even been considered as "essential" for Citizen Science projects (Davids et al., 2019).

Many Citizen Science experiences have reported tangible societal benefits, related to the understanding and improvement of governance of natural resources (McGreavy et al., 2016), flood management (Wehn et al., 2015), environmental advocacy (Johnson et al., 2014), policy influence (Couvet et al., 2008; Crabbe, 2012; Kennedy, 2016; Guerrini et al., 2018; Hecker et al., 2018; Nascimento et al., 2018) and behaviour and stewardship (Alender, 2016; Larson et al., 2016; Chase and Levine, 2018). Some have recurrently pointed out concerns on the quality of data generated by citizens (Sheppard and Terveen, 2011; Lukyanenko, 2014; Lukyanenko et al. 2016, 2019; Budde et al., 2017), on ways to assess it (Crall et al., 2011; Wiggins et al., 2011; Groom et al., 2017), while others concentrate on challenges related to motivation and barriers (Deutsch and Ruiz-Córdova, 2015; Gharesifard and Wehn, 2016; Gharesifard et al., 2017; Wehn and Almomani, 2019). These positive experiences, combined with the fact that sensing technology is at the

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**List of abbreviations**

| | |
|---|---|
| CDR | Cost of Data Record |
| CGD | Citizen Generated Data |
| CSI | Citizen Science Initiative |
| GT2.0 | Ground Truth 2.0 |
| SC | Spatial Complementarity |
| TC | Temporal Complementarity |

same time more powerful and more accessible (Baker, 2016; Castell et al., 2017), have stimulated scientists and practitioners in need of data to start formulating Citizen Science projects to fill this gap, presuming convenient time savings and budget benefits. In many cases, however, new initiatives diverge from the ideal of "treating citizens as scientists" to the opportunistic "use of citizens by scientists" (Lakshminarayanan, 2007).

From the perspective of data generation, recent literature on Citizen Science, particularly from the geosciences community, tends to conclude that Citizen Science is a *potentially* cost-effective data source. For example, Yang and Ng (2017) conclude that crowdsourcing –a special case of Citizen Science of rainfall data has "the potential to outperform traditional rain gauge data", and Yang et al. (2019, p3) states that it has the "ability to provide high spatio-temporal resolution data efficiently and economically"; Stehman et al. (2018, p47) report that Volunteered Geographic Information (VGI) – a type of location-specific crowdsourcing, is a "potentially inexpensive source of reference data" for land-cover monitoring; Starkey et al. (2017p816) conclude it has the "potential to add spatial detail" for catchment studies; Lisjak et al. (2017, p17) claim that the involvement of citizens "provides an opportunity for closing data gaps", although their case do not fully demonstrate this; Assumpção et al. (2018) conclude that crowdsourcing is a viable option to address data scarcity in flood modelling. Walker (2016) states that community-based monitoring programmes to fill data gaps has a "clear" potential and Fraisl et al. (2020) even substantiate this claim for monitoring progress of the Sustainable Development Goals. Finally, the comprehensive review of Citizen Science in hydrological monitoring provided by Njue et al. (2019) concludes that Citizen Science has a good potential to collect reliable, timely and long-term hydrological data.

A minor proportion of studies have assessed costs and benefits of Citizen Science, and they widely differ in methodology. For example, Thornhill et al. (2016) estimated the time invested by a team of two researchers in engaging and training citizens (including a training day in the field and follow-up online sessions), analysing the FreshWater Watch platform. They related it to the amount of collected data and the time saved in sampling and measurement, and concluded that 1 h of invested time by the team in training, engagement and feedback activities was equivalent to 6 h of sampling time by citizen scientists. They also report a global average of "3.4 participants per dataset". Although their definition of dataset is not clear, the effort to relate the amount of collected data and the amount of people involved is valid. Davids et al. (2019) suggested to evaluate the cost effectiveness of Citizen Science by relating cost and participant performance for hydrometric observations and found that, for the economic context of Nepal, the average cost per observation for all citizen scientists ranged from 0.07 to 14.68 USD and that this ranged changed from 0.30 to 11.99 USD when citizen scientists were paid. Blaney et al. (2016) suggested a method for estimating cost benefits of Citizen Science, classifying them as data-related costs, staff costs and other costs. Data related costs include data validation and verification, costs of IT systems for data collection and reporting, and costs of missing data due to the inability of citizens scientists to provide an observation; staff costs include the project planning, administration and support and related office costs, and induction and training; finally, other costs include advertising and recruitment, insurance, supplies and equipment (safety, mobile phones, kits), and travel expenses and out-of-pocket expenses. In terms of benefits, the method –which is much less detailed than the costs–, broadly classifies them as scientific benefits, public engagement benefits and participant's improved capacity benefits. Scientific benefits include size and quality of science databases, number of graduate theses and number of peer reviewed journal papers built with the collected data; public engagement benefits include aspects such as number of visits to the Citizen Science project website and number of volunteers, and the individual capacity benefit is measured by looking at aspects such as improved understanding of environmental science and better attitudes toward the environment.

A number of studies suggest comparing Citizen Science data and in-situ data to arrive at a cost benefit analysis. Goldstein et al. (2014) compared the presence of squirrels reported by Citizen Science and by traditional field measurements and they claimed that, although the Citizen Science approach was more expensive, overall it was more cost-effective than the traditional method. Hadj-Hammou et al. (2017) suggested to consider complementarity in space and time to evaluate the extent to which Citizen Science contributions were filling the gaps of water quality measurements done by government agencies in the Thames river basin. From the spatial perspective, Hadj-Hammou et al. (2017) found redundancy of Citizen Science data sites with agency data sites, which can be regarded as both convenient (for validation purposes) and undesirable (unnecessary duplication of efforts). Ferri et al. (2020) proposed a cost-benefit analysis of a Citizen Science initiative in the Brenta-Bacchiglione catchment related to the reduction of flood risk. Although their proposal to analyse cost-benefit based on the changes in social vulnerability before and after the implementation of a Citizen Science activity is valid, their work does not fully describe the role of citizens or the characteristic of the activity. Previous efforts in the same catchment demonstrated the possibilities of Citizen Science to improve the hydrological model (Mazzoleni et al., 2015).

The Ground Truth 2.0 project (GT2.0) presented the opportunity to analyse the scope of this potential by analysing Citizen Science data contributions in a range of demonstration cases. The aim of this 3-year EU project funded under the Horizon 2020 program was to set up and validate six citizen observatories in real conditions in Europe and Africa, and to demonstrate that citizen observatories are technologically feasible, sustainable, and that they provide benefits for society, environment, economy, and governance processes.[1]

We analyse these cases from the perspective of setting up Citizen Science initiatives with the primary intention of data collection for science and other applications.

In view of the known challenges with engaging citizens (and other stakeholders) in the short and especially in the long run in Citizen Science, citizen observatories and similar community-based monitoring schemes, the GT2.0 project aimed to demonstrate that sustainable citizen observatories are possible via a balanced socio-technical approach. GT2.0 defined citizen observatories to consist of: i) specific types of stakeholders (citizens, scientists, decision makers), forming a community; ii) a platform and tools for data collection, data processing and user feedback and collaboration; and iii) joint citizen observatories planning activities and data collection, and links to relevant policy and decision making processes (Wehn et al., 2020). To help set up sustainable citizen observatories in six countries (four in Europe, two in Africa), the project developed a co-design methodology that carefully combines the social, technological and operational dimensions of citizen observatories in a coherent process. The co-design methodology guided a structured process: a generic sequence of steps with room for iterations and structured interaction moments with relevant stakeholders, facilitating a community building process. By the end of the project (December 2019), the project delivered six citizen observatories coherent with the citizen

[1] For more information about GT2.0 visit https://gt20.eu.

observatories concept. In this paper, four of them are analysed in detail, namely those that had data collection as the key focus of their initiatives (the other two prioritising different stakeholder interactions), which are described below.

