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OGC DISASTER PILOT: PROVIDER READINESS GUIDE

ENGINEERING REPORT

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CONTENTS

LIST OF TABLES

LIST OF FIGURES

I ABSTRACT

Disasters are geographic events and, therefore, geospatial information, tools, and applications have the potential to support the management of, and response to, disaster scenarios to save lives and limit damage.

The use of geospatial data varies significantly across disaster and emergency communities, making the exploitation of geospatial information across a community more difficult. The issue is particularly noticeable when sharing between different organizations involved in disaster response.

This difficulty can be mitigated by establishing the right processes to enable data to be shared smoothly and efficiently within a disaster and emergency community. To do this requires the right partnerships, policies, standards, architecture, and technologies to be in place before the disaster strikes. Having such a set-up will enable the technological and human capabilities to quickly find, access, share, integrate, and visualize a range of actionable geospatial information, and provide this rapidly to disaster response managers and first responders.

For over 20 years, the Open Geospatial Consortium (OGC) has been working on the challenges of information sharing for emergency and disaster planning, management, and response. In Disaster Pilot 23 (DP23) the aims were to:

- develop flexible, scalable, timely and resilient information data workflows to support critical disaster management decisions, enabling stakeholder collaboration; and
- provide applications and visualization tools to promote the wider understanding of how geospatial data can support emergency and disaster communities.

The Disaster Pilot Provider Guide describes the technical requirements, data structures, and operational standards required to implement the data flows or tools developed in DP23 and Disaster Pilot 21 (DP21) where participants have worked on disaster scenarios relating to the following.

- Droughts
- Wildland Fires
- Flooding
- Landslides
- Health & Earth Observation Data for Pandemic Response

Case Studies have focused on the hazards of drought in Manitoba, Canada; wildland fires in the western United States; flooding in the Red River basin, Canada; landslides and flooding in Peru; and pandemic response in Louisiana, United States. The participants have developed a series of data specific workflows to generate either Analysis Ready Datasets (ARD) or Decision

Ready Indicators (DRI) alongside a number of tools and applications to support data discovery, collection, or visualization.

Annex A describes the tools and applications developed within the Pilots along with technical details and the benefits offered similar to the data flows. The Guide finishes with details of future possibilities and where the Disaster Pilot initiatives could focus next. Annexes B to E give descriptions of the data flows developed, including technical details of input data, processing and transformations undertaken, standards applied, and outputs produced with details of the aspect of disaster management or response supported, benefits offered, and the type of decisions assisted with.

The Provider Guide is one of three Guides produced within DP23 together with the User Guide and the Operational Capacity Guide. While the Guides are separate individual documents, the Provider and User Guides work together, mirroring each other in terms of structure. The Operational Capacity Guide is a stand-alone document effectively underpinning the other two.

II KEYWORDS

The following are keywords to be used by search engines and document catalogues.

Disasters, Natural Hazards, Analysis Ready Data, ARD, Decision Ready Indicators, DRI, Drought, Wildland Fire, Flooding, Landslides, Pandemic, Emergency Response, geospatial, ogcdoc, OGC document, DP23, DP21, Disaster Pilot, Provider Readiness Guide

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1

INTRODUCTION

1 INTRODUCTION

Disasters are geographic events in specific locations that impact the people, economy, and society in those and surrounding areas — often tens, or even hundreds, of miles away. For this reason, geospatial information has been shown to be effective in supporting both the understanding of, and the response to, disaster scenarios.

Geospatial tools and applications have the potential to save lives and limit damage, and the world is becoming better at using these resources. Unfortunately, the ability to manage, access, share, use, reuse, and exploit geospatial information and applications is often limited. This can be, in particular, between organizations as the right processes have not been established for these processes to happen smoothly and efficiently within disaster and emergency communities. Establishing such processes requires partnerships, policies, standards, architecture, and technologies to be in place before the disaster strikes.

For over 20 years the Open Geospatial Consortium (OGC) has been working on the challenges of information sharing for emergency and disaster planning, management, and response. The Disaster Pilot activities are part of the OGC Collaborative Solutions and Innovation Program (COSI) with the aim to address the gap, and provide support and guidance on how disasters and emergency communities can enhance sharing and use of geospatial information and applications.

