

Data quality in Citizen Science

Peter Mooney



Lucy Bastin



Citizen Science with Application to Nuclear, Seismic and Air Quality Monitoring



8 -12 March 2021 Introduction (smr 3565)
15 - 19 March 2021 Applications (smr 3596)
An ICTP Virtual Meeting
Trieste, Italy

Further information:
<http://indico.ictp.it/event/9462/>
<http://indico.ictp.it/event/9532/>
smr3565@ictp.it

And today we shall talk about

The multiple meanings and dimensions of citizen science – how it provokes different responses in scientists (Peter)

Commonly encountered issues around data quality (Peter)

Data Quality and Metadata – why are concepts such as metadata, vocabularies, testing, observation level quality, etc. important for the advancement of Citizen Science. (Lucy)

Introducing PPSR Core (Public Participation in Scientific Research) and the **OGC Citizen Science Interoperability Experiment** (Lucy)

Conclusions and discussions (Peter and Lucy)

Data quality in Citizen Science has different meaning for different people and use cases



Fitness for use?

Fitness for purpose?

Who baked the cake?

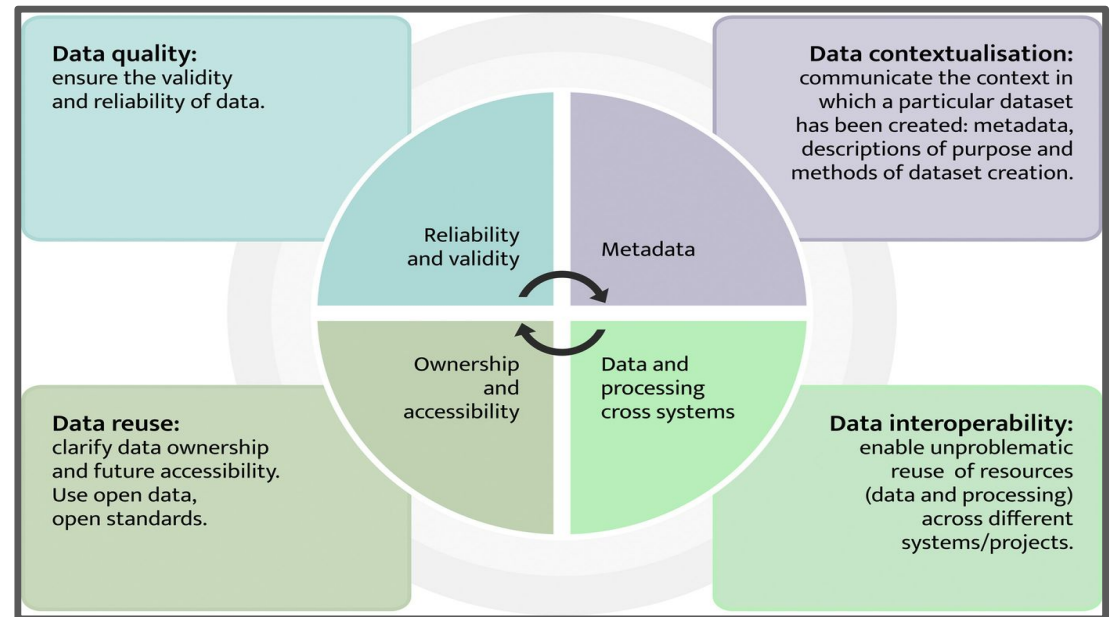
How was the cake baked?

Can I **compare** it to other cakes?

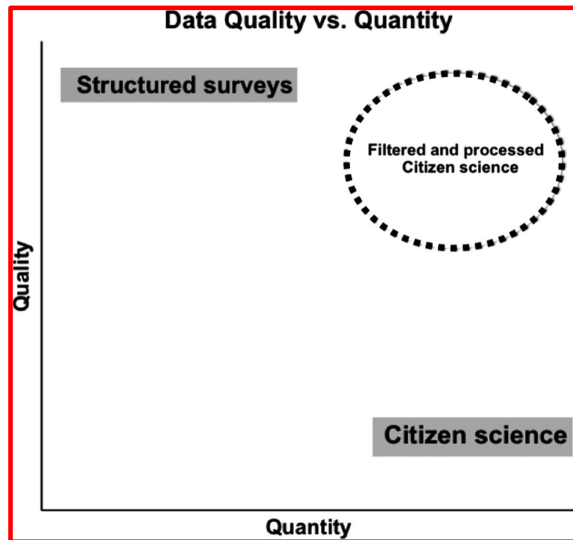


The huge remit of Citizen Science Data Quality

Example for context:
citizen air quality
monitoring in cities



https://doi.org/10.1007/978-3-030-58278-4_8



<https://doi.org/10.1111/ddi.13068>



<https://andrewsheppard.net/research/quality-citizen-science/>

So how did Lucy and I arrive here?

link.springer.com/book/10.1007/978-3-030-58278-4

 Springer Link



The Science of Citizen Science

Editors [\(view affiliations\)](#)
Katrin Vohland, Anne Land-Zandstra, Luigi Ceccaroni, Rob Lemmens, Josep Perelló, Marisa Ponti, Roeland Samson, Katherin Wagenknecht

