A Comparison of Open Data Observatories

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Open Data Observatories refer to online platforms that provide real-time and historical data for a particular application context, e.g., urban/non-urban environments or a specific application domain. They are generally developed to facilitate collaboration within one or more communities through reusable datasets, analysis tools, and interactive visualizations. Open Data Observatories collect and integrate various data from multiple disparate data sources—some providing mechanisms to support real-time data capture and ingest. Data types can include sensor data (soil, weather, traffic, pollution levels) and satellite imagery. Data sources can include Open Data providers, interconnected devices, and services offered through the Internet of Things. The continually increasing volume and variety of such data require timely integration, management, and analysis, yet presented in a way that end-users can easily understand. Data released for open access preserve their value and enable a more in-depth understanding of real-world choices. This survey compares thirteen Open Data Observatories and their data management approaches - investigating their aims, design, and types of data. We conclude with research challenges that influence the implementation of these observatories, outlining some strengths and limitations for each one and recommending areas for improvement. Our goal is to identify best practices learned from the selected observatories to aid the development of new Open Data Observatories.

CCS Concepts: • **Information systems → Information integration**; Data model extensions; *Data management systems.*

Additional Key Words and Phrases: Urban and non-urban data observatories, FAIR Open Data principles, Data integration, Data platforms.

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1 INTRODUCTION

Structured, semi-structured, and unstructured data can be generated from diverse sources, including government authorities, academic institutions, and citizens. These data categories apply to every sort of data, with structured data including inventories and catalogs organized in tables, semi-structured

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data such as operational manuals in JSON (JavaScript Object Notation) and XML (eXtensible Markup Language) formats, and unstructured data including text and media. These data are collected through various methods, such as questionnaires, web scraping and Internet of Things (IoT) devices. While many governments have embraced the "Open Data" principles and made some of their data public, some commercial organizations collect large volumes of data, but only a fraction is accessible. Open Data refer to data that are made available to the public by governments, organizations, and individuals [51]. They promote transparency, collaboration, and innovation, which can improve the quality of scientific research and contribute to the development of a sustainable ecosystem [15, 36].

Open Data portals, Open Data Observatories, and Repositories represent distinct systems within the data-sharing ecosystem, each serving unique functions and targeting specific audiences. Open Data portals serve as gateways to a wide range of datasets and resources from various sources. They provide search and discovery tools, data visualization capabilities, and options for downloading data [18]. Open Data portals are centralized platforms where governments, non-profit organizations, and private companies release datasets to the public, aimed at enhancing transparency, enabling societal and economic benefits, and fostering innovation through open access to information on a variety of topics such as government operations, demographics, and economics [43].

Open Data Observatories are online platforms that curate and integrate real-time and historical data from different sources, presenting them in a unified manner. They focus on monitoring and analyzing specific datasets for trends and insights, typically in public or research domains. The reliance on Open Data Observatories has become increasingly crucial in tackling the complex challenges faced by contemporary society and the environment. Previous research initiatives in [2] developed methods to survey Open Data platforms, providing insights into their availability and helping data publishers select the most suitable platforms for their data. A series of studies by Miller et al. [48], Moustaka et al. [49], Ma et al. [44], and Liu et al. [41] provided an understanding of the role of Open Data platforms in areas such as urban sustainability, smart city analytics, and ocean science.

Repositories provide broad platforms for sharing diverse research outputs. They can be domain-specific (storing data from a specific subject or field) or Generalist (serving multiple domains). Stall et al. [61] introduced the Generalist Repository Comparison Chart (GRCC) to assist researchers in identifying a generalist repository when a domain-specific repository [27] is unavailable for storing their research data. Generalist repositories (e.g., Zenodo, Figshare, and Dryad) archive diverse types of scholarly work, including datasets, articles, and preprints, thus supporting interdisciplinary research and increasing the visibility and impact of academic work beyond traditional publication venues. Such repositories require users to deposit their research outputs under open licenses, ensuring accessibility for further use.

Our study aims to compare different Open Data Observatories to highlight their distinct characteristics, methodologies, and challenges they encounter. By identifying and extrapolating best practices from these observatories, the goal is to facilitate the development of new Open Data Observatories and to better understand their impact on decision-making and policy formulation in urban and non-urban settings.

Our research questions are:

- What are the key features and functionalities of different Open Data Observatories?
- How do different Open Data Observatories compare regarding data coverage, accessibility, and usability?
- What are the strengths and limitations of different Open Data Observatories?
- What are the challenges organizations face when building Open Data Observatories, and how can these challenges be addressed?

To answer the research questions, we (a) selected and compared thirteen Open Data Observatories based on various criteria, such as data types, data coverage, accessibility, and usability; (b) investigated the data management approaches in the context of Open Data Observatories; (c) outlined their strengths and limitations and recommended areas for improvement; and (d) identified the critical challenges faced by organizations when building Open Data Observatories, such as technical and intellectual challenges.

This paper is structured as follows: Section 2 investigates the use of the term Open Data, its principles, and main sources (providers). Section 3 discusses the study's research methodology. Section 4 introduces the thirteen selected Open Data Observatories, individually describing their aim, data management approaches, and the (smart) services they support. Section 5 recapitulates the types of data they support, examining their themes, sources and the methods employed in their processing. Section 6 describes four key research challenges, namely data integration, quality, provenance, and privacy. Section 7 interpret the study's findings, compare them with existing knowledge, address research questions, evaluate implications, and guide future research directions. Finally, Section 8 concludes the paper.

2 OPEN DATA

Open Data are free data, released under open licenses [21] and shared in formats that follow established standards and conventions. Open Data are accompanied by metadata, which provides additional information about the data, such as their source, creation date, data dictionary, and other relevant details. The metadata helps users better understand and contextualize the data. High-quality Open Data are presented in formats that are designed to be easily read and processed by computer programs and algorithms [36]. This enables automated analysis, integration of the data, making them more accessible and useful for a wide range of applications [68].

2.1 Open Data Principles

The expansion of Open Data is influenced by fundamental frameworks such as the Berners-Lee Five-Star Model [51]. This model evaluates Open Data on a scale from one to five stars, with higher ratings indicating data that are open, machine-readable, and compliant with open standards. Kucera et al. [34] investigated the challenges related to publishing and reusing Open Government Data, emphasizing methodologies and best practices in this domain. This includes the establishment of a publication methodology within the COMSODE project, which highlights the role of Open Government Data in fostering transparency and citizen engagement. Open Data principles, further expanded upon by groups such as the Sebastopol [67] attendees and the Sunlight Foundation [25], establish a comprehensive framework to ensure government data are openly accessible.

The FAIR data principles [8, 30, 70] provide a set of guidelines aimed at enhancing data reusability for both humans and machines, stressing the importance of data being *Findable, Accessible, Interoperable, and Reusable.* Table 1 integrates Open Data principles, as discussed by both the Sebastopol group and the Sunlight Foundation, with the broader framework of the FAIR data principles, providing a comparative overview of their alignment. It shows ten critical principles identified for the openness and availability of government data, ranging from ensuring data completeness and primacy to guaranteeing accessibility, machine processability, and non-discrimination. Moreover, it introduces considerations for non-proprietary formats, license freedom, permanence, and the elimination of usage costs to foster a more inclusive and accessible digital ecosystem. This alignment is further enhanced by indicating which of these Open Data principles correspond to which element of FAIR data principles.

Table 1. Description and comparison of Open Data principles proposed by Sebastopol, the Sunlight Foundation and how they correspond to the FAIR (Findable, Accessible, Interoperable and Reusable) data principles.

Principle	Description	Sebastopol	Sunlight Foundation	FAIR Data Principles
1. Complete	Data must be a complete and accurate representation of the original observations, including all computational details.	✓	✓	Findable
2. Primary	Data collected at the source with detailed metadata.	✓	✓	Findable
3. Timely	Data published promptly after collection.	✓	✓	Accessible
4. Accessible	Data must be easily accessible in both printed and digital forms.	✓	✓	Accessible
5. Machine-processable	Data in a format that can be easily processed by computers.	✓	✓	Interoperable
6. Non-discriminatory	Data are accessible to anyone without restrictions.	✓	✓	Accessible
7. Non-proprietary	Data in a format that does not require proprietary software.	✓	✓	Interoperable
8. License	Data with clear open license to support unrestricted use.	✓	✓	Reusable
9. Permanence	Data remain accessible online, including all versions.		✓	Accessible
10. Usage costs	Accessing and obtaining data incur no fees.		✓	Accessible and reusable

2.2 Open Data Sources

Scientific research heavily relies on Open Data sources for replication, validation, and growth. Open Data can be obtained from various entities, including government bodies, academic institutions, and citizens. For example, government bodies publish a wide range of information such as demographics (age, gender, race), economic indicators (GDP, unemployment rates), weather data, and public health indices. These data types enable researchers to examine social trends, economic patterns, public health outcomes, and their interrelationships.

Researchers are increasingly required by funders to make the data contributing to a paper publicly available. This includes surveys and observational data that could be used to provide empirical evidence. By sharing these data openly, researchers foster collaboration, facilitate replication, and allow for the expansion of scientific knowledge. In recent years, citizen-generated data through smartphones and mobile devices have gained increasing value, particularly in social science and humanities studies [32]. These data include information collected through social media platforms, GPS tracking devices, and other mobile applications. Researchers can use citizen-generated data to study topics such as online communities, human behaviour, social interactions, urban dynamics and cultural trends. Sensor networks significantly contribute data on environmental conditions, vehicle movements, and electricity usage. These networks provide valuable information for research related to urban planning, environment sustainability, transportation patterns, and energy consumption. While Open Data sources offer numerous benefits, they also present challenges. Data quality assurance, privacy protection, and managing diverse data types are some hurdles researchers must address. However, the potential of Open Data sources is evident, and they are expected to play an increasingly significant role in scientific research.