Disaster Pilot 23 (DP23) is the latest in a series of initiatives focussed on:

- developing flexible, scalable, timely, and resilient information workflows to support critical disaster management decisions enabling stakeholder collaboration; and
- providing applications and visualization tools to promote the wider understanding of how geospatial data can support emergency and disaster communities.

This Provider Guide aims to provide data collectors, processors, and publishers with detailed technical requirements, data structures, and operational standards required to develop and offer data workflows and tools within the ecosystem of the OGC Disaster Pilot initiatives. The Guide also supports in the preparation and coordination needed to leverage standards-based cloud computing and real-time data sharing and collaboration platforms in support of disaster management and response efforts.

In addition, the Provider Guide gives emergency management, together with any other supporting stakeholders, information technology support functions and technical details to understand how to implement any of the workflows or tools developed in disaster and emergency user communities.

Geospatial information offers huge potential resources to enable disaster and emergency communities to enhance planning, prediction, and response to disaster events, helping save more lives and reducing the impact of disasters on communities.

2

TERMS, DEFINITIONS AND ABBREVIATED TERMS

2 TERMS, DEFINITIONS AND ABBREVIATED TERMS

This document uses the terms defined in OGC Policy Directive 49, which is based on the ISO/IEC Directives, Part 2, Rules for the structure and drafting of International Standards. In particular, the word “shall” (not “must”) is the verb form used to indicate a requirement to be strictly followed to conform to this document and OGC documents do not use the equivalent phrases in the ISO/IEC Directives, Part 2.

This document also uses terms defined in the OGC Standard for Modular specifications (OGC 08-131r3), also known as the ‘ModSpec’. The definitions of terms such as standard, specification, requirement, and conformance test are provided in the ModSpec.

For the purposes of this document, the following additional terms and definitions apply.

2.1. Terms and definitions

2.1.1. ARD; Analysis Ready Data and datasets

raw data that have had some initial processing, created in a format that can be immediately integrated with other information and used within a Geographic Information System (GIS)

2.1.2. CRS; Coordinate Reference System

coordinate system that is related to the real world by a datum term name

[**SOURCE:** ISO 19111]

2.1.3. DRI; Decision Ready Information and indicators

ARDs that have undergone further processing to create information and knowledge in a format that provides specific support for actions and decisions that have to be made about the disaster

2.1.4. **Indicator**

realistic and measurable criteria

2.1.5. **Lidar**
light detection and ranging ALTERNATIVE

common method for acquiring point clouds through aerial, terrestrial, and mobile acquisition methods

2.1.6. **GeoNode**

web-based platform for deploying a GIS

2.1.7. **GeoPackage**

open, standards-based, compact format for transferring geospatial information

2.1.8. **GeoRSS**

designed as a lightweight, community driven way to extend existing RSS feeds with simple geographic information

2.1.9. **GeoServer**

Java-based server that allows users to view and edit geospatial data

Note 1 to entry: Using open standards set forth by the Open Geospatial Consortium (OGC), GeoServer allows for great flexibility in map creation and data sharing.

2.1.10. Geospatial Data

data that include information related to a location, that can be used to map objects, events, and anything else with a specific geographic location

2.1.11. JSON-LD

JavaScript Object Notation — Linked Data ALTERNATIVE

lightweight linked data format based on JSON

2.1.12. Jupyter Notebooks

open-source web application that allows the creation and sharing of documents that contain live code, equations, visualizations, and narrative text

2.1.13. Radar

radio detection and ranging ALTERNATIVE

detection system that uses radio waves to determine the distance (range), angle, or velocity of objects

2.1.14. **REST API**

Representational State Transfer Application Programming Interface

Note 1 to entry: Commonly known as REST API web service.

Note 2 to entry: When a RESTful API is called, the server will transfer a representation of the requested resource's state to the client system.