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<https://doi.org/10.1007/978-3-030-58278-4>

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Chapter 8 Data Quality in Citizen Science



Bálint Balázs, Peter Mooney, Eva Nováková, Lucy Bastin, and Jamal Jokar Arsanjani

Abstract This chapter discusses the broad and complex topic of data quality in citizen science – a contested arena because different projects and stakeholders aspire to different levels of data accuracy. In this chapter, we consider how we ensure the validity and reliability of data generated by citizen scientists and citizen science projects. We show that this is an essential methodological question that has emerged within a highly contested field in recent years. Data quality means different things to different stakeholders. This is no surprise as quality is always a broad spectrum, and nearly 200 terms are in use to describe it, regardless of the approach. We seek to deliver a high-level overview of the main themes and issues in data quality in citizen science, mechanisms to ensure and improve quality, and some conclusions on best practice and ways forwards. We encourage citizen science projects to share insights on their data practice failures. Finally, we show how data quality assurance gives credibility, reputation, and sustainability to citizen science projects.

Keywords Peer verification · Expert verification · Quality assessment

Several factors combine to make structuring of data quality in citizen science challenging

- New citizen science projects appear daily, the academic literature grows so quickly
- 'The Knock-on Effect' of existing projects are taking different approaches to data quality and data sharing then makes follow-on projects problematic (including reproducibility)
- Different projects consider different dimensions of data quality
- Most citizen science projects have multiple goals and must all deal with the 'legitimacy' argument waged against them by certain stakeholders



Two objective task independent measures of **data quality that prompt the most professional skepticism are **accuracy** and **bias**.**

“Despite the wealth of information emerging from citizen science projects, the practice is not universally accepted as a valid method of scientific investigation” (Bonney et al, 2014) DOI: [10.1126/science.1251554](https://doi.org/10.1126/science.1251554)

“Most types of bias found in citizen-science datasets are also found in professionally produced datasets and can be mitigated using existing statistical tools” (Kosmala et al, 2016) doi: [10.1002/fee.1436](https://doi.org/10.1002/fee.1436)

“The only known bias specific to citizen science is the potentially high variability among volunteers in terms of demographics, ability, effort, and commitment.” (Kosmala et al, 2016)

Data Quality in Citizen Science - a multi-dimensional problem?

Lukyanenko et al (2016) <https://doi.org/10.1111/cobi.12706>

“caution is warranted in emphasizing a particular dimension of data quality in citizen science projects; *trade-offs in different dimensions of data quality are inevitable*”

We contend that in trying to hold amateurs to scientific standards, researchers not only ask nonexperts to perform often unrealistic tasks, but also risk missing the opportunity to fully engage with people in the core objective of discovery. The emerging problem of quality in citizen science is, therefore, writing a story in which citizens contribute to the plot.

Some key readings in Citizen Science Data Quality - for self study after the workshop

Wiggins et al. (2011) "Mechanisms for Data Quality and Validation in Citizen Science" <https://doi.org/10.1109/eScienceW.2011.27>

Hochachka et al (2012) "Data-intensive science applied to broad-scale citizen science" <https://doi.org/10.1016/j.tree.2011.11.006>

Sullivan et al. (2014) "The eBird enterprise: An integrated approach to development and application of citizen science" <https://doi.org/10.1016/j.biocon.2013.11.003>

Burgess et al. (2017) "The science of citizen science: Exploring barriers to use as a primary research tool" <https://doi.org/10.1016/j.biocon.2016.05.014>

Fraisl et al. (2020) "Mapping citizen science contributions to the UN sustainable development goals" <https://doi.org/10.1007/s11625-020-00833-7>

If a dataset was not explicitly identified as Citizen Science how would you know?

Given two datasets, how could you tell which is the professional dataset and which is the citizen science dataset?