The Belgian case, Meet Mee Mechelen ('Measure with us' in English), focuses on the two issues of air pollution and noise disturbance in the city of Mechelen. In this initiative, local stakeholders (including citizens, civil society organisations, scientists, the City of Mechelen and Flemish department of Environment) collaborate to monitor and improve environmental quality of life in all neighbourhoods of Mechelen.

The Swedish case, 'VattenFokus' (Focus on Water, in English), emphasised on the issue of water quality management in the Mälarendalen region, including Stockholm. Due to current lifestyle choices and consumption patterns, its water bodies are facing deterioration of water quality. The initiative aimed to contribute to water quality management in the region by collecting and testing water samples from lakes and streams. This is done through collaboration of local citizens, researchers and municipal as well as county council employees.

The Kenyan case, the Maasai Mara Citizen Observatory (MMCO), aimed to establish a multi-stakeholder platform for generating and sharing data and information for improving sustainable livelihoods and biodiversity management in the Mara ecosystem. The main categories of stakeholders involved in MMCO include local citizens, organized citizen groups, NGOs, scientists, as well as county and national level government organisations.

Finally, the Spanish case, RitmeNatura.cat (Follow the Rhythm of Nature), focuses on understanding phenological changes as a proxy of monitoring climate change in Catalonia. This is done through observations of changes in different species throughout the year. The main stakeholders involved include nature enthusiasts (including existing Citizen Scientists in Natusfera), nature associations, NGOs, scientists of CREAF and Meteorological Service of Catalonia' (Meteocat), as well as government organisations.

As terms such as observation, Citizen Science initiative, citizen-data, value of an observation, and complementarity may have different meanings depending on the area of research, in the remaining of the paper we understand them as follows. From ISO19156 Observations and Measurements, an observation is "… *an act associated with a discrete time instant or period through which a number, term or other symbol is assigned to a phenomenon. It involves application of a specified procedure, such as a sensor, instrument, algorithm or process chain. The procedure may be applied in-situ, remotely, or ex-situ with respect to the sampling location. The result of an observation is an estimate of the value of a property of some feature.*"; In the remainder of this paper, we refer to Citizen Science Initiative (CSI) as a collaborative process that includes Citizen Science activities, in which some citizen-based monitoring is expected; Citizen-Generated Data (CGD) (Fritz et al., 2019), is the data produced by citizens involved in activities related to collecting observations or measuring a particular environmental variable; we define value of an observation as a metric to characterise how useful a record of citizen-contributed data is from the perspectives of complementarity and costs.

The main contribution of this paper is to offer a way to quantify the potential of Citizen Science, in particular in terms of cost-effectiveness and data-gap filling, claims that are frequently made in the literature, but with little support, for these kinds of projects. It must be noted that we deliberately omit the associated societal benefits of Citizen Science such as awareness raising, scientific literacy and public engagement in governance (Bonney et al., 2009; Phillips et al., 2012; Wehn and Evers, 2015; Gharesifard et al., 2019), due to the difficulty to quantify them in a scientifically robust manner. In addition, we do not consider the value of random and opportunistic use of data records that are not intended when the data collection processes were designed.

## 2. Methodology

### 2.1. Value of citizen science for data generation

The overall methodology for evaluating the value of citizen-generated data consists of two main parts, one related to complementarity and other related to costs. The former aims to quantify the degree of complementarity that the data collected by citizens offers to existing observations in space and time. The latter aims to quantify the relation between the investments required to set up a CSI and the actual amount of data collected. The overarching idea is that the value of citizen-generated data with respect to existing observations is a function of complementarity (based on concepts presented by Hadj-Hammou et al. (2017)) and costs (based on ideas from Davids et al. (2019)). Therefore, a data record is to be considered of maximum value if its complementarity is the maximum and if the cost to produce it is the minimum. On the contrary, it has little value if its complementarity is the minimum and its cost is high.

#### 2.1.1. Estimation of complementarity

Complementarity is defined as the degree to which existing data gaps coming from in-situ networks or models are filled in space and time by citizen-based monitoring. This concept is closely related to data completeness, defined by Lukyanenko et al. (2014) as the extent to which an information system captures all phenomena of potential interest. Spatial complementarity occurs if citizens provide observations in places that are unreachable by in-situ networks, whereas temporal complementarity occurs if citizens provide observations at times for which the in-situ network is unable to provide data. By definition, complementarity is scale dependent, and therefore initiative-dependent. Based on the concepts of spatial and temporal complementarity proposed by Hadj-Hammou et al. (2017), we propose the indexes of Spatial Complementarity (SC) and Temporal Complementarity (TC), both defined using the following principle: the difference between the total required observations to be observed in a unit of space or time and the existing observations in such unit is the total information gap $g$; a CSI that produces observations that partially or totally fills this gap ($g^f$) is said to be complementary in a proportion given by the ratio $g^f/g$.

In some situations, CGD do not fill gaps, but coincide with existing observations. This is referred to as redundancy, and it can be both positive and negative (Hadj-Hammou et al., 2017). On the one hand, redundancy is desired to be minimised in order to avoid costs related to duplicated data collection efforts in monitoring network design (Alfonso et al., 2010). On the other hand, redundancy can add robustness to monitoring networks (Buytaert et al., 2016) and it can also allow Citizen Science to be peer-reviewed and self-corrected (Connors et al., 2012; Jonoski et al., 2012). To give flexibility to the method, we therefore chose to exclude redundancy in the definition of complementarity and suggest to report it separately (see Fig. 1).

*2.1.1.1. Spatial complementarity (SC).* To further explain SC, consider Fig. 2a, where $O_s$ represents the total spatial unit that is required to be observed, $E_s$ is the spatial portion that is being currently observed (e.g., by existing monitoring networks or agencies), and $C_s$ is the spatial portion that is observed by a CSI. The spatial portion that is observed by both $E_s$ and $C_s$ is said to be redundant in space ($R_s$). We define total spatial gap $g_s$ as the portion of $O_s$ that is not covered by $E_s$ (Fig. 2b). A CSI that observes part of $g_s$ is actually filling a gap $g_s^f$ and is said to be complementary to $E_s$ (Fig. 2c).

Therefore, Spatial Complementarity ($SC$) is defined as the ratio between the filled spatial gap and total spatial gap, and it describes the degree to which the citizen observations complement the existing spatial observations for the whole duration of the initiative, and at a relevant spatial discretization, Eq. (2):

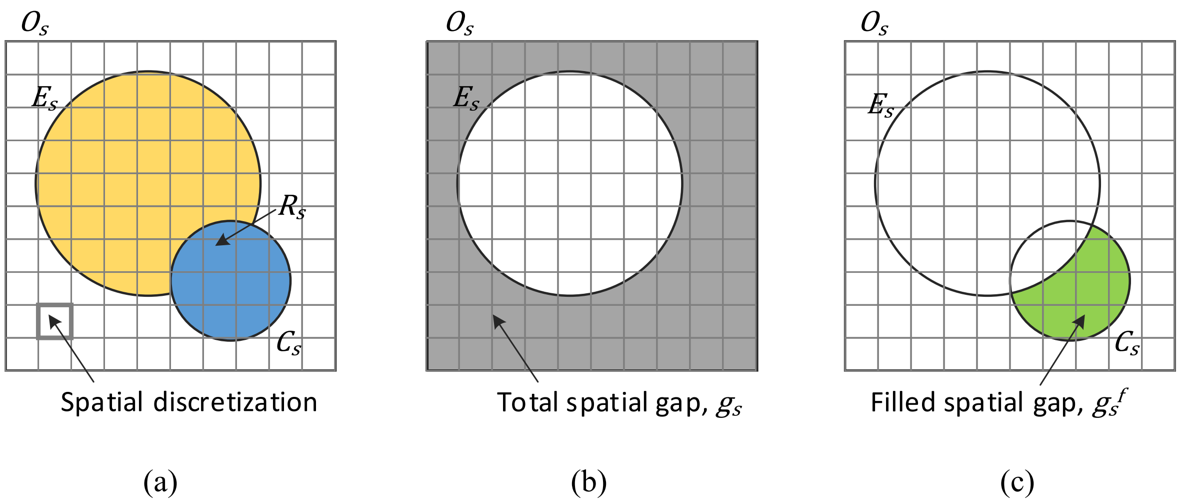


**Fig. 1.** Schematic representation of an area to be observed $O_s$, showing definitions of spatial discretization, redundancy ($R_s$), total spatial gap $g_s$ and filled spatial gap $g_s^f$, based on existing ($E_s$) and citizen ($C_s$) spatial observations.