2.1.15. **SAR; Synthetic Aperture Radar**

type of active data collection where a sensor produces its own energy and then records the amount of that energy reflected back after interacting with the Earth

2.2. Abbreviated terms

ACD	Amplitude Change Detection
AI	Artificial Intelligence
AMSR-E	Advanced Microwave Scanning Radiometer for EOS
API	Application Programming Interface
AR	Augmented Reality
ARD	Analysis Ready Data
ASMR-2	Advanced Microwave Scanning Radiometer 2
AWS	Amazon Web Services
BCSD	Bias corrected and spatially downscaled
C3S	Copernicus Climate Change Service
CAMS	Copernicus Atmosphere Monitoring Service
CDI	Combined Drought Indicator
CDS	Climate Data Store

CEMS	Copernicus Emergency Management Service
CNES	French Space Agency
COG	Cloud Optimized GeoTIFF
CONIDA	National Commission for Aerospace Research and Development's, Peru
COSI	OGC Collaborative Solutions & Innovation Program
CQL2	Common Query Language
CRS	Coordinate Reference System
CSA	Canadian Space Agency
CSW	OGC Catalog Service for the Web
DARSIM	Disaster Augmented Reality Simulation Table
DEM	Digital Elevation Model
DP21	Disaster Pilot 21
DP23	Disaster Pilot 23
DRI	Decision Ready Indicator
DT	Digital Twin
DTES	Digital Twin Encapsulation Standard
ECMWF	European Centre for Medium-Range Weather Forecasts
EDR	Environmental Data Retrieval
ENSO	El Niño/Southern Oscillation
EO	Earth Observation
ESA	European Space Agency
ESIP	Earth Science Information Partners
ETL	Extract, Transform and Load
FAIR	Findability, Accessibility, Interoperability, and Reuse of digital asset
FAPAR	Fraction of absorbed light by the plants
FME	Feature Manipulation Engine (Safe Software)

GDO	Copernicus Global Drought Observatory
GEPS	Global Ensemble Predication Service
GIS	Geographic Information System
GISMO	New York City Geospatial Information System & Mapping Organization
GPM	Global Precipitation Measurement Mission
ICU	Intensive Care Unit
IR	InfraRed
JAXA	Japan Aerospace Exploration Agency
JSON	JavaScript Object Notation
JSON_LD	JavaScript Object Notation — Linked Data
LEO	Low Earth Orbit
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MRLC	Multi-Resolution Land Characteristics
MSC	Meteorological Service of Canada
MTC	Multi-Temporal and Coherence
NAOMI	New AstroSat Optical Modular Instrument
NDVI	Normalized Difference Vegetation Index
NetCDF	Network Common Data Form
NIR	Near-InfraRed
NLCD	US National Land Cover Database
NNet	Neural Network
NOAA	US National Oceanic and Atmospheric Administration
NRCan	Natural Resources Canada's

NRT	Near-Real-Time
OGC	Open Geospatial Consortium
OLI	Operational Land Imager
ORLs	Operational Readiness Levels
OSM	OpenStreetMap
PDSI	Palmer Drought Severity Index
PHC	Public Health Center
PPE	Personal Protective equipment
RCM	RADARSAT Constellation Mission
RMSE	Root Mean Squared Error
S3	Amazon Simple Storage Service
SAR	Synthetic Aperture Radar
SatCen	European Union Satellite Centre
SDI	Spatial Data Infrastructure
SMA	Soil Moisture Anomaly
SPDI	Standardized Palmer Drought Index
SPEI	Standardized Precipitation Evapotranspiration index
SPI	Standardized Precipitation Index
SPoG	Single Pane of Glass
SRTM	Shuttle Radar Topography Mission
SST	Sea Surface Temperature
STAC	SpatioTemporal Asset Catalog
TIRS	Thermal Infrared Sensor
TRMM	Tropical Rainfall Measuring Mission
UAV	Uncrewed Aerial Vehicles
USGS	US Geological Survey

VGI	Volunteered Geographic Information
VIIRS	Visible Infrared Imaging Radiometer Suite
VR	Virtual Reality
WCS	Web Coverage Service
WFS	Web Feature Service
WHO	World Health Organization
WKT	Well-Known Text
WMS	Web Map Service
WMTS	Web Map Tile Service
WPS	Web Processing Service
WUI	Wildland-Urban Interface
XR	Extended Reality

3

RELATIONSHIP BETWEEN GUIDES

3 RELATIONSHIP BETWEEN GUIDES

The Provider Guide is one of a trilogy of Guides being developed through Disaster Pilot 2023 (DP23) alongside the User Guide and the Operational Capacity Guide. These three guides are shown in Figure 1.