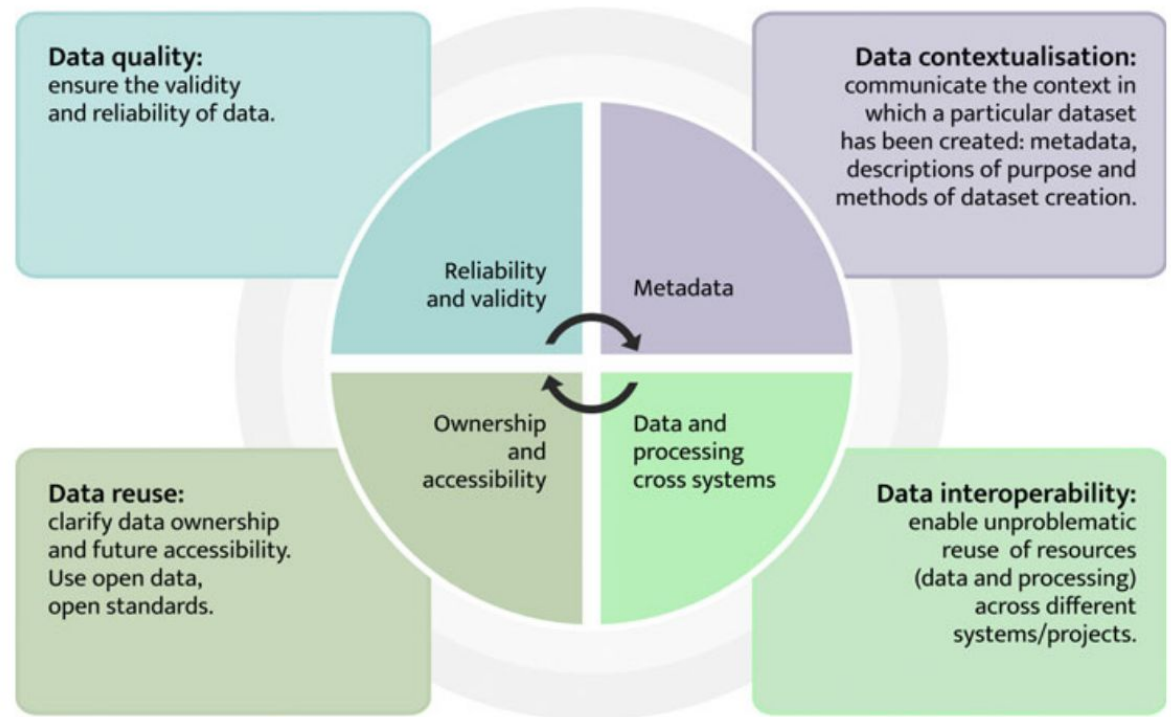
Suppose the dataset(s) are PM10 concentration measurements (hourly) in a city of population 50,000



Data as a risk factor in Citizen Science

Data from citizen science is unparalleled as it represents evidence that is otherwise difficult for professional science to generate or obtain.

For every stakeholder in citizen science, there appears to be a different definition of what constitutes data quality from an epistemological point of view, the question is how accurately does the data represent the real-world constructs to which they refer.



Kosmala et al (2016) Questions to consider when evaluating citizen science projects for data quality

- Does the project use **iterative design**?
- How **easy** or **hard** are the tasks?
- How systematic are the **task procedures** and data entry?
- What **equipment** are volunteers using?
- Does the project record relevant **metadata**?
- Are **good data management practices** used?
- Are the **data appropriate for the project's management objectives** or research questions?
- Does the project assess data quality by **appropriate comparison with professionals**?
- Is **collection effort standardized** or accounted for in data analysis?

Cross-section of the most commonly encountered issues around data quality in citizen science

1. Data collection **protocols are not followed by participants.**
2. Data collection **protocols do not match the goals of the project or the probable participants.**
3. Data collection **protocols are incorrectly implemented.**
4. Data collection **protocols are not comprehensive** and are used by stakeholders with **different data quality expectation levels.**
5. **Data used are not fit for purpose.**

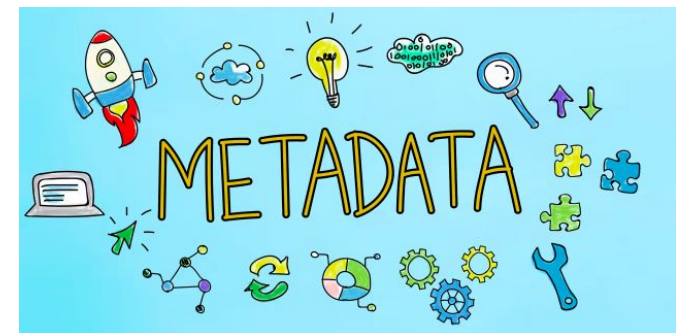
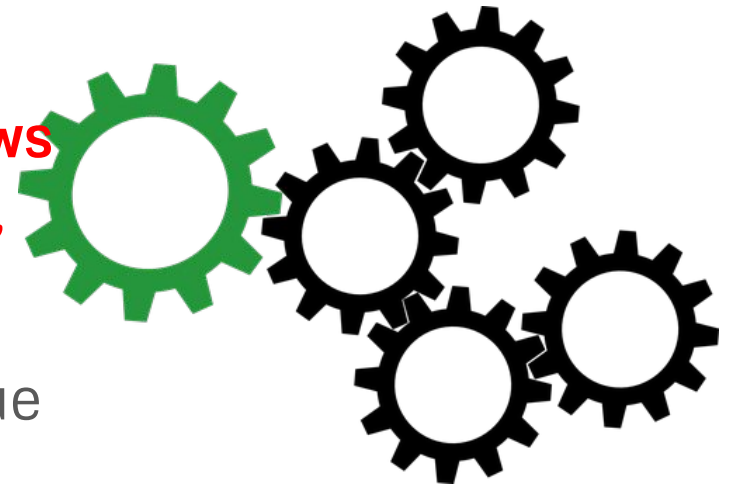


Protocols, data quality processes, observations, etc. are linked by metadata

Metadata is what makes protocols happen, it allows us to 'describe' the processes, record experiences, make systems & data interoperable etc.

As two Computer Scientists we appreciate the value of metadata (*but we also know that most practitioners find it very boring*)

For the remainder of the presentation we turn our focus to **metadata**.