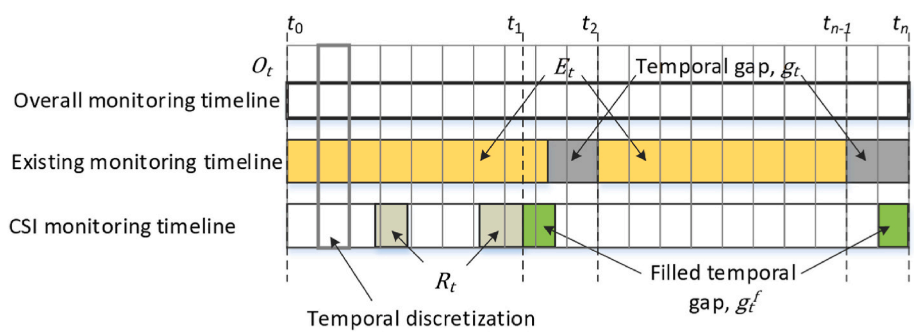


**Fig. 2.** Schematic time line representation of an area to be observed $O_t$, showing definitions of temporal discretization, redundancy ($R_t$), total temporal gap $g_t$ and filled temporal gap $g_t^f$, based on existing ($E_t$) and citizen ($C_t$) temporal observations.

$$SC = \frac{g_s^f}{g_s} \qquad (2)$$

*SC* ranges from 0, –when $C_s$ is fully contained in $O_s$ (areas that are observed by the citizens have already been observed by the existing in-situ network), to 1, when the area $g_s$ is completely observed by citizens, or $g_s = g_s^f$. For the case in which the area is fully covered by existing observations, $g_s = 0$ and SC can be set as zero.

Spatial Complementarity is sensitive to the spatial discretization, so it must be selected carefully. In principle, it can be defined by establishing the relevant scale of a variable, with the help of existing charts developed by researchers in different fields, for example Raudsepp-Hearne and Peterson (2016), Swanson and Sparks (1990) and Blöschl and Sivapalan (1995), or considering the concepts of accuracy and precision in Citizen Science (Lukyanenko et al., 2019). As spatial discretization plays a role in the variables involved in spatial complementarity, the number of observations of the CGD per cell should also be reported.

*2.1.1.2. Temporal complementarity (TC).* Similarly, TC can be defined by considering the timeline in Fig. 3, where the row $O_t$ represents the total timeline required for a variable to be observed; $E_t$ is a period within $O_t$ that has been observed and $C_t$ is the period that is observed by a CSI. Temporal redundancy ($R_t$) occurs whenever $E_t$ and $C_t$ are simultaneous. Analogous to the spatial case, we define total temporal gap $g_t$ as the periods contained in $O_t$ that are not covered by $E_t$ (Fig. 2b). A Citizen Science initiative that observes a period within $g_t$ is actually filling a temporal gap $g_t^f$ and is said to be complementary, in time, to $E_t$ (Fig. 3).

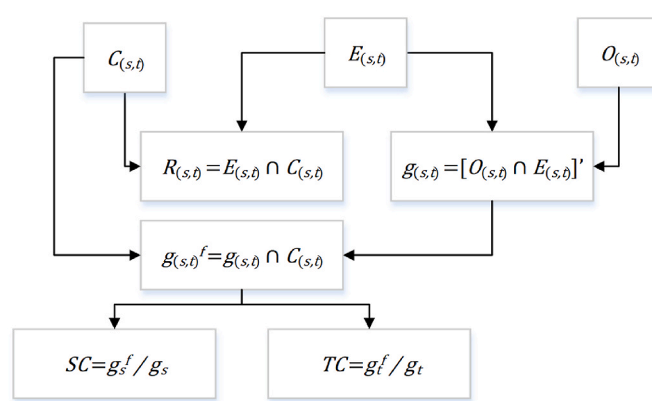


**Fig. 3.** Flowchart to estimate *SC* and *TC* given the inputs *C*, *E* and *O*. Sub-indexes *s* and *t* refer to space and time, respectively.

Therefore, Temporal Complementarity (*TC*) is defined as in Eq. (3), and describes the degree to which the citizen observations complement the existing temporal observations for the whole spatial domain, at a relevant temporal discretization.

$$TC = \frac{g_t^f}{g_t} \qquad (3)$$

The temporal discretization can be extracted from existing charts, such as those by Swanson and Sparks (1990), Blöschl and Sivapalan

(1995), or, with a more Citizen Science perspective, using the concepts of accuracy and precision (Lukyanenko et al., 2019). In this study, we analyse three different discretization periods for all case studies, namely annual, quarterly and monthly, to demonstrate the method. To this end, the daily observations are aggregated in these periods, and then Eq. (3) is estimated.

Both *SC* and *TC* can be estimated following the flowchart in Fig. 3, provided the inputs *C*, *E* and *O* in time and space are given. After discretization, these inputs can be operated in terms of sets representing space (cells) and time (records). In this way, the set of redundant observations *R* is obtained by intersecting the set of existing observations *E* and the set of observations *C*, collected by the CSI. Similarly, the set of missing observations (*g*), is obtained by intersecting the overall set that needs to be observed (*O*), and the set of existing observations *E*. Then, the set representing the gap to be filled ($g^f$) is obtained by intersecting the latter set and the set *C*.

The operations in the flowchart in Fig. 3 were applied to each case study. GIS tools were used to perform the spatial analysis, whereas spreadsheets were used to perform the temporal analysis.

### 2.1.2. Cost of a data record (CDR)

In addition to complementarity, an important variable, albeit almost never explicitly reported in projects involving Citizen Science, to evaluate the value of Citizen Science for data generation is related to the costs invested to produce these observations. As mentioned before, the statement that Citizen Science is a cost-effective approach to data collection frequently found in literature, needs to be based on evidence. This is important for prospective project teams that are considering setting up a Citizen Science initiative with this goal in mind. As CSIs take time to develop, the temporal analysis of these costs is of our interest. We propose to estimate of the monetary value of one data record collected via the CSI in a similar fashion to Davids et al. (2019), but analysed in time. This brings the concept of Cost of a Data observation or Record (*CDR*), which include the investment costs of the CSI from the beginning until any time *T*, and it can be estimated as shown in Eq. (4):

$$CDR_T = \frac{\sum_{t=0}^{T} C_b}{\sum_{t=0}^{T} N_o} \tag{4}$$

where $C_b$ is the cost of building a CSI and $N_o$ is the number of collected observations of a particular variable of interest. In this paper, $C_b$ considers the contributions of *applying* the GT2.0 co-design methodology (see section 3), and exclude the costs of *developing* the methodology. Although making a clean separation of these two costs is difficult, a valid approximation is to consider that the tasks related to research, project management, business development and dissemination are not related to *building* the initiative. An estimation of this cost for the lead partner of the project (IHE Delft), yields that approximately 38% of its total expenditures were dedicated to activities that support the application of all six CSIs of the project. We use this conservative figure as a reference for the rest of the partners.