3 RESEARCH METHOD

We employed the SPIDER (Sample, Phenomenon of Interest, Design, Evaluation, Research type) methodology [17] to guide our search for Open Data Observatories. SPIDER is specifically designed for conducting transparent and reproducible research. To ensure comprehensive coverage, we extracted keywords for each SPIDER element based on synonyms and related terms derived from our research questions. We conducted searches using the Google search engine, Google Scholar, ACM digital library, and Cardiff University library, focusing on the following terms:

(1) **S**ample: Open Data observatory.
(2) **P**henomenon of **I**nterest: domain-specific data observatory, multi-domain data observatory.
(3) **D**esign: Open Data platforms.
(4) **E**valuation: relevance, transparency, accessible.
(5) **R**esearch type: descriptive, survey, research article.

3.1 Search Plan

Our search plan used the Boolean operators AND and OR to connect the search items corresponding to each SPIDER element. This approach allowed us to construct comprehensive search queries that incorporated relevant terms. For instance, the search query for the SPIDER elements would look like this: Sample AND Phenomenon of Interest AND Design AND Evaluation AND Research type ("Open Data platform" OR "Open Data observatory") AND ("domain-specific data observatory" OR "multi-domain data observatory") AND ("accessible online platforms" OR "data platform") AND ("relevance" OR "transparency") AND ("descriptive" OR "survey" OR "research article"). Using the OR operator within parentheses, we expanded the search to include variations and synonyms for terms such as "Open Data platform" and "Open Data observatory." We incorporated terms related to the phenomenon of interest, such as "domain-specific data observatory," and "multi-domain data observatory". To capture different aspects of the design and evaluation, we included phrases like "accessible online platforms" and "data platform." We also encompassed terms related to the desired research attributes, such as "relevance" and "transparency", and the research types, such as "descriptive" and "survey". This search strategy ensured we covered a wide range of relevant literature and maximized the chances of identifying relevant data platforms.

3.2 Observatories Selection Process

The results obtained from the previous step yielded additional platforms, some of which were not directly relevant to our research questions. We established specific inclusion and exclusion criteria to refine the selection process and ensure that only the most relevant platforms were included in our study. These criteria, outlined in Figure 1, were based on several factors, including the domain experts' suggestions, platforms' establishment date, and relevance to our research questions. By setting these criteria, we aimed to focus our analysis on the most recent platforms available in english. We prioritized platforms that demonstrated clear relevance to our research questions.

3.3 Observatories Selection Result

The initial search process yielded 40 Open Data environments. We manually checked each one to ensure that we focused specifically on Open Data Observatories. Through this evaluation, we were able to filter out and identify 34 environments that met the criteria of being Open Data Observatories. After completing a thorough manual evaluation, we arrived at a final selection of 13

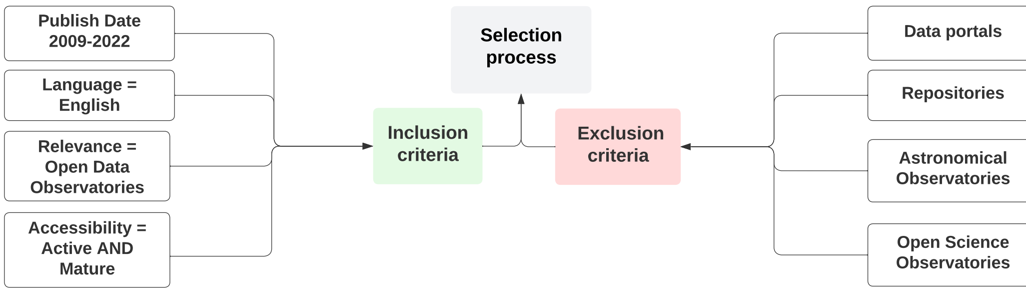

Fig. 1. Inclusion and exclusion criteria for selecting the reviewed Open Data Observatories.

Open Data Observatories that satisfied all the necessary criteria. These 13 observatories (Figure 2) will be introduced and discussed in the subsequent section. By employing this rigorous manual verification process, we ensured that the selected Open Data Observatories were reliable, accessible, and relevant to our research questions.

4 OPEN DATA OBSERVATORIES

This section investigates the selected Open Data Observatories in chronological order according to their release date. Each observatory is concisely outlined and characterized by its attributes, kinds of data, and significant accomplishments and challenges.

4.1 The Terrestrial Ecosystem Research Network (TERN)

TERN[1] is a national research infrastructure program in Australia that supports ecosystem science, observations, and data management. TERN was established in 2009 by the Australian Government in response to a growing need for a coordinated approach to terrestrial ecosystem research and management. The network comprises a range of field sites and data infrastructure that supports long-term environmental monitoring and research, including measurements of ecosystem processes, biodiversity, and land surface properties. TERN's infrastructure includes over 600 environmental monitoring sites across Australia and advanced data management systems that allow researchers to access and analyze data from multiple sources. TERN aims to support evidence-based decision-making for ecosystem management and conservation in Australia and to promote a greater understanding of terrestrial ecosystems and their role in maintaining global environmental health.

TERN hosts a substantial and growing collection of diverse ecosystem datasets from across Australia, covering topics such as terrestrial and coastal vegetation data, land cover processes, phenology and abiotic data. It provides a variety of data tools and services, including *SHaRED* for data submission and harmonization, aligning with the FAIR principles, a *Data Discovery Portal* for accessing diverse ecosystem datasets, tools for data analysis and visualization such as *MCAS-S* and the *Data Visualizer*, cloud-based research platforms like *CoESRA*, and resources for field data collection, including a network of monitoring sites. In addition, the *Threatened Species Index -TSX* (tsx.org.au) is a dynamic tool that helps understand how Australia's threatened species are faring over time. It provides visualizations and detailed data on temporal trends for 286 species of threatened and near-threatened mammals, birds, and plants in Australia.

[1]tern.org.au/

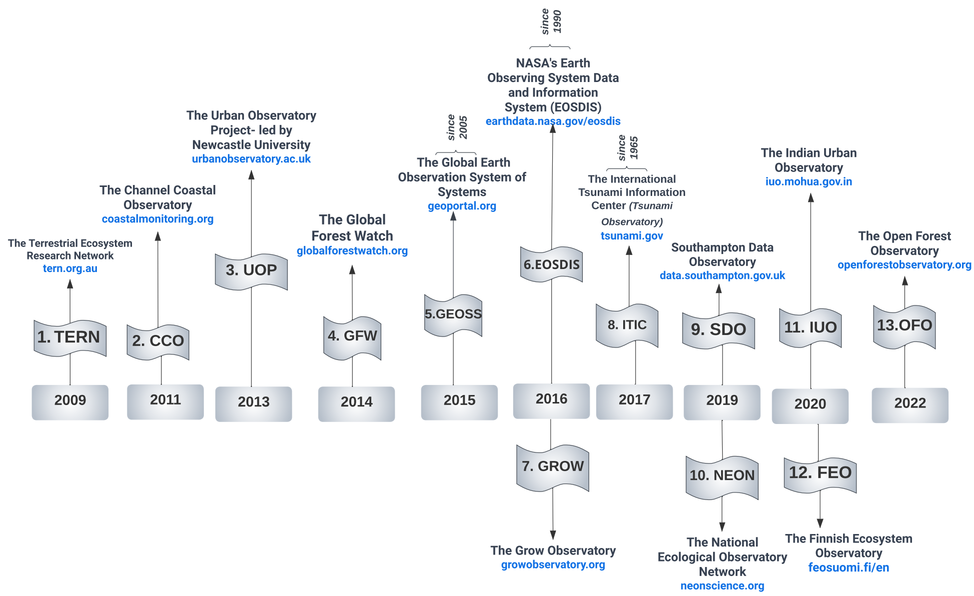

Fig. 2. Timeline displays the selected Open Data Observatories. 1. The Terrestrial Ecosystem Research Network (TERN) [14], 2. The Channel Coastal Observatory (CCO), 3. The Urban Observatory Project (UOP), 4. The Global Forest Watch (GFW) [64], 5. The Global Earth Observation System of Systems (GEOSS) [13, 19], 6. NASA's Earth Observing System Data and Information System (EOSDIS) [7], 7. The Grow Observatory (GROW), 8. The International Tsunami Information Center (ITIC)- Tsunami Observatory, 9. Southampton Data Observatory (SDO), 10. The National Ecological Observatory Network (NEON) [6], 11. The India Urban Observatory (IUO) 12. The Finnish Ecosystem Observatory (FEO) [66], 13. The Open Forest Observatory (OFO).

4.2 The Channel Coastal Observatory (CCO)

Since 2011, the National Network of Regional Coastal Monitoring Programmes has supported six projects along the English coastline. The overarching objective of these projects is to gather in-situ coastal monitoring data [38]. However, Contarinis et al. [16] highlighted some inconsistencies in the quality of the data and the data collection methodologies. The CCO[2] was established in response to these challenges. In England, 520,000 properties face the risk of coastal flooding, while 8,900 are threatened by coastal erosion. The CCO aims to provide consistent and reliable data to aid decision-makers in understanding coastal behaviour and identifying potential risks associated with coastal flooding and erosion [46]. The CCO covers various coastal regions, including the Northeast, East Riding of Yorkshire, Anglian, Southeast region (low-lying land), and Northwest. The primary data types collected and displayed on its platform include topographic and hydrographic surveys. Topographic surveys focus on features such as beaches, cliffs, dunes, and coastal defence structures, while hydrographic surveys extend from the Mean Low Water (MLW) contour to 1 kilometre offshore. The CCO offers a collection of real-time data on waves, tides, meteorology, and GPS measurements, which are crucial for understanding and managing coastal environments. The CCO has a public API that allows developers to access and integrate the real-time coastal data (waves,

[2]coastalmonitoring.org/

tides, meteorology) collected by the monitoring programs. It also provides information on how to access the coastal data through Web Map Services (WMS) in GIS software such ArcMap and QGIS.