Discovering data... and metadata

There is huge potential for citizen science data to be combined together, and with other data, to understand earth systems and human impacts in a more powerful way.

This approach might cross traditional disciplinary boundaries...

... for example,

a museums project interpreting historic painting and documents might be combined with modern datasets on weather, air quality and health to uncover trends and patterns.

Discovering data... and metadata

But to do this, we need to understand the nature and quality of all the data sources.

e.g.

What's being measured / recorded / observed, how and where?

and...

What measures are being taken to ensure a certain level of quality?

The importance of metadata

Some useful elements for quality evaluation:

- **completeness, consistency and representativity**: do observers sample at random or according to some plan?
- **accuracy and precision**: are the volunteers trained, and is their data double-checked?

If metadata communicates this provenance, we can decide whether it's scientifically **appropriate** to re-use datasets.

Ideally, the metadata needs some level of machine-readability

- and **interoperability**.

In the wider scientific field, there are several standards that try to achieve interoperability for data and metadata.

You can record the quality of a geospatial dataset (along with many other dataset characteristics) with a standard like ISO 19115 or FGDC.

Typically, an XML document, with structured information embedded in it.

<http://www.fao.org/geonetwork/srv/en/iso19139.xml?id=37134>

```
<gmd:dataQualityInfo>
  <gmd:DQ_DataQuality>
    <gmd:scope>
      <gmd:DQ_Scope>
        <gmd:level>
          <gmd:MD_ScopeCode
            codeList="http://www.isotc211.org/2005/resources/codeList.xml#MD_ScopeCode"
            codeListValue="dataset"/>
        </gmd:level>
      </gmd:DQ_Scope>
    </gmd:scope>
    <gmd:lineage>
      <gmd:LI_Lineage>
        <gmd:statement>
          <gco:CharacterString>Due to the map generation method, the quality of the map can never be uniform. The overall quality of the map depends heavily on the individual quality of the data for the different countries.</gco:CharacterString>
        </gmd:statement>
      </gmd:LI_Lineage>
    </gmd:lineage>
  </gmd:DQ_DataQuality>
</gmd:dataQualityInfo>
```

Metadata for citizen science

Historically not standardised.

Can be laborious to produce, especially for small projects with little resource.

Often very descriptive, but can contain a wealth of useful information.

The challenge is to discover, harmonise and interpret that information.

dataQualityAssuranceMethod	<ul style="list-style-type: none">-Data owner curated-Subject matter expert record verification-Crowd-sourced record verification-Record annotation-System supported data attribute configuration-No DQ methods used-Not applicable
----------------------------	---

A set of possible labels for citizen science to describe how data QA was carried out.

Work in progress - more on this example later

<https://core.citizenscience.org/>

Does dataset-level quality make sense?

Many citizen science repositories are not static ‘datasets’

They can be ‘sliced and diced’ and queried in a range of ways.



Download details

IDENTIFIER	DOI doi:10.15468/dl.wjrus4
CITE AS	GBIF.org (12th July 2015) GBIF Occurrence Download http://doi.org/10.15468/dl.wjrus4
QUERY	TAXON <i>Ruwenzorornis johnstoni</i> (Sharpe, 1901) COUNTRY Rwanda GEOREFERENCED true
FORMAT	DwCA
STATUS	Preparing

4 datasets contributed data to this download



DATASET	rmca-albertine-rift-birds
RECORDS	35 records from this dataset included at time of download
IDENTIFIER	doi:10.15468/i2phti
CITATION	BeBIF Provider: rmca-albertine-rift-birds

DATASET	EOD - eBird Observation Dataset
RECORDS	6 records from this dataset included at time of download
IDENTIFIER	doi:10.15468/aomfnb
CITATION	2013. EOD - eBird Observation Dataset.

DATASET	Royal Museum of Central Africa - Albertian Rift Birds (ENBI wp13)
RECORDS	35 records from this dataset included at time of download
IDENTIFIER	doi:10.15468/evhiqt
CITATION	BeBIF Provider: Royal Museum of Central Africa - Albertian Rift Birds (ENBI wp13)

DATASET	iNaturalist research-grade observations
RECORDS	1 records from this dataset included at time of download
IDENTIFIER	doi:10.15468/ab3s5x
CITATION	iNaturalist.org: iNaturalist research-grade observations



Variability among volunteer weather stations...
7 typical examples, co-located with a gold-standard weather station.