In this paper, the costs are estimated proportionally according to the efforts of the GT2.0 partners involved in each case. Regardless the method to calculate these costs, however, it is expected that the CDR lowers over time due to the decrease in effort in applying the co-design methodology and, simultaneously, because of the increase in the number of observations. The temporal analysis of costs implies the estimation of the effort of each partner in each of the case studies during the execution of the project, which is very demanding from the point of view of data availability. In this regard, the most trustful and accurate source of data available was the so-called Periodic Activity Sheets, an online tool that was used by the Project Coordinator to keep track of the progress of each case study. Each Periodic Activity Sheet, which was updated every month, comprehensively reported the current and planned activities from January 2017 to March 2019 (25 months in total). We extracted the names of each involved partner (or the names of the personnel of each partner) and evaluated the amount of times their names were mentioned. Based on this data, Table 1 shows the estimated proportion of participation of each partner in each case study -during the considered period. It must be noted that although the project ran until December 2019, the data in the Periodic Activity Sheets goes only until March 2019, so the analyses were made until this date. To calculate CDR (Eq. (4)), the cost of building the CSI was assumed to remain constant since March 2019, in all case studies.

Furthermore, the total costs of building the CSI includes the cost of event-based interactions with stakeholders, which involves CSI co-design sessions, measurement campaigns and other meetings[2]. In the remainder of the paper, we will use the generic term *event* to encompass all of these types of meetings. This means that our analysis is based on conservative values, including the full CSI design and implementation process. The data for calculating the costs of these events is derived from detailed CSI design logbooks (spreadsheets and documents with details about each meeting, including dates, location, activities, duration, number of participants, among others), as well as in platform and launch compendia (documents to collect instructions, guidelines and requested information in specific phases of the project). After analysing the costs of these events, we found that they correspond approximately to 5% of the total cost of all involved partners in the corresponding case study. Moreover, the temporal distribution of costs is assumed to be proportional to the number of stakeholders involved in each event.

Finally, the values of cost and the number of observations were mapped against the dates and both were collected as they were occurring. This allowed us to calculate the CDR values with Eq. (4). The resulting values were used to produce the graphs shown below for each case study.

## 3. Results

The results of applying the methodology presented in this paper to each case study are presented in this section. First, the calculation of spatial and temporal complementarity is presented, followed by the estimation of the costs per data record. In order to demonstrate the methodology, two different spatial discretization per case, and three different temporal discretization (monthly, quarter, yearly) are considered. For all cases, the period of analysis for temporal complementarity $O_t$ is Jan 1, 2017 to Oct 1, 2019. The existing observations were obtained from different sources, including official data (Sweden), non-official platforms (Kenya, Spain) and mathematical model estimations (Belgium), each of them exposing different spatial and temporal observation gaps. The implications of their use are explained in the discussion section.

### 3.1. Meet Mee Mechelen (Belgium)

The method of data collection in this case study is campaign-based, with sensors that are given to cyclists who carry them for some hours. Although basic training is given to participants about the equipment, they have limited interaction with it. This is the reason why this case has the greatest number of collected observations (8607 for black carbon concentration, between January 2017 and March 2019). These observations cover streets with a total length of 45.6 km, in an area of about 30 km$^2$. Due to the nature of this case study, where the observations are made in pre-defined linear paths and not in areas, the spatial discretization to apply the method includes a conversion from length to

[2] The range of events includes meetings by the Ground Truth 2.0 partners to prepare co-design events with stakeholders as well as the implementation of these co-design sessions; planning meetings with and by the citizen observatory stakeholders to set up measurement campaigns; data collection campaigns; public outreach meetings (to promote the existince of the citizen observatory and invite participation, and to share the results of measurement campaigns).

**Table 1**
Proportion of participation of each partner in each case study for the period Jan 2017–March 2019. Although the Dutch and Zambian case studies are not included in the analyses, they are reported here to make all contributions sum up 100%.

| GT2.0 partner | Belgium | Sweden | Spain | Netherlands | Kenya | Zambia |
|---|---|---|---|---|---|---|
| IHE | 16.0% | 11.5% | 8.4% | 26.2% | 21.9% | 16.0% |
| HR | | | | 100.0% | | |
| Upande | | 4.4% | | 4.4% | 84.4% | 6.7% |
| Gavagai | 38.7% | 8.0% | 6.7% | 37.3% | 9.3% | |
| VITO | 95.6% | | | 3.7% | | 0.7% |
| AKVO | 27.0% | 30.3% | | 13.0% | 21.6% | 8.1% |
| Starlab | 2.0% | 25.8% | 39.1% | 18.1% | 3.2% | 11.7% |
| ALTRAN | 20.3% | 0.8% | 54.2% | 18.6% | 0.8% | 5.1% |
| CREAF | | 0.9% | 99.1% | | | |
| Stockolm Univ. | | 100.0% | | | | |
| Earthwatch | | 100.0% | | | | |
| TAHMO | | | | | 60.7% | 39.3% |
| WWF | | | | | | 100.0% |
| Tygron | 40.0% | 60.0% | | | | |

area. The estimation is based on the fact that, in Belgium there are, on average, 500 km of roads per 100 km$^2$ of land (knoema.com). Therefore, for the Mechelen municipality (33.71 km$^2$), this is equivalent to 170 km of roads to be observed in total. If a spatial discretization of 200 m is applied, then $O_s = 170\text{km}/0.2\text{ km} = 850$ cells of 200 × 200 m can be considered. Similarly, if a discretization of 1000 m is taken, then 170 cells are considered. These cell sizes are considered convenient to estimate the air quality in an urban setting for different purposes (Schneider et al., 2017), and were considered for the spatial complementarity analysis. Fig. 4a shows the spatial distribution of the observations (black lines in Fig. 4aI are actually multiple continuous points), for cell sizes of 200 m (Fig. 4 aII) and 1 km (Fig. 4 aIII).

Regarding $E_s$, two situations can be formulated. First, the situation for which outputs of a mathematical model are considered as existing observations, obtained by interpolating two distant air pollution stations at Brussels and Antwerp, owned by the Flemish Environmental Agency, VMM (Milieumaatschappij, 2017). In this situation, no gaps in time and space are considered to be present in the existing observations. Therefore, in terms of spatial complementarity, for a resolution of 200 m, $O_s =$ 850 cells, and $C_s = 228$ cells, and for a resolution of 1 km, $O_s = 170$ cells and $C_s = 46$ cells. In both resolutions, $Cs$ are redundant, and $g_s = g_s^f =$ 0 (and therefore no grey areas are shown). The second situation is when such model outputs cannot be considered as observations, and there are no other sources for existing information. In this situation, all CGD are filling a gap, so for a resolution of 200 m, $g_s = 850$, $g_s^f = 228$ and SC = 0.27, which is the same value for a resolution of 1000 m with $g_s = 170$ and $g_s^f = 46$. Regarding temporal complementarity, yearly, quarterly and monthly temporal discretization TC yield 0.67, 0.33 and 0.15, respectively, which are average values across the project period, assuming that $E_t = 0$. Average values of $O_t$, $E_t$, $C_t$, $R_t$ across the project timeline for the different temporal discretization periods can be found in Table 2. The first row in Fig. 5 shows the distribution of existing and citizen-generated data for Met Mee Mechelen aggregated in different time periods. Citizen generated data is concentrated in four main periods covering 2017 and 2018, in distinct quarters and different months. For comparison reasons, if existing observations are assumed to be available every day, then redundancy appears to be very high in specific periods.