4.3 The Urban Observatory Project (UOP)

The UOP[3] was launched in 2013 and sponsored by the UK Collaboratorium for Research on Infrastructure and Cities (UKCRIC) - led by Newcastle University in collaboration with five other British universities: Sheffield, Bristol, Cranfield, Birmingham, and Manchester. The UOP aims to monitor and analyze urban areas through the deployment of various sensors across these cities. It collects vast amounts of real-time data from sensors and other sources to gain insights into urban dynamics. Each participating university focuses on specific aspects of urban life. For instance, Sheffield Urban Flows Observatory examines the impact of energy and resource flows on economic performance and social well-being. At the same time, Bristol Urban Flows Observatory transforms Bristol into a living laboratory for community engagement. Cranfield Urban Observatory provides data-centric and remote-sensing solutions for addressing environmental, social, and economic issues. Birmingham Urban Observatory monitors critical infrastructure and its interplay with the environment, economy, and society. Lastly, Manchester Urban Observatory collects, analyzes, and shares urban data to support decision-making processes. The collaborative efforts of these observatories contribute to a better understanding of urban dynamics and offer insights for sustainable and efficient urban development [59]. The UOP's data types include traffic flow, parking spaces, cycling docking, pedestrian count, weather data, air quality, water quality, seismic activity, noise-level, water-level (rainfall), beehives, energy usage data, thermal imaging, visual and hyper-spectral mapping, social media feeds, employee feedback, and quantifying the impacts of COVID-19 measures. More details about UKRIC observatories are available as supplement materials in Appendix A 8.

4.4 The Global Forest Watch (GFW)

The GFW initiative[4] is a non-profit organization that is part of the World Resources Institute (wri.org). The GFW collaborates with over 100 organizations to provide a transparent and actionable platform that is supported by satellite technology and cloud computing. This initiative empowers various stakeholders, including law enforcement, companies, and governments, in forest management and combating deforestation. The GFW's web-based platform (observatory), which was launched in 2014, provides data and tools for monitoring forests and land use. The platform has amassed over four million users worldwide, benefiting diverse groups such as local law enforcement, park managers, international corporations, and civil society organizations in their endeavors to safeguard forests. The GFW's key applications include the *Forest Watcher* mobile app for real-time threat detection, The GFW Pro for managing deforestation risks in supply chains, and the *Global Forest Review* for monitoring global forest objectives. Moreover, national governments employ the GFW's technology for forest resource management, while small grants and fellowships support additional advocacy and research. Collectively, the GFW assists in forest surveillance and management, combats illegal deforestation, promotes sustainable commodity sourcing, and supports conservation research on a global scale. The GFW data types include satellite imagery for observing changes in forest cover, forest change data for tracking deforestation and regrowth, and land cover data for understanding land usage. In addition to data about biodiversity, climate dynamics, and commodity supply chains, as well as legal and administrative boundaries, fire alerts, and water resources. The GFW provides both developer-focused tools (APIs and open-source code)

[3] urbanobservatory.ac.uk

[4] wri.org/initiatives/global-forest-watch

and a user-friendly MapBuilder platform to enable the creation of customized interactive mapping applications that leverage the GFW's robust spatial data and analysis capabilities.

4.5 The Global Earth Observation System of Systems (GEOSS)

GEOSS[5] was created following directives from the 2002 United Nations World Summit on Sustainable Development and the G8's 2005 commitment. Its purpose was to improve the development and application of earth observation technologies for environmental monitoring and management. Initiated in 2005 with a 10-year implementation plan, GEOSS aimed to provide comprehensive, coordinated, and sustained observations of the Earth, focusing on nine key societal benefits such as sustainable agriculture, biodiversity conservation, and climate change adaptation. The success of GEOSS's first decade led to the implementation of a renewed 10-year plan (2016-2025), which aligned with global initiatives such as the UN Committee of Experts on Global Geospatial Information Management (UN-GGIM) and the G8 Open Data Charter to enhance data sharing and management. GEOSS evolved into more than just a technological project; it became a global partnership that advocated for the significance of earth observations and engaged with stakeholders to tackle global challenges. One of GEOSS's notable achievements was the establishment of GEOSS's data sharing principles, which advocated for Open Data access, minimal use restrictions, and prompt availability of data and metadata. These principles significantly influenced global data policies, including the European Union's Copernicus program [19]. GEOSS encompasses a wide array of data types, aiming to facilitate comprehensive, coordinated, and continuous observations of the Earth system. Data types include but are not limited to, satellite imagery, atmospheric data, oceanographic data, geological data, biodiversity information, and climate metrics.

4.6 NASA's Earth Observing System Data and Information System (EOSDIS)

EOSDIS[6] is a vital part of NASA's Earth Science Data Systems Program, providing extensive capabilities for managing data from various sources, including satellites, aircraft, field measurements, and other programs. EOSDIS supports the Earth Observing System (EOS) satellite missions by handling tasks such as command and control, scheduling, data capture, and initial processing. These mission operations are overseen by NASA's Earth Science Mission Operations Project. EOSDIS's Science Operations, managed by NASA's Earth Science Data and Information System Project, involve generating higher-level science data products (levels 1-4), archiving, and distributing data products from EOS missions, as well as other satellite missions, aircraft, and field measurement campaigns. This function is carried out within a distributed system that consists of interconnected nodes of Science Investigator-led Processing Systems and Distributed Active Archive Centers (DAACs), which are discipline-specific. EOSDIS offers a variety of curated data types that are crucial for evaluating ecosystem conditions, predicting species' geographical distributions, identifying materials based on spectral properties, and monitoring human-induced environmental changes. These data types include vegetation health, spectroscopy, species distribution, and environmental change tracking data.

4.7 The Grow Observatory (GROW)

GROW[7] serves as a citizens' observatory that has enabled individuals and communities to take proactive measures about soil and climate across Europe. GROW collected soil moisture, temperature, and light level data from low-cost "Flower Power" sensors deployed across 24 locations in

[5]geoportal.org/
[6]earthdata.nasa.gov/eosdis
[7]growobservatory.org/

13 European countries, resulting in a network of 6,502 ground-based soil sensors and a dataset of 516 million rows of soil data. The sensors were installed and maintained by a network of citizen scientists, community groups, land managers, and researchers. The sensors' data were collected every 15 minutes and uploaded to GROW servers using mobile phones. GROW integrated the sensors' data through an online platform, allowing members to register their sensors and visualize the data through time-series graphs and maps. GROW also used GEOSS (observatory 6) data to provide public access to archived earth observation data. This information was then used to more accurately predict extreme events, such as floods, droughts, and wildfires. In addition, GROW data played a significant role in validating and calibrating satellite observations, such as those from the European Space Agency's (ESA), SMOS (Soil Moisture and Ocean Salinity) mission and the future SMAP (Soil Moisture Active Passive) satellite. Artists and designers have played a significant role in GROW, with the former creating artworks reflecting the importance of soil ecosystems and remote sensing satellites and designing dynamic visualizations for agriculture and climate forecasting. It has also helped farmers in the Canary Islands reduce their water usage for irrigation by 30%. GROW received awards, including the Land and Soil Management Award 2019, the Stephen Fry Award for Excellence in Public Engagement 2020, and recognition as the first in the European Commission's annual GEO Plenary Statement on significant Earth Observation developments in 2019.

4.8 The International Tsunami Information Center (ITIC)- Tsunami Observatory

In March 2017, NOAA's National Tsunami Warning Center and Pacific Tsunami Warning Center, in partnership with the Tsunami Service Program, centralized their information on a Tsunami Observatory[8]. Serving as a hub for information on tsunamis, it provides warnings, advisories, watches, and threat evaluations for Alaska, British Columbia, Washington, Oregon, and California regions. The observatory offers real-time updates on seismic events that could cause tsunamis. These updates include specific information such as event magnitude, depth, coordinates, and the time the seismic event occurred. It also shares bulletins and statements about the current tsunami status, clearly indicating if there are any warnings, advisories, watches, or threats in effect for the mentioned areas. Tsunami Observatory aims to inform the public about tsunami risks following seismic activities, promoting safety and preparedness among residents of potentially affected regions. It also provides connections to various initiatives, such as the Deep-ocean Assessment and Reporting of Tsunamis (DART) project, which is a component of the U.S. National Tsunami Hazard Mitigation Program. DART employs seafloor bottom pressure recorders (BPR) and surface buoys to identify and report tsunamis in real-time. DART system has two generations, with the second-generation DART II enabling bidirectional communication since 2008. This system can detect tsunamis as small as 1 cm and transmits information to ground stations through a GOES satellite link for early detection and data collection. Moreover, the NOAA Tsunami Stations offer information on tide stations equipped to detect tsunamis along various coastlines, while the IOC Sea Level Monitoring Facility provides real-time monitoring of sea level stations worldwide.