Bell, S, Cornford, D & Bastin, L, 2015. *Weather*, 70 (3), pp. 75-84

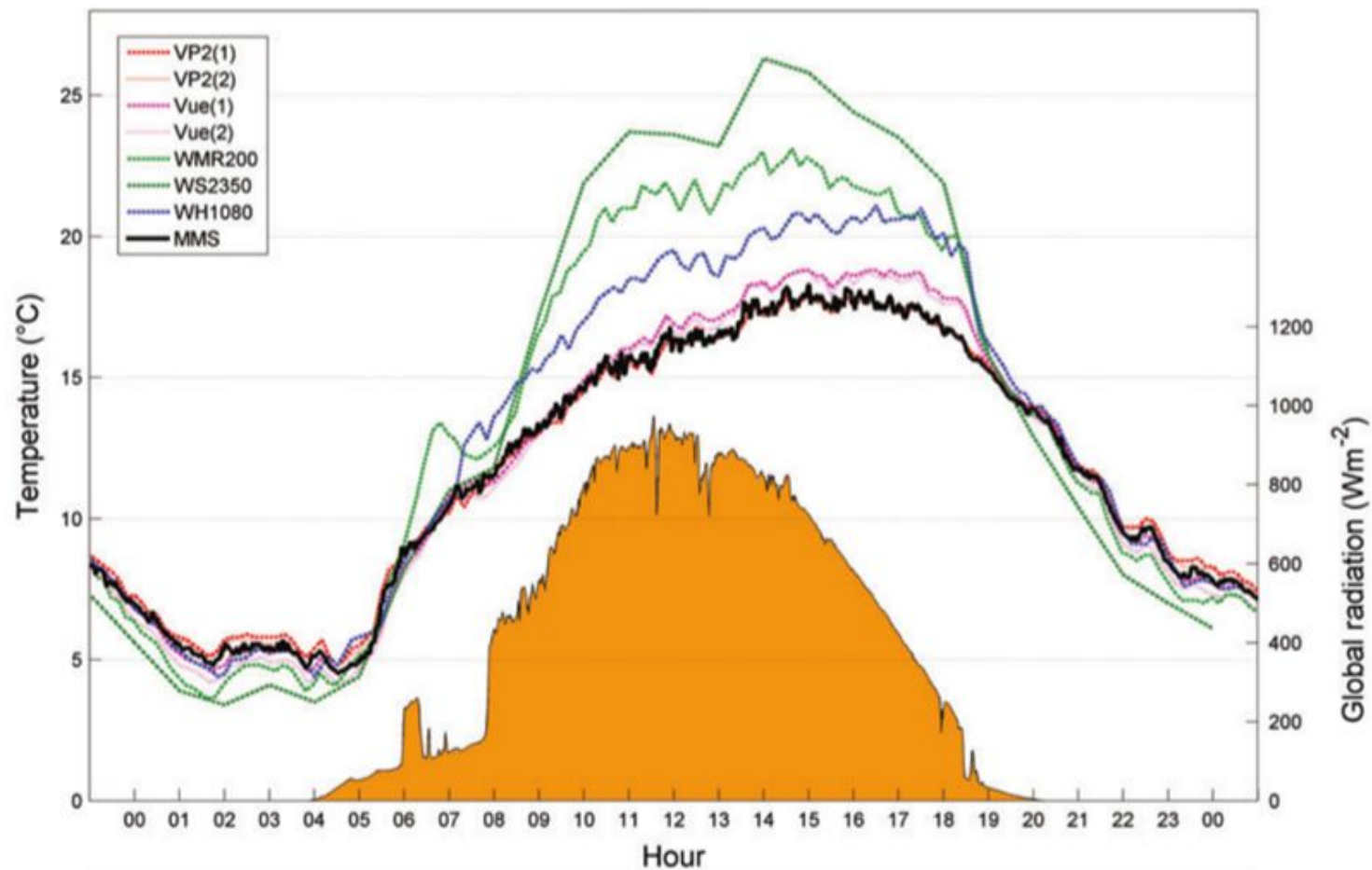
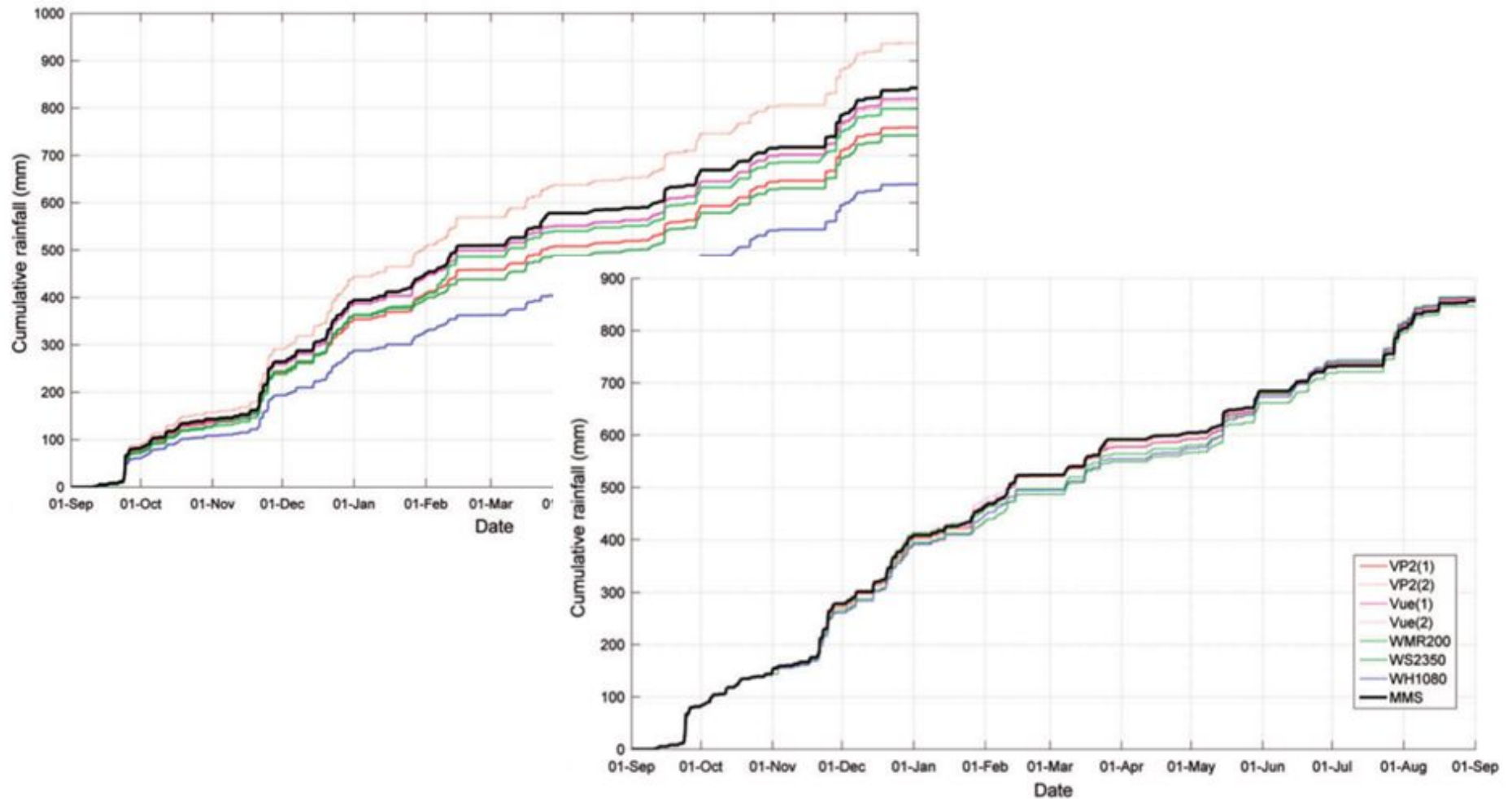