Seven partners were active in this case along the project (see Table 1), and 14 preparatory and campaign events were held (Fig. 6a). The evolution of CGD cost in time, shows a stable effort increase of partners along the project for the Belgian case. Small but frequent events are mainly concentrated at the beginning, whereas major events (campaigns with up to 50 people) happen towards the mid part of the project, separated by several months. Note that observations only start to appear after several preparatory events take place. In fact, the cumulative number of observations increase in four main steps, which correspond to the major data collection campaigns. Both effort and number of observations affect CDR, with a considerable peak of almost 300 Eur/observation, which drops in the same steps, first to 75 Eur/observation, then to 45 Eur/observation, to finally stabilise in about 37 Eur/observation.

The Belgian case is an example of a CSI that fully complement information spatially and temporally (if model outputs are not accepted as existing information), and where the significant amount of observations brings down the cost of a single data record.

### 3.2. VattenFokus (Sweden)

In this case study, dedicated campaigns were used as the main method for data collection, which were prepared by means of twelve meetings. Participants displaced within the municipality of Flen, and record 8 variables including nutrients in the water bodies (phosphate and nitrate). These tests were carried out with measurement kits provided by Earthwatch, including the ‘FreshWater Watch’ app, where ecological, hydrological and chemical parameters were also recorded. Some of the events were dedicated to train the participants. From January 2017 to March 2019, this case study produced 412 data records at 56 water bodies within an area of 107 km$^2$. Therefore, the total area in terms of cells to be observed for a cell size of 1000 m is $O_s = 107$ cells, and for a cell size of 5 km is $O_s = 40$ cells. Fig. 4b shows the spatial distribution of the with relevant cell size for analysis of 1 km (Fig. 4bII) and 5000 m (Fig. 4 bIII), noting that the distribution concentrates exclusively on the water bodies, so an analysis for the whole area is not applicable as for the other case studies. The existing observations were taken from the platform Vatteninformationsystem Sverige (Water Information System of Sweden),[3] in which a query retrieving monitoring stations in Flen measuring Nitrates was performed. According to this information, samples are taken every six years in most of the stations. The spatial information of the locations of water bodies was taken from the Swedish Meteorological and Hydrological Institute (SMHI), with metadata detailed in Henestål and Björkert (2017). These existing observations, for a resolution of 1 km, are concentrated in $E_s = 16$ cells. Applying the flowchart in Fig. 3, $R_s = 2$ cells, $g_s = 91$ cells, $g_s^f = 40$ cells, and therefore SC = 0.44. For a resolution of 5 km, $E_s = 14$ cells, $R_s = 6$ cells, $g_s = 26$, $g_s^f = 8$ and SC = 0.31 (Table 2). The redundant of 2 and 6 cells are the black spots in Fig. 4bII and bIII. Regarding temporal complementarity, second row in Fig. 5 shows the distribution of existing and citizen-generated data for Sweden in different time periods, aggregated yearly, quarterly and monthly. As the last set of existing observations are dated Feb 2017, the temporal complementarity is important for any temporal aggregation, ranging from 0.31 to 0.40 (Table 3).

Eleven events were held during the considered period; only three of

[3] https://viss.lansstyrelsen.se.

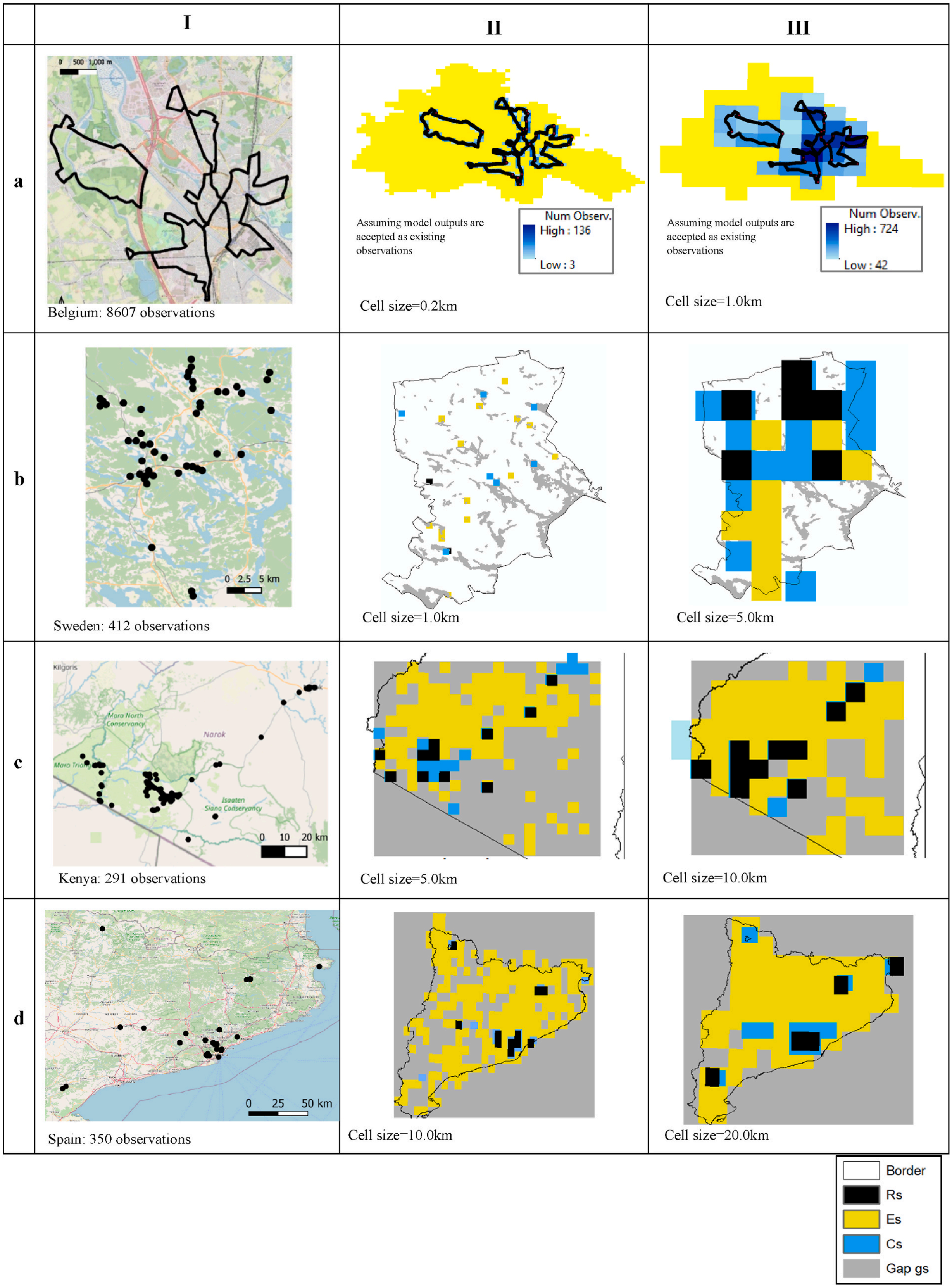


**Fig. 4.** Spatial location of observations during the project period. (a) Belgium, (b) Sweden, (c) Kenya, and (d) Spain; columns II and III present observed cells (yellow), cells with gaps (grey), redundant cells (black) and filled cells with citizen observations (blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

**Table 2**
Summary of inputs for the spatial complementarity analysis and results for each case, for different spatial resolutions.