4.9 Southampton Data Observatory (SDO)

SDO[9] collects data from various stakeholders in Southampton and Hampshire and combines them with nationally published data, providing access to professionals, businesses, the voluntary sector, citizens, and communities. The observatory has been developed in partnership with statutory partners, including the National Health Service (NHS) Hampshire, Southampton, Isle of Wight (CCG), and Southampton Voluntary Services- with data contributions from other partners such

[8] tsunami.gov
[9] data.southampton.gov.uk/

as the National Office of Statistics (ONS), Hampshire Constabulary, Hampshire Fire and Rescue Service, and South Central Ambulance Service. SDO is accountable to the Southampton Health and Well-being Board and the Southampton Safe City Partnership for delivering the Joint Strategic Needs Assessment (JSNA) and the Safe City Strategic Assessment. It considers data protection issues and ensures sufficient safeguards and disclosure controls are in place to protect the identity of individuals. SDO's data types include links to demographics, economy, education, health, housing, road safety and environment specific to Southampton and its immediate surroundings within the United Kingdom.

4.10 The National Ecological Observatory Network (NEON)

NEON[10] is an Open Data Observatory funded by the National Science Foundation. Initiating its operational phase in the summer of 2019, NEON allows access to data on various topics, including climate, land use, and biodiversity. NEON adopts a specialized method for selecting its study locations spanning across the United States, including Hawaii and Puerto Rico, to capture a diverse range of environmental conditions. These areas were divided into 20 distinct zones, each comprising its own set of ecosystems, landscapes, and natural processes. This approach allowed NEON to gather extensive data on various aspects, such as the well-being of plants and animals, soil and water quality, and more, using state-of-the-art sensor technology and direct field observations. As a result, NEON provides standardized data on a continental scale collected from 81 field sites equipped with automated sensor systems and field instruments that continuously collect data on environmental factors. NEON's focus on long-term, standardized data collection allows researchers to track and analyze changes in ecological systems over time, providing insights into the impacts of climate change and other environmental factors. The program also encourages engagement with the scientific community, allowing researchers to use NEON data for their research projects.

4.11 The India Urban Observatory (IUO)

IOU[11] is an Open Data Observatory established by the Ministry of Housing and Urban Affairs (MoHUA) in India. IOU serves as a centralized hub for data and insights related to urban areas in the country. Its primary objective is to provide policymakers, researchers, and citizens access to reliable urban planning and development information. IUO aims to facilitate evidence-based decision-making and improve the efficiency of urban planning processes. It offers a wide range of data, including city-level indicators encompassing population statistics, infrastructure development, and economic growth. The observatory also provides data on various urban services such as water supply, sanitation, and waste management. IUO offers visualization and analysis tools to enhance data re-use and understanding. These tools enable users to explore and interpret the data in a user-friendly manner, promoting more significant insights and informed decision-making.

4.12 The Finnish Ecosystem Observatory (FEO)

FEO[12] is a research and monitoring infrastructure that serves as a resource for obtaining high-quality ecosystem data across diverse terrestrial and aquatic ecosystems in Finland. It aims to facilitate access to data and observations for researchers, policymakers, and the general public. The data available through FEO encompass a wide range of parameters, including climate, hydrology, biogeochemistry, and biodiversity. To gather such data, FEO employs various monitoring techniques such as eddy covariance flux towers, radiometers, anemometers, and infrared gas analyzers. FEO

[10] data.neonscience.org/
[11] iuo.mohua.gov.in/portal/apps/sites
[12] feosuomi.fi/en/

also provides standardized field monitoring methods, calibration guidelines, and field data collection apps to ensure consistent and reliable data collection. One of the research at FEO, Mäyrä et al. [47] combined deep learning and remote sensing to improve forest monitoring, specifically by classifying tree species using airborne hyperspectral imagery and LIDAR data. Conducted in Finland's Boreal forests, the study demonstrated the effectiveness of high-resolution hyperspectral data and ground reference measurements in efficiently distinguishing between different tree species for improved biodiversity monitoring.

4.13 The Open Forest Observatory (OFO)

The OFO[13] employs drones to map and identify trees without needing traditional ground surveys. It establishes more than 100 forest plots, each roughly 25 hectares in size, to gather data vital for forest management in the face of issues such as droughts and wildfires. This initiative aims to improve research in forest ecology and disturbance ecology by creating three innovative cyberinfrastructure tools. The first tool is an AI-driven software workflow that efficiently transforms drone-captured imagery into detailed forest inventory information. This includes creating maps that accurately pinpoint individual trees, along with their size and species. The second tool is a searchable and open database that contains tree maps from over 100 plots, each covering 25 hectares. These plots are coordinated with existing forest inventory networks, such as the NSF's NEON, and cover a range of environmental and disturbance gradients. Lastly, the initiative includes comprehensive documentation and training programs, both online and in-person, to empower researchers to generate and share their data and tools. The software used in this observatory employs advanced photogrammetry to create 3D models of forest structures. It also uses multi-view computer vision, supported by neural networks, for accurate species classification and to filter out incorrect tree identifications. The OFO is primarily funded by the National Science Foundation with additional support from the Nature Conservancy. It is housed in three academic institutions, the Department of Plant Sciences at the University of California, Davis, the CIRES Earth Lab at the University of Colorado, Boulder, and the Bio5 Institute at the University of Arizona. It relies on ground-reference forest inventory data from two sources, the USDA Forest Service Pacific Southwest Region and NEON 4.10. The OFO also uses CyVerse (cyverse.org/) and Jetstream2 computing infrastructure to support its operations.

5 DATA THEMES AND MANAGEMENT

This section delves into the data from the selected Open Data Observatories, examining their themes, sources and the methods employed in their processing. Our thematic analysis, referencing [11], revealed two main themes, urban data and non-urban data. This division was motivated by the need to distinguish the selected Open Data Observatories at the highest level, as urban and non-urban settings present fundamentally different characteristics. We started the thematic analysis by reading through the data types collected for the selected observatories and taking notes. Table 2 shows data types managed by the selected observatories. Then, using NVIVO 12 software, we generated codes that helped us with the data themes. Words coded under "Transport" are indicative of `urban data`, while the words coded under "Soil Data" and "Seismic Events" fell under the `non-urban` data theme. Table 3 lists the selected Open Data Observatories' geographic scopes and the data themes classification.

[13] openforestobservatory.org/

Table 2. Lists the Open Data Observatories and their data types.

Open Data Observatory	Data types available
1. The Terrestrial Ecosystem Research Network (TERN)	Terrestrial and coastal vegetation data, land cover processes, phenology and abiotic data.
2. The Channel Coastal Observatory (CCO)	Topographic and hydrographic surveys. Real-time data about waves, tides, weather and GPS data .
3. The Urban Observatory Project (UOP)	Urban data include traffic flow, parking spaces, cycling docking, pedestrian count, weather data, air quality, water quality, seismic activity, noise-level, water-level (rainfall, river and tides), beehives, energy usage data, thermal imaging, visual and hyper-spectral mapping, social media feeds, employee feedback.
4. The Global Forest Watch (GFW)	Satellite imagery, biodiversity, soil, climate dynamics, commodity supply chains, legal and administrative boundaries, fire alerts, and water resources.
5. The Global Earth Observation System of Systems (GEOSS)	Satellite imagery, soil, atmospheric data, oceanographic data, geological data, biodiversity information, and climate metrics.
6. NASA's Earth Observing System Data and Information System (EOSDIS)	Soil, vegetation, spectroscopy, species distribution, and environmental change.
7. The Grow Observatory (GROW)	Soil, temperature, and light level.
8. The International Tsunami Information Center (ITIC)	Water-level data, historical tsunami, recent tsunamis.
9. Southampton Data Observatory (SDO)	Urban data include links to demographics, economy, education, health, housing, road safety and environmental data.
10. The National Ecological Observatory Network (NEON)	Soil, atmospheric data for climate change, biogeochemistry, ecohydrology, land cover processes, organisms, populations, and communities.
11. The India Urban Observatory (IUO)	Urban data include population statistics, infrastructure development, and economic growth, water supply, sanitation, and waste management.
12. The Finnish Ecosystem Observatory (FEO)	Climate, soil, hydrology, biogeochemistry, and biodiversity.
13. The Open Forest Observatory (OFO)	Forest drone imagery, forest structure metrics, tree sizes and species.

5.1 Urban Data

Urban data refer to information generated within the context of cities, including data on smart transportation, human behavior, demographics, and social systems. Smart transportation data involve metrics such as traffic flow, vehicle counts, public transit usage, parking availability, congestion levels, average speeds, journey times, and pedestrian counts. Urban observatories, such as the UOP, SDO, and IUO, collect and analyze various types of urban data. The UOP focuses on providing real-time data on city transportation, including traffic congestion, parking availability, and public transit usage. SDO gathers links to data on transportation usage and behavior, including walking, cycling, and driving patterns, as well as transportation infrastructure like roads and public transit systems. Similarly, IUO collects data on transportation infrastructure (roads, highways, railways), transportation usage and behavior (vehicle ownership, mode choice, travel patterns). These observatories aim to provide insights into how urban transportation systems function and how they can be improved to better meet the needs of city residents. The data collected by these observatories cover a range of urban data metrics, as analyzed in Figure 3. Environmental data are collected in cities by one of the UOP observatories, to illustrate the concept, Figure 4 shows the environmental data types and parameter counts at Newcastle's Urban Observatory Project. Table 4 lists examples of the data types' parameters and their measuring units. Here, weather data include temperature, humidity, wind speed, and precipitation through a network of sensors deployed across Newcastle and the surrounding region, and the water level data entail river and tide levels. Raw data were obtained from (newcastle.urbanobservatory.ac.uk/api-docs/doc/sensors-dash-types-csv/).