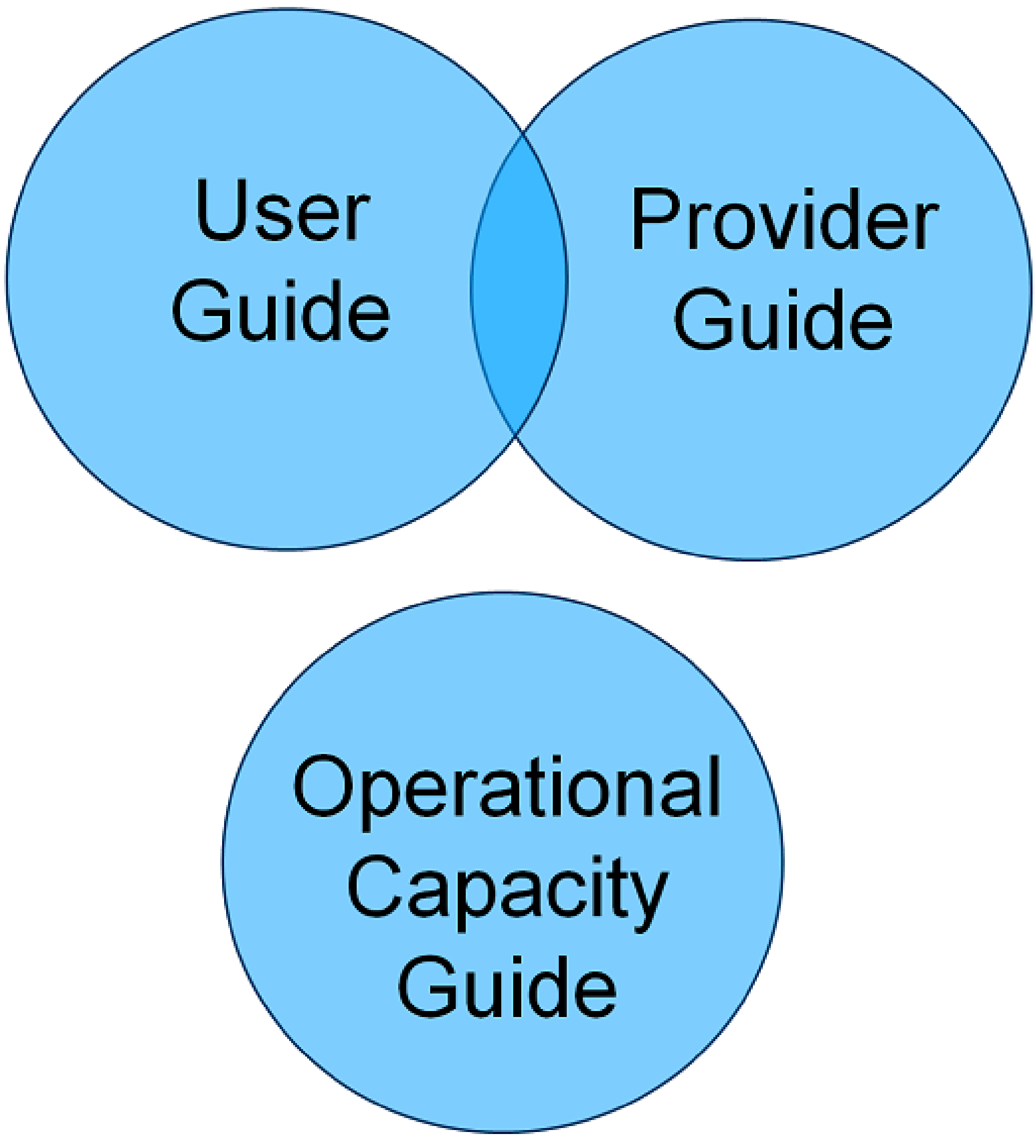

Figure 1 — Three Guides

The details of the three Guides are as follows.