Figure 4. Time series plot of air temperature recorded by the seven CWS and the professional platinum resistance thermometer housed within a Stevenson screen for 26 May 2013. A time series of MMS global radiation is shown in orange.



Bell, S, Cornford, D & Bastin, L (2015)

How good are citizen weather stations? Addressing a biased opinion.

Weather, 70 (3), pp. 75-84.

Observation-level quality

- more useful in a context where an individual outlier will have a large effect on a decision or modelling output

e.g in contexts where the decisions are high-stakes,

Allows filtering, where, to be fit for **your** purpose, all data points **MUST** conform to a certain standard.

An example from the Biodiversity Information Standards working group (TDWG)

→ ↻ 🏠 🔒 tdwg.org/community/bdq/tg-2/ ☆

TDWG Standards **Journal** Community Conferences About

Data quality tests and assertions

The Task Group will provide a report of the practical tests, assertions, principles, software and key references associated with assessing data quality of biodiversity records. This should provide a basis, along with the other Data Quality Task Groups of a standard approach to data quality that should be used by all agencies providing biodiversity-related data.

For EACH observation, record whether tests are passed

```
{"name":"zeroCoordinates","code":4,"isFatal":true,"description":"Supplied  
coordinates are zero", "category":"warning","fatal":true},
```

```
{"name":"countryCoordinateMismatch","code":16,"isFatal":false,"descriptio  
n":"Coordinates dont match supplied country", "category":"error",  
"fatal":false},
```

```
{"name":"invertedCoordinates","code":3,"isFatal":false,"description":"Coordi  
nates are transposed", "category":"warning","fatal":false},
```

<https://biocache.ala.org.au/ws/assertions/codes>

Many of these errors are not specific to biodiversity data

- for example, typical errors like getting the x and y coordinates the wrong way round.

The definition is openly available – anyone can find out the meaning of a particular test failure, and decide whether that observation is acceptable for their own purpose.

- Like a shared **vocabulary**

```
"name":"invertedCoordinates",
```

```
"code":3,
```

```
"description":"Coordinates are transposed",
```

```
"fatal":false
```

Vocabularies, dictionaries, thesauri...

- There are many such contexts where it might be useful to share or even re-use a definition.
- Many scientific communities have collated terms for their domain so they can be unambiguously referenced.
- This often involves hosting the definition on the Web and referencing it via a **URI**

EIONET

Data Dictionary

You are here: [Eionet](#)» [Data Dictionary](#)» [Vocabulary](#)

[Help and documentation](#)[Datasets](#)[Tables](#)[Data elements](#)[Schemas](#)[Vocabularies](#)[Services](#)[Namespaces](#)

Concept: *Particulate matter < 10 µm (aerosol) in the pollutant vocabulary*

[← Back to vocabulary](#)

Concept URI	http://dd.eionet.europa.eu/vocabulary/aq/pollutant/5
Preferred label	Particulate matter < 10 µm (aerosol)
Definition	PM10 - recommended unit: µg/m3
Notation	PM10
Status	Valid
Status Modified	20.09.2013
Accepted Date	20.09.2013