5.2 Non-urban Data

Non-urban data refer to information and metrics collected from areas outside city boundaries, including rural, wilderness, and natural environments. The non-urban and natural environments data collected by our selected Open Data Observatories span a wide array of environmental variables

Table 3. Lists Open Data Observatories, including their geographic scope and the data themes they provide.

Open Data Observatory	<abbr>	Geographic Scope	Data API	Urban Data	Non-urban Data
1. The Terrestrial Ecosystem Research Network	TERN	Australia	Yes		*
2.The Channel Coastal Observatory	CCO	UK	Yes		*
3. The Urban Observatory Project	UOP	UK	Yes	*	
4. The Global Forest Watch	GFW	USA	Yes		*
5. The Global Earth Observation System of Systems	GEOSS	Worldwide	Yes		*
6. NASA's Earth Observing System Data and Information System	EOSDIS	USA	Yes		*
7. The Grow Observatory	GROW	Europe	No		*
8. The International Tsunami Information Center	ITIC	Worldwide	Yes		*
9. Southampton Data Observatory	SDO	UK	No	*	*
10.The National Ecological Observatory Network	NEON	North America	Yes		*
11. The India Urban Observatory	IUO	India	No	*	
12. The Finnish Ecosystem Observatory	FEO	Finland	No		*
13. The Open Forest Observatory	OFO	USA	No		*

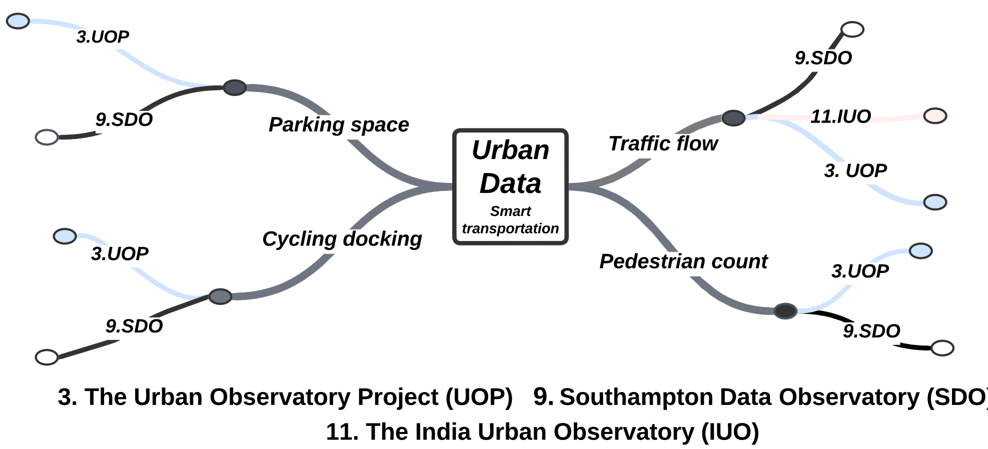

Fig. 3. Transport data metrics collected by Open Data Observatories.

crucial for understanding ecosystem dynamics, climate change, and biodiversity. This diverse range of data supports a holistic understanding of Earth's non-urban environments, facilitating research and conservation efforts across multiple disciplines. Notably, variables related to vegetation, soil, and environmental change are prominently collected across these observatories.

5.3 Data Sources

Open Data Observatories obtain data from various sources including Open Data portals, wireless sensor networks, and smart devices. Table 5 lists and compares data sources used by each observatory. Sensing devices play a significant role in urban and non-urban data collection [26]. For urban data, the UOP uses a network of over 3600 sensors to capture diverse data streams from different physical environments. For non-urban data, GROW employs Flower Power sensors to monitor in-situ soil moisture, fertilizer levels, and air temperature at 15-minute intervals [33, 71]. Other technologies contributing data to these observatories include LIDAR, ARGUS cameras, and satellites. The ITIC- tsunami observatory provides data on water-levels, historical and recent tsunamis. The water-levels data sourced from the DART (Deep-ocean Assessment and Reporting of Tsunamis) system and the National Oceanic and Atmospheric Administration (NOAA) coastal

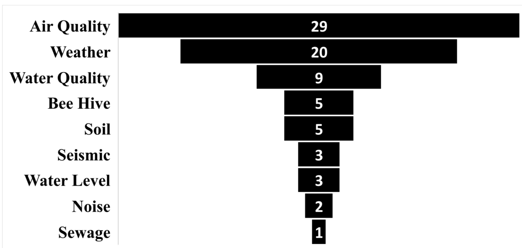

Fig. 4. Newcastle Urban Observatory parameters count by data type.

Theme	Parameter	Unit
Air Quality	CO	ugm -3
Weather	Rain	mm
Water Quality	Dissolved Oxygen	mg/l
Bee hive	Brood nest temperature	Celsius
Soil	Soil Moisture	%VWC
Seismic	Vertical Displacement	m
Water Level	River Level	m
Noise	Sound	db
Sewage	Sewage Level	mm

Table 4. Newcastle Urban Observatory parameters examples and their measuring unit.

water-level stations. The DART system obtains water-levels data from bottom pressure recorders on the seafloor, which measure water pressure with a resolution of approximately 1 mm of sea water and take 15-second averaged samples. The data are then transmitted to a ground station via satellite telecommunications, enabling real-time reporting. The DART II systems transmit standard mode data containing 24 estimated sea-level height observations at 15-minute intervals, once every six hours. The OFO uses drone imagery in a multi-step process to source data. First, numerous overlapping drone photos are taken from various angles to estimate each tree's three-dimensional structure. Next, the Canopy Height Model (CHM) is generated by processing the data to create a high-resolution Digital Surface Model (DSM) that displays the vegetation's height in each pixel above the ground. Then, an algorithm identifies individual trees in the forest area using drone imagery and CHM data, resulting in tree-level maps of forest stands. NEON sources data and samples using a combination of automated instruments, field technicians, and airborne remote sensing. TERN gathers data using a variety of sensors, including Eddy covariance flux towers, heat flux plates, radiometers, anemometers, infrared gas analyzers, spectrometers, CosmOz soil moisture meters, groundwater bores, ecoacoustic sensors, phenocams, terrestrial laser scanners, UAV/drones, camera traps, and photopoints [57]. The analysis of data sources used by our selected Open Data Observatories shows that smart devices are the most common, used by 85% of observatories. Wireless sensors follow at 77%, while satellite/LIDAR and field surveys are each used by over 60%. Weather stations and crowd-sourcing are used by around 50%, citizen data and drones by 46%, and digital cameras by 38%. Sensing vehicles are the least used, appearing in 23% of the observatories.

5.4 Data Processing

Most of the selected Open Data Observatories develop open-source software to harmonize and integrate diverse open data sources. Such data processing techniques are set to realize the potential value of Open Data by making them FAIR (Findable, Accessible, Interoperable, and Reusable) for researchers, decision-makers, and the broader community. TERN includes several tools and applications for data processing and analysis. To mention a few, SHaRED Data Submission (shared.tern.org.au) allows ecologists to upload their research data to the Australian Ecological Knowledge and Observation System (ÆKOS) and assists in creating structured metadata and assigns Digital Object Identifiers (DOIs). CoESRA Virtual Desktop (coesra.tern.org.au) enables access to a web-based virtual desktop from any device and equipped with scientific software such as RStudio, Jupyter

Table 5. Lists and compares the Open Data Observatories' data sources.

Open Data Observatory	Wireless sensors	Smart devices	Citizen Data	Weather stations	Digital cameras	Satellite/LIDAR	Field surveys	Sensing vehicles	Drones	Crowd-sourcing
1. The Terrestrial Ecosystem Research Network (TERN)	*	*		*	*	*	*		*	
2. The Channel Coastal Observatory (CCO)	*	*		*	*	*	*	*	*	
3. The Urban Observatory Project (UOP)	*	*	*	*	*	*		*	*	*
4.The Global Forest Watch (GFW)			*			*	*			*
5. The Global Earth Observation System of Systems (GEOSS)	*	*		*		*	*		*	
6. The Earth Observing System Data and Information System (EOSDIS)	*	*		*		*				
7. The Grow Observatory (GROW)	*	*	*	*			*			*
8. The International Tsunami Information Center (ITIC)	*	*		*		*				*
9. Southampton Data Observatory (SDO)		*	*							*
10. The National Ecological Observatory Network (NEON)	*	*	*	*	*	*	*	*	*	*
11. The Indian Urban Observatory (IUO)	*	*	*							*
12. The Finnish Ecosystem Observatory (FEO)	*	*				*	*			
13. The Open Forest Observatory (OFO)			*						*	*

Notebook, and QGIS. EcoImages (ecoimages.tern.org.au) serves as a repository that organizes images of vegetation, soil, and landscapes. To process live streams of diverse data, the UOP deploys real-time machine learning models on CCTV feeds and uses data queues, data sharding, and many edge processors along with hourly replication to reduce the occurrence of problems during live data streaming. The GFW uses machine learning for detecting and mapping tree cover and loss, involving image segmentation, classification, and change detection to produce forest datasets. At the ITIC tsunami observatory, raw data from the tide gauges and DART buoys are processed by the PMEL (Pacific Marine Environmental Laboratory) and NGDC (National Geophysical Data Center) to remove errors and archive. NEON developed proprietary software to process raw data from sensors and field apps into standardized data products. NEON employs a unique "NEON Ingest Conversion Language" to establish and update data processing protocols as necessary. The OFO presents three cyber-infrastructure innovations to enhance data processing capabilities. These include a scalable, reproducible, AI-enabled software workflow for converting drone imagery into forest inventory data, a searchable database of tree maps that are aligned with forest inventory plot networks and accessible to the public, and documentation and training resources to encourage researchers to contribute their own data and analytical tools. Moreover, research [73], which offers resources for individuals who want to create efficient and detailed tree maps of conifer forests without requiring extensive customization of image acquisition and processing parameters.