Provider Guide

- *Audience:* Existing and potential, data and technical application providers, data collectors, processors, publishers, emergency management information technology support functions, together with other supporting stakeholders.

- *Purpose:* To describe the detailed technical requirements, data structures, and operational standards providers need to implement to integrate the data flows or tools developed in DP23 to enable data or applications to be operationalized by disaster and emergency user communities.

User Guide

- *Audience:* First responders, commanders, decision-makers, and associated people interested in using the data in practice and encouraging culture change to realize the potential value of having available data to support disaster and emergency planning and response.

- *Purpose:* To provide a non-technical showcase of the workflows and tools demonstrating what is possible and what opportunities there are for disaster and emergency management communities to use these solutions to support and enhance disaster planning, management, and response.

Operational Capacity Guide

- *Audience*: Disaster and emergency management administrators, operational managers, and policy makers, together with emergency management teams.

- *Purpose:* Stand-alone document, providing an outline of the strategic actions required for any disaster or emergency management team wishing to establish, enhance, or improve the team's geospatial readiness, delivering a robust and effective geospatial function to respond to disaster events including emergency management program funding functions and information technology support functions.

The Guides work together, with each individual Guide focusing on the key information for each Guide's specific audience and providing signposting to further details should it be required. Figure 2 gives an overall structure for the Guides.

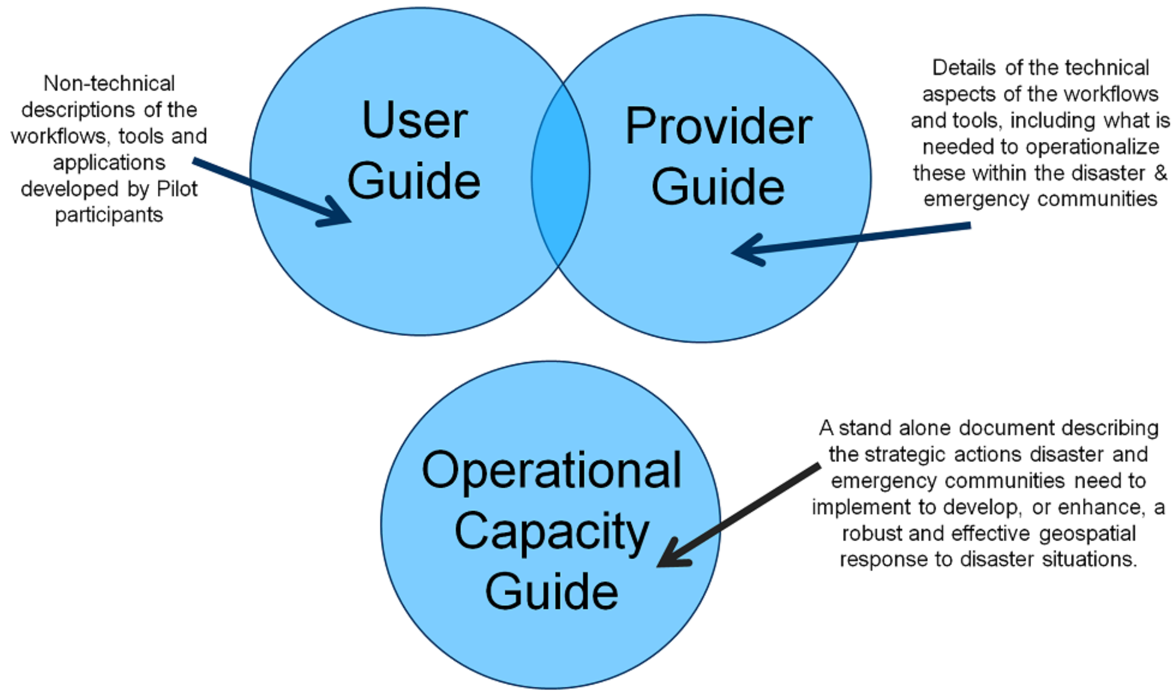

Figure 2 — Detailed Guides relationship.