| | Spatial resolution (m) | $O_s$ | $E_s$ | $R_s$ | $C_s$ | Gap $g_s$ | gap filled $g_s^f$ | SC |
|---|---|---|---|---|---|---|---|---|
| | | (Number of cells) | | | | | | |
| Belgium (model outputs as observations) | 200 | 850 | 850 | 228 | 228 | 0 | 0 | 0.00 |
| | 1000 | 170 | 170 | 45.6 | 45.6 | 0 | 0 | 0.00 |
| Belgium (model outputs not observations) | 200 | 850 | 0 | 0 | 228 | 850 | 228 | 0.27 |
| | 1000 | 170 | 0 | 0 | 45.6 | 170 | 45.6 | 0.27 |
| Sweden | 1000 | 107 | 16 | 2 | 42 | 91 | 40 | 0.44 |
| | 5000 | 40 | 14 | 6 | 14 | 26 | 8 | 0.31 |
| Kenya | 5000 | 378 | 126 | 11 | 24 | 252 | 13 | 0.05 |
| | 10,000 | 110 | 59 | 10 | 12 | 51 | 2 | 0.04 |
| Spain | 10,000 | 606 | 202 | 11 | 15 | 404 | 4 | 0.01 |
| | 20,000 | 176 | 73 | 5 | 11 | 103 | 6 | 0.06 |


**Fig. 5.** Number of existing and citizen-generated observations per case study, aggregated in yearly, quarterly and monthly periods, from January 2017 to October 2019.

them had the presence of more than 10 people, which unveils the difficulty of engaging citizens in the exercise despite the stable effort increase of partners along the project. The evolution of CGD cost over time shows a steep increment, from zero to 150 Eur/observation in the first half of the project, coinciding with the time in which most of the preparatory and campaign events were held (Fig. 6b). Although the effort was reduced in the second half of the project, a few observations were consistently provided to the platform, and for this reason the value of CDR towards the end of the GT2.0 project slowly decreased down to a value close to 120 Eur/observation. The case of Sweden is an example

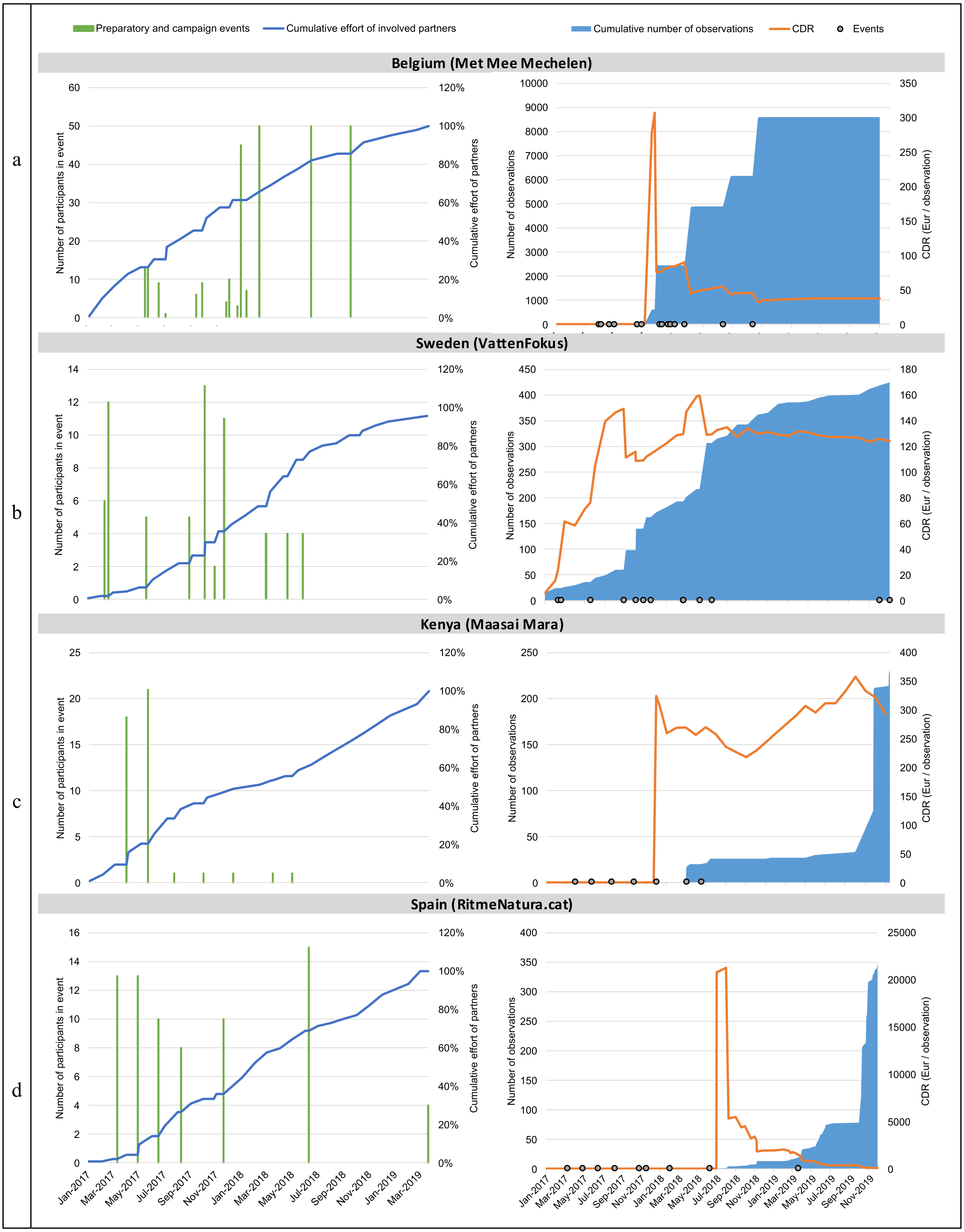


**Fig. 6.** Results Evolution of CGD costs in time for the four case studies under consideration. Left: evolution of cumulative effort of relevant partners; right: evolution of the number of observations in the platform and its effect on the Cost of Data Record (CDR). Occurrence of events are included for reference.

where the CSI offers a relatively high benefit in terms of complementarity in space and time, at a relatively high cost per record.

### *3.3. Maasai Mara (Kenya)*

Data on species in the Mara region currently exists within a few national organisations and is often outdated, not digitized and incomplete. The Maasai Mara citizen observatory was created to fill these observation gaps, with the help of tools such as the Mara Collect app for data collection of biodiversity and the deployment of the Trans-African Hydro-Meteorological Observatory, TAHMO's low cost weather stations. In this section we concentrate on the former, in which 291 entries (at the time of edition of this document) were received on the platform,

**Table 3**
Summary of inputs for temporal complementarity analysis and results for each case, for different temporal discretization periods.