5.5 Data Visualization

Data visualization transforms information into meaningful graphical representations that intended audiences can interpret [72]. The selected observatories employ various visualization techniques to present and communicate their collected data effectively. Visualizations include static and interactive maps [24], charts such as time series, scatter plots, histograms [60], bar, and pie graphs. TERN-ANU Landscape Data Visualizer (maps.tern.org.au) is a user-friendly atlas that offers comprehensive spatial data on Australian landscapes, soil, ecosystems, and water resources. The data can be visualized on a map and explored through time-series data for specific locations. The UOP employs interactive maps, digital comparison tools, thematic cartography, real-time data visualization to explore and understand urban dynamics. NEON collaborates with Google to enhance the visualization and accessibility of its environmental data via the Google Cloud Platform, incorporating tools such Google Earth Engine and BigQuery. This integration enables users to engage with and visualize extensive datasets directly in the cloud. The GFW visualizes data through its Open Data portal, interactive map features, downloadable datasets, geospatial monitoring frameworks, and software like the Forest Trends Analysis Tool. EOSDIS visualizes data through the Earthdata Cloud, which provides users with free access to NASA Earth science data for research purposes. The ITIC - tsunami observatory provides real-time and historical tsunami data through 1-minute water level readings, event search tools, and interactive maps. These resources offer numerical and graphical representations of water-levels, crucial for early tsunami detection. IUO employs diverse visualization methods such as data stories, interactive maps using ArcGIS, thematic dashboards, and an Open Data portal to share urban insights with stakeholders such as government bodies, researchers, and the public. GROW uses interactive maps, visualization tools to effectively visualize the soil moisture data it collects and share them with its stakeholders [62].

6 RESEARCH CHALLENGES

Establishing Open Data Observatories involves addressing various challenges related to integrating diverse data sources and systems. These challenges include ensuring data interoperability, scalability, and replicability since each data source has its own design and computing specifications. Combining and merging disparate data, without careful consideration, can lead to service conflicts, resulting in degraded data quality, loss of data provenance, and potential privacy breaches. This section explores these challenges, as depicted in Figure 5 and how each observatory addresses each challenge.

6.1 Data Integration

Data integration is the process of combining data from disparate sources into a unified view [39]. Integrating heterogeneous data can positively impact decision-making; however, achieving valid integration faces many challenges, as noted by various researchers [5, 20, 22]. Figure 5 outlines the main data integration components that Open Data Observatories may encounter. The interoperability challenge refers to the difficulty of integrating and harmonizing disparate data sources and systems, ensuring that different datasets with varying formats, structures, and standards can effectively work together and exchange information. Interoperability is one of the Open Data FAIR principles, as explained in section 2.1 [5, 50]. Integrating data from disparate sources may also involve using ontologies, managing large data volumes, and handling high-velocity data streams. Effective use of APIs is crucial for accessing and integrating data from different platforms.

To overcome this challenge, several observatories implemented various strategies. For instance, TERN harmonized the plot-based ecology using EcoPlots (ecoplots.tern.org.au), a semantic data integration system that maps each data source to TERN's Plot Ontology. The term 'ontology' is a structured framework that defines the relationships between concepts within a specific domain, providing a shared vocabulary for that domain [12, 28]. OWL (Web Ontology Language) [4] is a formal language used to create and share these ontologies on the web, enabling better data interoperability. The UOP deployed a platform called the "Urban Data Exchange (UDX)" (urbandatacollective.com/urban-observatories-case-study) that acts as a central hub for onboarding, harmonizing, and serving the real-time data streams from the different urban observatory systems. EOSDIS enhanced data interoperability through standardization of data formats and metadata, a distributed and interoperable architecture across nodes like the Science Investigator-led Processing Systems (SIPS) and Distributed Active Archive Centers (DAACs), which enabled efficient data retrieval [55].

6.2 Data Quality

Applied research defined the term data quality differently [54], a commonly used definition by Strong et al. [63] describing data quality as data fit for the intended purpose. Byabazaire et al. [10] and Taleb et al. [65] testified that data quality is a mature research topic in big data and database management. However, Perez-Castillo et al. [54] claimed its youth in Smart Connected Products (SCP) [74] and the Internet of Things. Data quality plays a significant role in Open Data Observatories, as a sufficient quality level can build trust between the cyber and physical world [10, 54]. Each observatory addresses data quality using different strategies, the UOP manages data quality by using automated checks for data anomalies, calibrating sensors against precision stations, and incorporating user feedback. They also recognize the limitations of low-cost sensors and design their data use accordingly. The GFW ensures data are up-to-date by automating updates or requesting providers to notify them of changes. EOSDIS methodology ensures metadata quality of Earth observation data hinges on a framework prioritizing correctness, completeness, and consistency. NASA uses automated and manual reviews to identify and rectify issues, demanding active collaboration with data providers to implement enhancements [9].

The CCO and NEON implement quality assurance and control practices. The CCO ensures the reliability of marine observations, flagging poor data but not eliminating them, while NEON applies rigorous quality measures to ensure data quality. For example, observation system data use mobile apps with constraints and validation rules. Instrument System data benefit from sensor placement, maintenance, and calibration. Airborne Remote Sensing data are calibrated and tested pre- and post-flight. Automated checks and expert reviews ensure reliability, while flags and metrics provide transparency. IUO handles quality through trusted data sources, accuracy, transparency, and interactive visualizations but has limitations in completeness and update frequency.

The OFO prioritizes data quality through standardized, open-source workflows for drone-based forest mapping, accessible via its GitHub repository. It also employs cloud-based tools to process drone imagery into detailed forest maps, facilitating ease of use as well as a central database to support data sharing and quality enhancement through community feedback. As shown in Figure 5, data quality challenges in the selected Open Data Observatories are closely related to the FAIR principles, particularly data findability, accessibility, and reusability. Using trusted sources and maintaining rigorous data entry standards minimize anomalies, facilitating easier data discovery. Sensor calibration, data entry rules and constraints implementation provide reliable data and enhance their accessibility. Data completeness and consistency through quality assurance processes also contribute to better metadata and documentation, making the data reusable.

6.3 Data Provenance

Data provenance, which traces the origins and lineage of data, is crucial in Open Data Observatories. Maintaining rigorous data provenance allows observatories to ensure data transparency, reliability, and reproducibility [3, 29, 52]. TERN releases weather data accompanied by their lineage, including (a) the type and model of the automatic weather station used for collection; (b) the specific location and characteristics of the site; (c) the instruments used for measuring different weather parameters, along with their accuracy and resolution; (d) the methodology for data recording and the intervals at which data were stored; (e) the procedures followed in case of sensor failure including using alternative data sources for gap filling and indicating this within the dataset; and (f) the availability of the data and contact information for access to more granular data (hourly data).

Similarly, SDO commits to full metadata inclusion for all its published data compendiums and resources, encompassing data sources and time frames. NEON's dedication to rich metadata and thorough documentation strengthens the provenance and traceability of its data offerings. This commitment includes the provision of Digital Object Identifiers (DOIs) for NEON data packages, enhancing their findability and citability. NEON's approach to data provenance involves metadata management, adherence to FAIR principles, data citation tracking, and handling data from diverse sources, focusing on transparency and accessibility. In a different vein, research [69] recommends applying blockchain technology for data provenance. Blockchain can revolutionize how data are managed, enhancing transparency, security, and trust. By leveraging its immutable ledger, data integrity and authenticity can be guaranteed, ensuring that once data are recorded, it cannot be altered. Moreover, the decentralization offered by blockchain reduces risks associated with centralized data storage by distributing data across a network, thus enhancing data resilience and accessibility through peer-to-peer sharing. Furthermore, blockchain's encryption and smart contracts safeguard sensitive data and automate data access permissions, ensuring only authorized access. It also offers a transparent audit trail for all data modifications and transactions, facilitating traceable data lineage and enforcing open data licenses automatically. Data provenance in our selected Open Data Observatories aligns with the FAIR principles through elements like data access licenses, documentation, transparency, data lineage, and citations. As shown in Figure 5, clear data access licenses enhance accessibility and reuse, while documentation and transparency improve findability and interoperability. Data lineage ensures reliability and supports reusability, and citations facilitate proper attribution, enhancing findability.

6.4 Data Privacy

Data privacy is critical in protecting personal and sensitive information from unauthorised access and disclosure. Open Data Observatories implemented various measures to address data privacy challenges, including data anonymization, access controls, and encryption [29, 40, 45, 56, 58]. These observatories handle massive amounts of data from various data sources through orderly collection, aggregation, and analytics. However, these data may contain sensitive details such as personally identifiable information and endangered species locations [1, 23, 35, 42, 53, 58].

TERN, the CCO, and the UOP all have dedicated privacy statements that outline their data privacy practices. These include compliance with regulations like GDPR, providing privacy notices, defining lawful data processing, implementing security measures, and respecting user rights. Similarly, the GFW and GEOSS approach data privacy through transparency, consent-based processing, security, and clear points of contact for users. NASA's EOSDIS also has a privacy policy that emphasizes protection and proper use of information in line with relevant laws and regulations. GROW addresses privacy by using an open data license, collecting only anonymized sensor data without personal identifiers, and operating under institutional oversight. The ITIC-tsunami observatory's privacy policy covers aspects like cookies, email handling, and user rights under the Privacy Act. Southampton Data Observatory adheres to the overall privacy policy of Southampton City Council, while NEON securely manages user accounts, anonymizes data reporting, and applies Creative Commons licensing. In contrast, IUO has a privacy-focused approach, avoiding automatic capture of personal information and only collecting such data if explicitly provided by users, with appropriate security measures.