<https://dd.eionet.europa.eu/>



Natural
Environment
Research Council



National Oceanography Centre
British Oceanographic Data
Centre BODC

The NERC Vocabulary Server (NVS)

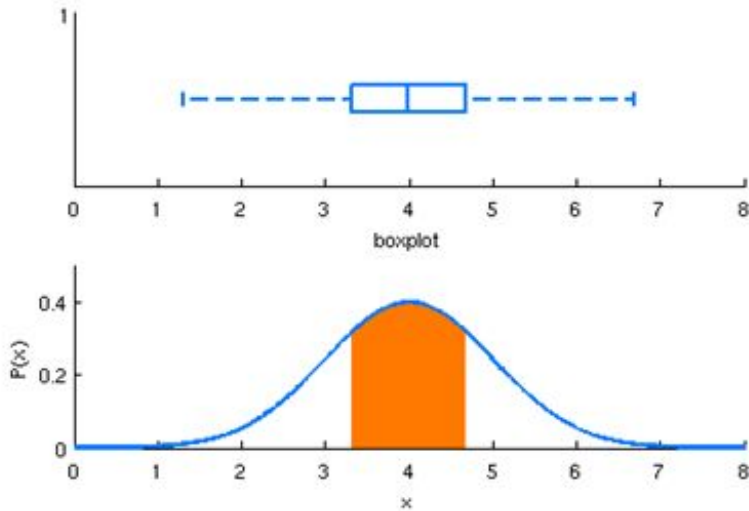
Service Status

Concept

Not usable

URI	http://vocab.nerc.ac.uk/collection/L31/current/4/
Within Vocab	Geo-Seas data object quality flags
Preferred Label	Not usable
Definition	The data object (such as a seismic section) quality is so poor that it cannot be exploited
Note	accepted
Deprecated	false
Alternative Label	bad

Some vocabulary terms refer specifically to **quality conformance** and the methods used to measure it. For example, this URI takes you to a page with a clear definition of what the quality code means, and who it is used by.

URI:	http://www.uncertml.org/statistics/interquartile-range
UncertML name:	InterquartileRange
Alternative names:	IQR
Definition:	 <p>The interquartile range is the range between the 1st and 3rd quartiles. It contains the middle 50% of the sample realisations (or of the sample</p>

This vocabulary unambiguously defines statistical terms, so that users can be sure they are talking about the same clearly-defined measure or metric.

More at
<http://www.qualityml.org/>

Citizens as reviewers?

Emerging tools allow a user to **annotate or tag** a dataset or an observation.

- can describe how and where they used the data.
- can flag up problems that they discovered.

Zabala et al (2021) *Geospatial User Feedback: How to Raise Users' Voices and Collectively Build Knowledge at the Same Time*. <https://doi.org/10.3390/ijgi10030141>

Add user feedback to the layer 'Corine Land Cover 2012'

Add a user feedback

Previous user feedback to the layer 'Corine Land Cover 2012'

AlaitzZabala, 2019-06-21 10:12:21

NiMMbus Id.:
[19964QKA67M0AR25AQITFK118JSGE67B3YO9MOT1TNLPS61](#)
Abstract: Corine Land Cover 2012 in NextGEOSS
Purpose: Small issues have been found
User role: Research end user
Date (creation): 2019-06-21
Date (revision): 2019-06-21
Rating: 4/5

Comment: CLC 2012 has been used in NextGEOSS pilots. In general CLC 2012 is a good resource to derive train and test data, but it has some scale and thematic limitations
Comment motivation: Comment

Aspect reported: Usage, Limitation, Problem

Specific usage description: CLC has been used to derive train and test data for remote sensing classification within NextGEOSS pilots
Usage date and time: 2019-05-06T14:22:00Z
User determined limitations: Legend of the CLC has some confusion on urban/bare soil classes, thus those categories should not be trusted if not confirmed with other national data
Response: Use other source of information to get training and test for urban and bare soil categories

Known problem: Urban and bare soil confusion on CLC 2012

These examples have been rather biased towards spatial and biodiversity concepts.

...in your fields of expertise, you may be using other standards for documenting the data you create and publish.

If interoperability and metadata interest you... I would like to highlight two international initiatives working to bring together these standards, **specifically for citizen science.**