| | Season | $O_t$ | $C_t$ | $E_t$ | $R_t$ | gap, $g_t$ | gap filled $g_t^f$ | $TC$ |
|---|---|---|---|---|---|---|---|---|
| | | (Number of records) | | | | | | |
| Belgium | Yearly | 344.7 | 2869.0 | 0.0 | 2625.7 | 344.7 | 243.3 | 0.67 |
| | Quarter | 86.2 | 717.3 | 0.0 | 686.8 | 86.2 | 30.4 | 0.33 |
| | Monthly | 30.4 | 253.1 | 0.0 | 248.6 | 30.4 | 4.5 | 0.15 |
| Sweden | Yearly | 344.7 | 137.3 | 11.3 | 0.0 | 333.3 | 137.3 | 0.40 |
| | Quarter | 86.2 | 34.3 | 2.8 | 1.8 | 83.3 | 32.5 | 0.38 |
| | Monthly | 30.4 | 12.1 | 1.0 | 2.7 | 29.6 | 9.6 | 0.31 |
| Kenya | Yearly | 344.7 | 70.7 | 279.7 | 43.0 | 65.0 | 27.7 | 0.47 |
| | Quarter | 86.2 | 17.7 | 69.9 | 15.8 | 16.3 | 1.9 | 0.21 |
| | Monthly | 30.4 | 6.2 | 24.7 | 5.7 | 5.7 | 0.5 | 0.12 |
| Spain | Yearly | 344.7 | 26.0 | 218.7 | 52.0 | 156.3 | 4.3 | 0.03 |
| | Quarter | 86.2 | 6.5 | 54.7 | 28.7 | 55.0 | 1.3 | 0.02 |
| | Monthly | 30.4 | 2.3 | 19.3 | 13.1 | 23.2 | 1.2 | 0.05 |

for the equivalent of 25 different environmental variables of biodiversity within an area of 7000 km$^2$. The existing observations were obtained from the World Resources Institute website, WRI,[4] in particular the spatial distribution of diverse mammals observed from low altitude flights from 1994 to 1996, sets used in diverse reports about the area (Ojwang et al., 2017), and observations reported via the iNaturalist platform,[5] extracted using a query involving verified mammal observations between 2017 and 2019, totalling 6920 observations. This data was further filtered to include only the district of Narok. Fig. 4c shows the spatial distribution of the CGD (dots in Fig. 4cI), as well as cell sizes for analysis of 5 km (original WRI data), Fig. 4 cII and 10 km, Fig. 4 cIII. The value of $O_s$ is, respectively, 378 and 110 cells. It can be seen that citizen observations seem to be marginally complementary, in particular for smaller cell sizes, because the spatial gaps of the existing observations are better exposed at these resolutions. Redundancy for 5-km resolution is $R_s = 11$ cells and for 10-km resolution it is $R_s = 12$ cells, spatial complementarity yielding respectively SC = 0.05 and 0.04 (Table 2). Regarding temporal complementarity, third row in Fig. 5 shows the distribution of existing and citizen-generated data for Kenya aggregated by year, quarter and month, and shows that the existing observations cover reasonably well the period of observations, and that the data collected by Maasai Mara becomes particularly redundant for the last months of 2019, with TC ranging from 0.12 to 0.47 (Table 3).

The application of Eq. (4) in time yields the estimated evolution of the cost of data record (CDR) per variable per time shown in Fig. 6c, where the effort of the involved partners, the number of events with citizens and the number of observations along the project can be found. It can be observed that the effort to carry out events with stakeholders at the beginning of the project does not correlate with the number of collected data at those times. This is because these events were held to define what and how the data would be collected, and the relevant partners took this time to develop the tools from scratch (hence their stable increment of effort in time). Moreover, given the sensitivity of the data collected, the involved stakeholder required considerable time to agree on a data policy for the CGD. As a consequence, actual data collection started to happen towards the middle term of the project, although not in large volumes. In fact, before the last two months of the project, less than 50 records were collected. The CDR was therefore fluctuating, reaching a maximum of 350 Eur/observation. Towards the end of the project, about 200 records were collected, bringing CDR down to less than 300 Eur/observation.

### 3.4. RitmeNatura.cat (Spain)

Long, multi-year series of observations about the same species in flora or fauna provides conclusive and robust results to understand the rhythm of nature changes. RitmeNatura.cat facilitates the collection of such phenological information (10 variables) by observing individual species or by area, and record and photograph their changes throughout the year in an area of about 100 km$^2$ in Catalonia. As for the Kenyan case, the existing observations are assumed to be those collected in the iNaturalist platform. The citizen observations stored in the RitmeNatura.cat platform are the considered citizen generated data.

Fig. 4d shows the spatial distribution of the observations. Although smaller resolutions are desirable for in-depth phenological analyses, (Park et al., 2021), cell sizes of 10 km (Fig. 4 dII) and 20 km (Fig. 4dIII), were considered to demonstrate the method, with $O_s$ values of 606 and 176 cells and $E_s$ values of 202 and 73 cells. Applying the flowchart in Fig. 3, for a resolution of 10 km, $R_s = 11$ cells, $g_s = 404$ cells, $g_s^f = 4$ cells, and therefore SC = 0.01; for a resolution of 20 km, $R_s = 5$ cells, $g_s = 103$, $g_s^f = 6$ and SC = 0.06 (Table 2), evidencing less pronounced data gaps in space (Table 2). With respect to temporal complementarity, last row in Fig. 5 shows that the existing observations cover reasonably well the period of observations, and that the data collected by RitmeNatura.cat, concentrated towards the end of the project, makes these observations particularly redundant for the second quarter of 2019, explained because in spring months these observations tend to increase. TC ranges from 0.03 to 0.05 (Table 3).

Sixteen events, attended by more than eight participants, were held. These events, as well as the cumulative effort of the GT2.0 partners to build the CSI are presented in Fig. 6d. It can be observed that about 350 data records were collected, and that all of these records happened in second part of the project. For this reason, the first records show a CDR of about around the mid-term of the project was about 20,000 Eur/observation, as important efforts were made in the preparation of the events that mainly occurred in the first part of the project. The important increment in observations towards the end of the project reduced significantly the CDR, to a value of about 80 Eur/observation.

### 3.5. Summary of results and analysis

The summary of input data and results for each case study is presented Tables 2 and 3.

These results are further analysed as follows. First, the Belgian case study (Meet Mee Mechelen) is remarkable because of the amount of collected data. In this case, the effort required by the citizen scientists was limited to carrying a sensor while biking through predetermined paths, in campaign-based events. In contrast, for the variables we considered here, the effort required by a citizen scientist in the Kenyan case study (Maasai Mara Citizen Observatory) implies the use of a smartphone app that has a comprehensive survey and that includes taking and uploading photos, which requires a more deliberate and active effort. This partly explains the difficulty in collecting data in the Kenyan case study, which was solved towards the end of the project by a

[4] https://www.wri.org/data/kenya-gis-data.
[5] https://www.inaturalist.org/.

campaign-like event. However, another reason for delays with data collection in the Kenyan case was the need to develop an agreed data sharing policy for the sensitive CGD. This process was challenging due to the diverse set of stakeholders[6] involved which held opposing views about control over data. While stakeholders such as researchers and community members often believe that data and information about natural resources should be publicly accessible, most government organisations believe that these are sensitive information and access to such information should be centralized and via a relevant organization (Gharesifard, 2020; Wehn et al., 2020).

On the other hand, the comprehensive way of generating and submitting observations in the Spanish and Kenyan cases may explain the common effect of observations coming at the later stages of the project. Therefore, it can be suggested that the amount of collected observations depends on both the effort required by citizens (e.g., the extent to which devices or sensors need to interact with the user) and the degree of guidance in the field (e.g., dedicated campaign-based events within groups vs independent initiative). This concurs with the findings of Roy et al. (2012) about the need for increased usability of Apps and providing support such as personal training for participants, as well as Gharesifard et al. (2017), who identified “effort required by participant” and “support offered by platform providers” as influential factors in the functioning of Citizen Science initiatives. While these use cases are mainly “class-based” as they are about classifying species (Lukyanenko et al. (2014); Lukyanenko et al. (2019)), they are open in terms of skills, training and uses, and therefore prone to negatively impacting information quality. This is an aspect worth analysing in future research.

The evolution of the GT2.0 CSIs in terms of effort of all partners over time did not show salient changes in any of the case studies when compared to the actual occurrence of events, as it was initially expected. In none of the case studies did an increment in events translate into an immediate increase in collected observations.