Finally, the OFO focuses on openly sharing its forest mapping data and tools, rather than collecting or managing personal user information, implying a commitment to data transparency and accessibility. Data privacy in our selected Open Data Observatories involved encryption, access controls, disclosure of information, anonymization, privacy notices, secure collection of personal information, privacy statements, and GDPR compliance. As shown in Figure 5, encryption and access controls ensure secure and restricted data access, aligning with FAIR principles. Disclosure and privacy notices enhance transparency, improving findability and interoperability. Anonymization and secure collection practices ensure data reusability without compromising privacy. Privacy

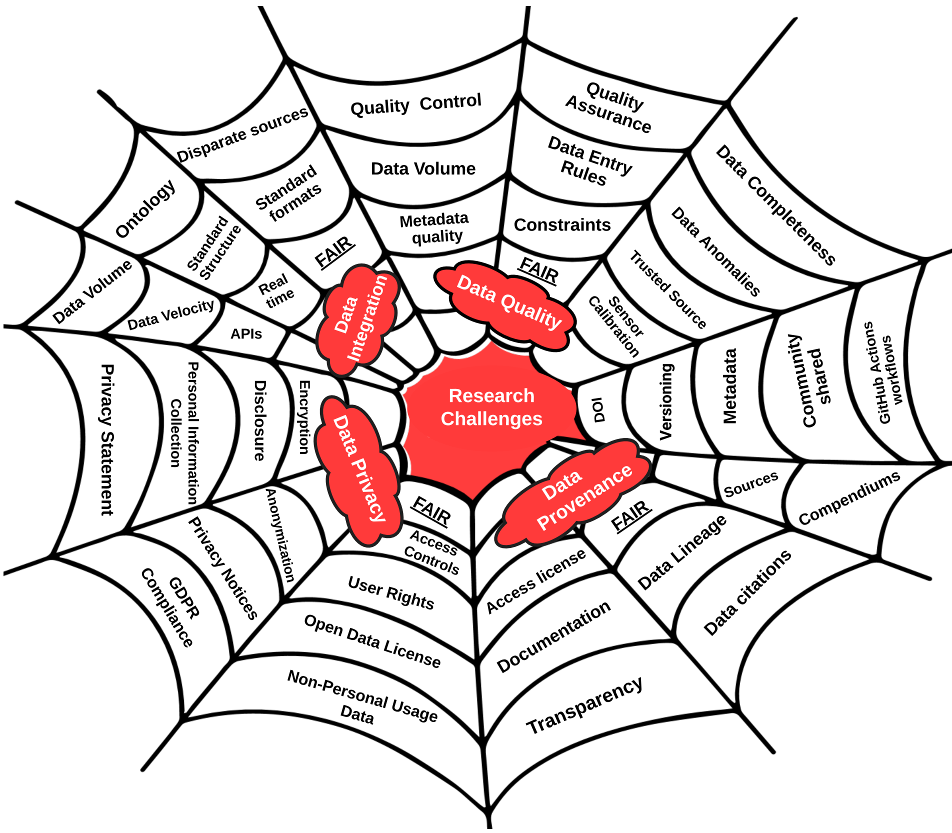

Fig. 5. This diagram captures the intricate web of research challenges in data management, segmented into four primary categories, Data Integration, Data Quality, Data Privacy, and Data Provenance. Each challenge extends into related subtopics and approaches to overcome them that touch the periphery of the web, symbolizing the complex and interconnected nature of these issues. The visual metaphor of a spider web conveys the idea that each aspect is a critical thread in the overall structure of data management.

statements and GDPR compliance maintain legal and ethical standards, supporting data integrity and user trust.

7 DISCUSSION

The selected Open Data Observatories are pushing the boundaries of the FAIR principles through the creation of open-source software and the application of advanced data processing methods. TERN, for example, not only simplifies the process of data submission and organization through the SHaRED Data Submission tool but also promotes data discoverability and citability with structured metadata and Digital Object Identifiers (DOIs). On another front, the UOP's deployment of machine learning models for the real-time analysis of CCTV data showcases innovative data handling techniques. The application of machine learning by the GFW for analyzing forest coverage highlights the pivotal role of advanced technology in the efforts to preserve natural habitats. Moreover, proprietary software developed by NEON and the drone imagery processing innovations introduced by the OFO mark progress in data standardization and quality improvement. Through these diverse data processing efforts, these observatories are not just elevating the value of Open

Data but are also providing deeper insights into urban and non-urban challenges, thereby equipping researchers and stakeholders with the necessary resources for informed decision-making. Urban data observatories such as the UOP, SDO and IUO provide essential insights into the fabric of city life, tracking urban expansion and infrastructure development to support urban sustainability, and smart city analytics [41, 44, 48, 49]. Non-urban observatories like the CCO and the ITIC tsunami observatory contribute to our preparedness and response strategies for coastal hazards, safeguarding communities and ecosystems by relying on real-time and historical data. The observatories offered a variety of data types, with soil, vegetation, and climate data being among the most common. Our study embarked on facilitating the development of new Open Data Observatories. This effort led us through a complex maze of challenges, from making different data sources work together to ensuring the data were reliable and protected.

Interoperability, a cornerstone of the FAIR principles for Open Data, presents a notable challenge in data integration for Open Data Observatories. Efforts, including the implementation of semantic data systems for data integration, demonstrate advancements in overcoming this obstacle. Similarly, adopting standardized formats and metadata improved the ease of access and usefulness of integrated data. Different observatories adopt tailored strategies to maintain and enhance the quality of their data. For instance, some focus on rigorous quality control measures and real-time data verification, while others prioritize the accuracy, transparency, and up-to-dateness of their data through both automated systems and manual oversight. These methods reflect a shared commitment across observatories to uphold the integrity and reliability of their data. Tracing data back to their origins is also essential for establishing trust and ensuring transparency within data-centric environments. Observatories that rigorously document their data sources set a benchmark for data management, enhancing both the reliability and reproducibility of their data. Using detailed metadata documentation and Digital Object Identifiers (DOIs) improves the traceability and accessibility of data. Implementing standardized workflows and open-source software also contributes to transparency, making it easier for the wider scientific community to verify data.

The methods used by different observatories to tackle data privacy issues demonstrate their commitment to meeting regulatory standards, yet they vary in their approaches to data collection, use, and management. For example, while some observatories comply with the General Data Protection Regulation (GDPR), others emphasize data anonymization and the use of open data licenses to reduce the collection of personal data. The depth and breadth of these privacy policies also differ significantly. Some observatories have developed comprehensive policy frameworks that address a broad range of legal and operational concerns, whereas others adopt more focused privacy strategies that rely on obtaining explicit user consent before gathering personal data.

Table 6 highlights the strengths and limitations of the selected Open Data Observatories, along with future recommendations and key takeaways. The future recommendations are grounded in specific concerns raised by the observatories, existing systems that can be enhanced, or limitations observed during our examination. For example, GEOSS's flexibility is a strength, but the lack of guaranteed data accuracy requires investment in quality assurance and control measures to build user trust. Recommendations for GROW, the ITIC, and NEON similarly address their respective limitations by suggesting the integration of additional data sources, improving data quality, and implementing robust power solutions.

Both urban and non-urban data are indispensable for environmental and societal research, supporting informed decision-making and sustainable development practices. For instance, non-urban data on weather and climate can help urban areas prepare for extreme weather, while urban data on pollution can influence non-urban conservation efforts. When comparing urban and non-urban data in terms of social aspects, several differences emerge. Urban social data typically shows higher population density, greater diversity, and more extensive social services such as education,

Table 6. Strengths and limitations of the selected Open Data Observatories, future recommendations and some takeaways.

Data Observatory	Strengths	Limitations	Future Recommendation	Takeaways
1. TERN[14]	High-quality data on environmental monitoring, along with tools and expertise, provided to researchers.	Limited coherent national capability for monitoring freshwater ecosystems.	Integrating blockchain for data provenance and artificial intelligence for Linked Data.	Semantic data integration and the Threatened Species Index (TSX)[15]
2. CCO[16]	Access to tools and models to analyze coastal data and predict morphological changes.	Outsourcing data storage may impose security concerns.	Incorporate extreme events alert system.	Extreme events analysis.
3. UOP[17]	Ability to provide a wide variety of real-time and historical data on different aspects of the urban environment.	Urban observatories do not extend their coverage to all cities across the UK, resulting in a limited geographical reach.	Lack of evident research documenting the positive impact of the project (e.g., reduce crime rates).	Real-time data integration.
4. GFW[18]	Forest Watcher mobile app for real-time threat detection, the GFW Pro for managing deforestation risks in supply chains, grants and fellowships.	Limited data lineage.	Provide details how data are collected and evolved over time to enhance data provenance.	Real-time forest monitoring via satellite imagery and remote sensing.
5. GEOSS[19]	Data platform flexibility enabling users to adapt it to their needs.	GEOSS does not guarantee its Earth Observations' accuracy or take responsibility for their use.	Invest in quality assurance and control.	Platform flexibility.
6. EOSDIS[20]	Global, long-term and reliable Open Data.	Limited validation for satellite-based data with ground-based measurements.	Consider real-time update and alert system for extreme events.	Data long-term archiving useful for analysis and training AI applications.
7. GROW[21]	Empowers citizens and communities to have a say on soil and climate matters across Europe.	Limited data types.	Integrate more data sources such as air quality and noise level.	Citizen science.
8. ITIC[22]	Centralized and authoritative source for providing real-time information, and warnings about tsunami events and risks.	Data quality and provenance challenges causing errors in tsunami database.	Addressing data quality for improving the reliability and usability of the tsunami data.	Alert system.
9. SDO[23]	Crowd-sourcing, allowing citizens to understand local issues and contribute to problem-solving in urban development and sustainability matters.	Lack of real-time data and APIs.	Extend geographic scope.	Civic engagement and transparency.
10. NEON[24]	Open Data with good quality and sufficient documentation.	Sensor locations at certain sites are seasonally adjusted or removed due to unfavorable or unsuitable measurement conditions.	Implement hybrid power solutions combining wind power, solar power and energy storage systems for the Oksrukuyik Creek (OKSR) site, where operations cease during winter.	Educational resources such as the learning and code hub.
11. IOU[25]	Wide range of urban data.	Inconsistent data frequency.	Consider using applications for data quality assurance.	Urban data diversity.
12. FEO[26]	Ongoing monitoring and research initiatives related to Finland ecosystems.	Limited data coverage, lack of data privacy statement.	Expand geographic scope.	Platform presentation in multiple languages.
13. OFO[27]	Educational resources to understand forests.	Limited data diversity, privacy policy not shared in the website.	Integrate more remote sensing wildlife data, supplemented with contextual information	Drones and Artificial Intelligence (AI).