PPSR Core

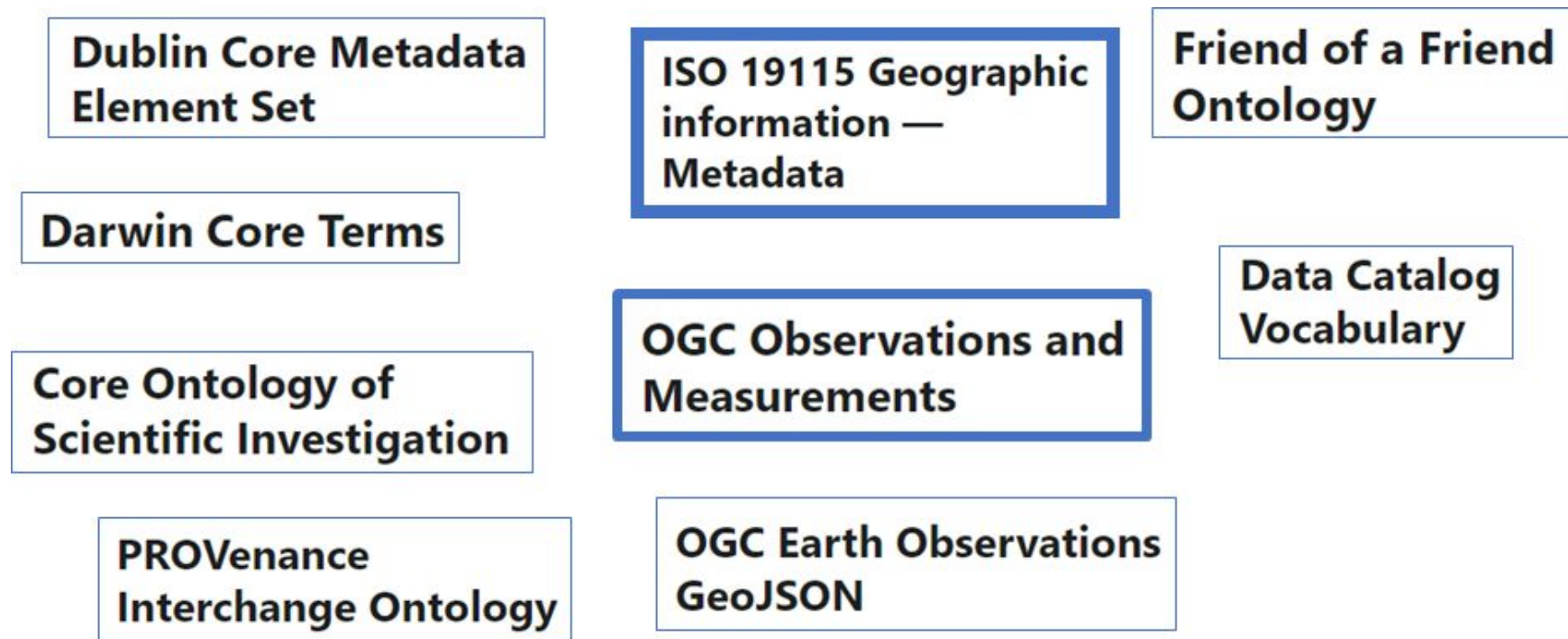
A Data Standard for Public Participation in Scientific Research
(Citizen Science)

Maintained by the Data and Metadata Working Group of the Citizen Science Association
<https://core.citizenscience.org/>

PPSR Core is a set of global, transdisciplinary data and metadata standards for use in **P**ublic **P**articipation in **S**cientific **R**esearch (**Citizen Science**) projects. These standards are united, supported, and underlined by a common framework illustrating how information is structured within the citizen science domain. This allows data to be used across platforms and projects in a consistent manner, furthering the research goals of the scientific community.

PPSR-Core – not about creating a whole new standard for the sake of it.

Aims to unify EXISTING standards and ontologies and re-use or map to definitions which already exist.



dataQualityAssuranceMethod	<ul style="list-style-type: none">-Data owner curated-Subject matter expert record verification-Crowd-sourced record verification-Record annotation-System supported data attribute configuration-No DQ methods used-Not applicable
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Elements of the PPSR-CORE remit:

- decide what information is essential
- construct vocabularies that reflect actual practice across citizen science

<https://core.citizenscience.org/>

The OGC* Citizen Science Interoperability Experiment

*Open Geospatial Consortium

https://external.ogc.org/twiki_public/CitSciE/WebHome

Ongoing initiative to demonstrate how current ICT-based tools can be applied to allow easier citizen participation and better data reuse.

2019 Engineering report at <http://docs.opengeospatial.org/per/19-083.html>

Some outputs specifically address quality:

e.g. <https://doi.org/10.1117/12.2570814>

**Assess citizen science based land cover maps
with remote sensing products: the Ground Truth
2.0 data quality tool**

Summary

There is **often huge suspicion about citizen science data quality**

It can be an excellent complement to research datasets; sometimes of equivalent or better quality.

Often, it contains rich information, additional to what scientists want:

- *e.g., where are people observing, and which people:* tells you something about digital inclusion and how different social groups experience their local surroundings.

We have to be transparent about the quality aspects of all data, so that a user can decide if it is fit for their purpose.

Huge momentum right now – potential for a really open Citizen Science data ecosystem that crosses disciplinary boundaries.

Some references and further links

Website of the PPSR-CORE initiative <https://core.citizenscience.org/>

Engineering Report of the OGC Citizen Science Interoperability experiment
<http://docs.opengeospatial.org/per/19-083.html#DataQuality>

Yu et al. (2015) Towards Linked Data Conventions for Delivery of Environmental Data Using netCDF.
<https://hal.inria.fr/hal-01328530/document>

A collection of resources related to dataset quality and FAIR principles.
https://wiki.esipfed.org/FAIR_Dataset_Quality_Information

Thanks for watching and listening



Questions?
Comments?

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