## 4. Discussion

The objective of this paper is to substantiate frequently made claims about the potential of Citizen Science in terms of filling data gaps and cost-effectiveness by providing a methodology for quantifying these benefits and applying it to real world cases. To this end, benefits have been associated with the complementarity of the collected data in time and space, and the costs related to the effort of setting up the CSI. The application of the methodology proposed in this paper in four case studies of the GT2.0 project shows that complementarity and costs are aspects that are relevant to evaluate the potential of a CSI, having the most potential those with SC and TC close to 1, and the lowest possible cost per data record. These aspects are fully dependent on the context of the initiative, including variables to observe, technologies and the effort required to collect the data. Although the development of an expression that would take both complementarity and CDR into a single, aggregated index to qualify the potential of CSIs would be convenient to make the methodology generic and allow for comparisons, we restrain from taking this direction. The reason is twofold: first, aggregating these criteria implies the use of weights of difficult estimation and justification; second, the results of such expression are difficult to interpret, in particular in view of the many contextual conditions of the case studies.

An alternative way to analyse the data is by means of visualising the criteria in one graph, such as the one shown in Fig. 7, where SC and TC are represented in the $x$ and $y$ axes respectively, and the size of the circle represents the relative size of the CDR. An ideal CSI would be depicted as a small circle with centre in (1,1). In our case, the VattenFokus initiative (Sweden) shows the best complementarity in both space and time at relatively high cost. Met Mee Mechelen (Belgium) and Maasai Mara

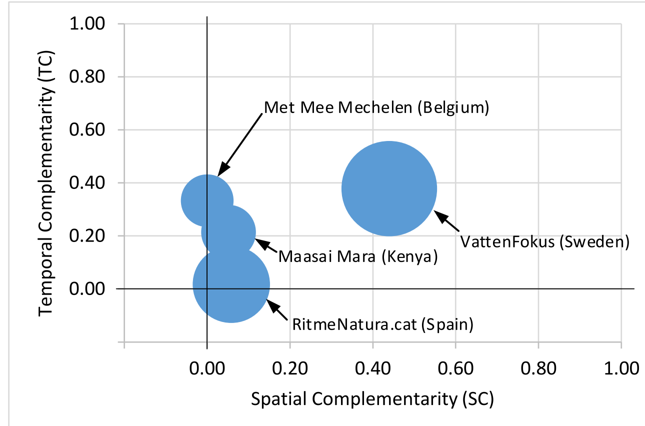


**Fig. 7.** Visualisation of complementarity and CDR to evaluate the potential of CSI, applied to the four case studies. The size of the circle is relative to the CDR at the end of the project.

(Kenya), with a similar cost range, provide better temporal than spatial complementarity. Finally, RitmeNatura.cat (Spain) shows a marginal spatial and temporal complementarity at a relatively high cost.

However, in the presented analysis, one should avoid direct comparison among cases, due to their very different nature, purpose and evolution. Not all CSI’s had the same focus on collecting additional data; differing topics and differing local stakeholder requests can lead to a completely different approach for data collection.

A particular issue regarding the sources of existing observations is worth discussing. The premise of the GT2.0 co-design methodology is that the variables to be observed are chosen (co-designed) by the stakeholders while building the Citizen Science initiative, instead of being imposed or even suggested from the beginning by scientists in need of data. As a consequence, the non-existence of observations is not a controllable variable. This situation, nonetheless, enriches our approach and makes it more generic, as different ways to overcome this challenge, which is very common, are presented. For example, for the Belgian case, the use of outputs of a mathematical model as existing observations is proposed; for the Kenyan and Spanish cases, no models or official platforms of existing observations are available (there are no sensors or instruments that can monitor species as required by these communities). In these cases, Citizen Science platforms such as iNaturalist can be considered as sources of existing observations, because they provide comparable data as the observed by the GT2.0 communities in the demo cases, and at similar temporal and spatial extents. However, this is only possible if both observation datasets are completely independent (i.e., there is no duplication of the observations in both initiatives), a requirement that was satisfied in the case studies in Kenya and Spain.

The results also show that setting up a CSI for the sole purpose of data collection is an expensive undertaking, for the demand side, e.g., for scientists who need the data, or for agencies in need of complementing the existing in-situ monitoring network. The impact of a CSI can be better attributed to societal aspects, the assessment of which requires its own approach (e.g., Bonney et al., 2009; Phillips et al., 2012; Wehn et al., 2020)). Having said that, it is important to point out that these findings are based on the analysis of a particularly comprehensive form of CSI, namely the co-designed citizen observatories by the Ground Truth 2.0 project, which conceives them as socio-technical systems consisting of a community of specific types of stakeholders, platform and tools for data collection, data processing and user feedback and collaboration; and joint planning activities and data collection and linking to relevant policy and decision making processes (Wehn et al., 2020). Other, lighter forms of CSI may – in the short run - result in a more favourable CDR. The methodology presented and applied in this

[6] Citizens and community organisations, scientists and data aggregators, and decision makers and policy makers at county and national level.

paper can serve to assess precisely that.

The presented methodology could be used to inform the decision by first gathering information about the relevant spatial-temporal scales of the variable to be observed, the effort required to organise the community of observers and the interaction moments and campaign events, as well as the effort required by the observers in terms of technology use. The amount of collected observations in the reported case studies seems to depend on both the effort required by the citizens (e.g., the extent to which devices or sensors need to interact with the user) and the degree of guidance in the field (e.g., dedicated campaign-based events within groups vs independent initiative). These aspects, therefore, may affect both complementarity and CDR, and therefore the value of the initiative with respect to data generation.

The methodology has a number of limitations that are important to state: first, the data about the effort invested per partner were inferred from weekly reports of meetings, which may not precisely reflect their actual effort. Second, the methodology applied in the selected case studies considered various spatial and temporal scales and resolutions for the sake of demonstration. However, the relevant scales of the physical processes to be analysed should drive the decision about the relevant resolutions and scales to consider.

## 5. Conclusions

In this paper, a way forward in understanding the frequently claimed cost-benefit potential of citizen science initiatives was presented. The proposed methodology considers the degree to which the citizen science observations complement the existing observations in space and time, as well as the costs involved to produce a data record. The methodology was applied in four real CSIs cases built in the framework of the GT2.0 project.

The results show that setting up a CSI for the sole purpose of data collection is an expensive undertaking, for the demand side (e.g. for scientists who need the data, or for agencies in need of complementing the existing in-situ monitoring network). The impact of a CSI can be better attributed to societal aspects, the assessment of which requires its own approach.

For the analysed cases, spatial and temporal complementarity varied from 0 to 40%, whereas CDR at the end of the project varied from as low as 37 Eur/observation to as much as 300 Eur/observation. These figures, analysed in the context of the cases, can guide decision makers who are considering to embark on a Citizen Science project with the primary purpose of data collection.

The application the proposed methodology in future Citizen Science projects may offer explicit, objective indicators to substantiate claims regarding potential of these initiatives. Scientists, practitioners and decision-makers can use it to better support their decisions before embarking on initiatives with the primary purpose of data collection.

Further research is required to evaluate the sustainability of the CSI after a few years of project termination, including new estimations of Spatial Complementarity, Temporal Complementarity and Cost of a Data Record. In addition, research on the perception of stakeholders about the value of data can provide new insights to further improve the methodology.

## Author contributions

**Conceptualization: L. Alfonso**; Methodology: **L. Alfonso** and **M. Gharesifard**; Formal analysis and investigation: **L. Alfonso**; Writing – original draft preparation: **L. Alfonso**; Writing – review & editing: **M. Gharesifard** and **U. Wehn**; Funding acquisition: **U. Wehn**

## Declaration of competing interest

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

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2021.114157.

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