healthcare, and public safety. In contrast, non-urban social data usually reflects smaller, more homogenous populations with fewer social services.

Study limitations: Determining the precise size and quality of data was difficult due to variations among the chosen observatories; ideally, a summary of the data inventory should have been provided. A model like that of 4TU.ResearchData (data.4tu.nl/) would have simplified the inventory process. Consequently, this information was not readily available in each observatory examined. In addition, our study lacked detailed information on the funding and sponsorships of the observatories, which can be useful for understanding their sustainability and longevity.

Building Open Data Observatories is challenging but also filled with potential for significant impact. The collaboration between technology, policy, and practice is key to navigating these challenges, ensuring that observatories can thrive long-term. As we move forward, the lessons learned from our work will undoubtedly facilitate the development of new Open Data Observatories.

8 CONCLUSION

This study compared thirteen Open Data Observatories, spanning both urban and non-urban settings on a regional and global scale. These observatories, including global initiatives such as GEOSS and ITIC, and region-specific ones such as the GFW, EOSDIS, and the OFO in the USA, GROW, FEO, the CCO, SDO and the UOP in Europe, IUO in Asia, and TERN in Australia, were evaluated for their core features, data accessibility, and usability. Despite the inherent difficulty in comparing the observatories due to their varied sizes and development phases, we noted significant collaborations and connections, for example, between NEON and the OFO, and between GROW and GEOSS. The data were organized into urban and non-urban themes, highlighting commonalities in data types and processing approaches across the observatories. Challenges related to integrating diverse data sources while maintaining their reliability and integrity were explored, revealing that solutions varied widely depending on the source of the data. We pinpointed specific strengths and limitations for each observatory, forming the basis of our recommendations for future developments. These findings mark the importance of collaboration, the standardization of data, and adaptable strategies for overcoming heterogeneous data integration challenges, essential for developing new urban and non-urban observatories.

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A SUPPLEMENTARY MATERIALS

A.1 Urban Observatory Project (UOP)

The overall framework uniquely applies scientific methods to support decision-making through a multi-scale urban system that observes, analyses, and models both real-time and historical data. For example, air quality monitoring sensors deployed across Newcastle and Gateshead measure key air quality parameters such as Nitrogen Dioxide, Ozone, Carbon Monoxide, and Particulates, generating accurate readings for both authorities and citizens to act upon, thus reducing exposure to air pollution. There are over 50 data types, including many real-time datasets, freely available at the *urbanobservatory.ac.uk* website. These data encompass earth observations, traffic flow, air pollution readings, water quality parameters, and more [59].

(1) Newcastle Urban Observatory[28] collects and analyses a vast amount of real-time data from sensors and other sources in urban areas. It uses a wide array of smart devices capturing more than a hundred different metrics per second, in addition to static images, videos, radar, and laser-scan matrices acquired separately. The data generated by these sensors are precise and actionable by both authorities and citizens to mitigate issues such as air pollution and traffic congestion. Nevertheless, managing such massive data volumes presents a significant challenge, necessitating an efficient data management approach. Among the Newcastle Urban Observatory many projects, we examined the Predicting Rainfall Events by Physical Analytics of Real-time Data (Flood-PREPARED) project. This initiative represents a pioneering resource for assessing real-time water surface flood risks and their impacts on cities, equipping them with innovative physical, analytical methods to predict surface water flooding and providing decision-makers with actionable real-time predictions. The project's implementation progressed through five correlated stages, as shown in Figure 6. Another work by James et al. [31] quantifies the impact of COVID-19 measures in the UK. Leveraging existing Internet of Things data and a comprehensive analytics infrastructure, the authors developed an interactive COVID-19 dashboard. It visualizes various indicators that update in real-time, comparing data changes against baselines and offering frequent

[28]newcastle.urbanobservatory.ac.uk/

automated comparative descriptive statistics (e.g., daily, weekly updates) to facilitate decision-making. For instance, data from air quality stations, car parks, and traffic sensors analyzed showed a significant decline in pedestrian footfall and traffic volume across Tyne and Wear city during the UK COVID-19 national lockdown in March 2020. Moreover, the Newcastle Urban Observatory archives a collection of historical data for various metrics, serving as a reference for validating the new predictions generated by James et al.'s dashboard. Overall, this dashboard aims to repurpose part of the observatory's real-time data for crisis and disaster management, with analyses replicated in other cities like Sheffield, yielding similar results. Newcastle Observatory may offer insights that could be adapted by observatories in rural locations, including an interactive map of various data and sensors, the ability to download data in multiple formats, and the integration of live Twitter feeds.

(2) Sheffield Urban Flows Observatory[29]: Sponsored by the Engineering and Physical Sciences Research Council (EPSRC) and in partnership with UKCRIC Universities, the Sheffield Urban Flows Observatory actively aims to foster a carbon-free, healthy environment. It has developed a dynamic understanding of how the flows of energy and resources impact economic performance and social well-being. The observatory collects, stores, and analyzes city data to monitor the city's environmental performance interactively, engaging citizens and social systems. Its technical platform captures real-time data, including air quality, weather, energy consumption, and both thermal and visual imaging. It consists of various types of sensors (fixed, mobile, and atmospheric), middleware (to gather, integrate, and transform data into meaningful information), data storage, and a data analytics unit.

(3) Bristol Urban Flows Observatory [30]: The UKCRIC Bristol Infrastructure Collaboratory aims to transform Bristol into a living laboratory, engaging diverse communities from academia, business, and the citizenry. It uses Open Data, Wireless Sensor Network (WSN), and smart technology solutions to address environmental and social sustainability concerns.

(4) Cranfield Urban Observatory[31]: The Cranfield Urban Observatory provides data-centric and remote sensing solutions for environmental, social, and economic issues. It boasts a well-established information technology unit that connects a network of spatially distributed sensors. Its Internet of Things (IoT) network consists of various types of sensors to monitor noise and air pollution, water consumption, and citizens' observations. The observatory extracts data from these sensors and publishes them in real-time, alongside dedicated analytics tools and visualizations, enabling domain experts to monitor the city's environmental performance and make informed decisions to improve life quality, health, and well-being.

(5) Birmingham Urban Observatory[32]: With the UK's second-largest population after London, Birmingham's high population density may strain infrastructure, public services, and the environment. Consequently, city administrators invest resources in managing housing, transportation, health, and energy conditions to sustain adequate living standards, particularly monitoring the environmental, economic, and social factors impacting these critical infrastructures.

(6) Manchester Urban Observatory[33]: An interdisciplinary research hub that collects, analyzes, and shares urban data for decision support. The observatory collaborates on various themes with other universities, operating under the dedicated platform "Manchester-I". It offers free and real-time air quality, flood monitoring, and traffic flow information. Linked to Triangulum,

[29] urbanflows.ac.uk
[30] bristol.ac.uk/engineering/research/ukcricbristol/collaboratory/
[31] cranfield.ac.uk/facilities/urban-observatory
[32] cityobservatory.birmingham.gov.uk/
[33] manchester-i.com/home

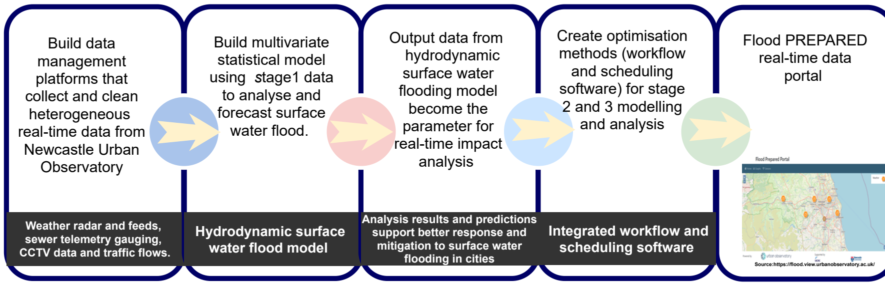

Fig. 6. Predicting Rainfall Events by Physical Analytics of REaltime Data (Flood-**PREPARED)**

a European Union-funded smart city data ecosystem, the Manchester Urban Observatory team has comprehensively rebuilt the platform, integrating data from numerous city-wide sensors. They have also developed a web API that leverages the capabilities of semantic web technology, using JSON-LD [37].