4

USE OF GEOSPATIAL INFORMATION IN DISASTER RESPONSE

4 USE OF GEOSPATIAL INFORMATION IN DISASTER RESPONSE

Disaster management is generally understood to consist of four phases: mitigation, preparedness, response, and recovery. Mitigation describes activities aimed at reducing the occurrence of emergency situations, preparedness focuses on active preparation, response is the acute phase occurring during and after the event, and recovery covers a wide range of processes that support getting back to a state of acceptable operation. While all phases are interrelated and important, the response and recovery phrases are often viewed as the most critical in terms of saving lives. The timely provision of geospatial information can greatly help in the decision-making process, save lives, and aid those affected.

4.1. Geospatial Data

Geospatial data can be defined as data that describe objects, events, or features using locations on the Earth's surface. The simplest form of presenting such information is a map. Whilst the earliest maps began with the Babylonians and Greeks in the 6th Century BC, the use of geospatial data in disasters is a bit more recent. Arguably, one of the first uses was in 1854 when Dr. John Snow mapped, by hand, the deaths from a cholera outbreak in London.

The term geospatial data covers a lot of different sources of data which have spatial references, meaning the data have geographical references, which give the data locations. There are many types of geospatial data, and all could offer benefits in a disaster scenario depending on the circumstances. Examples of the types of geospatial data that could be available include the following.

- Satellite data — can include optical, thermal, radar or lidar data
- Airborne imagery/photography — could be collected by aircraft, helicopters, or drones and can also include optical, thermal, radar, or lidar data
- Oblique angle photography
- Building or Computer Aided Design drawings
- 3D Renderings
- Citizen Science data – namely, data collected by first responders or general citizens, usually on handheld devices, giving precise snapshots of what is happening at specific locations.

The type of disaster, the location, or the information required, will determine which data sources may be helpful. However, it is unlikely that one single data source will answer all the questions about the disaster. The way problems are often solved is through the integration of multiple data sources, and it is these combinations of datasets and looking at the data in different ways that give additional insights.

Together, geospatial data and technologies such as Geographic Information System (GIS) offer the potential to provide first responders with invaluable information. This information can be used to support both the planning and the implementation of the response, through maps and information, directly to the field responders on the ground, improving awareness of the current situation. Therefore, providing access to these technologies allows saving lives and helping people respond to disaster events. The following look at some of the more common types of geospatial data in more detail.

4.1.1. Satellite Data

Earth Observation (EO) started around the same time as Dr. Snow's map when Gaspard-Felix Tournachon took photographs of Paris from his balloon in 1858. However, it was a century later with the launch of the Explorer VII satellite in 1959 that satellites were used to make observations of the Earth. The first real mapping satellite was NASA's Earth Resources Technology Satellite launched in 1972, later renamed to Landsat-1. To date, Landsat offers a fifty-year archive of satellite observations of the planet. Other space agencies around the world have also launched EO missions including the European Space Agency (ESA) which is involved with the European Union's Copernicus program, the Japanese Space Agency (JAXA) that has the National Security Disaster ALOS-3 optical and ALOS-4 microwave missions, and the Canadian Space Agency (CSA) whose RADARSAT series of satellites support disaster monitoring activities.

While there are now lots of satellite datasets and products, both commercial and governmental, there are also some programs focused solely on supporting disaster and emergency scenarios, such as the following.

- International Charter: Space and Major Disasters was signed on 22 October 2000 by ESA, the French Space Agency (CNES), and the CSA. Currently, there are 17 contributing members including the US Geological Survey (USGS) and the National Oceanic & Atmospheric Administration (NOAA). This charter is triggered when a disaster situation occurs and makes satellite data available from different providers around the world, giving the teams responding and managing the specific disaster access to a wide range of data. Since its inception, the Charter has been activated for over 800 disasters in 127 countries; during 2022 it was activated 51 times.

- Copernicus Emergency Management Service (CEMS) is a European focused service that provides Disaster and Emergency communities with geospatial information to inform decision making. CEMS constantly monitors Europe to forecast, analyze, and provide information for resilience strategies. The datasets are created using satellite, in situ (ground), and model data, and offers on-demand maps, time-series, or other relevant information to better manage disaster risk.

4.1.2. Airborne Imagery or Photography

Aircraft are often requisitioned as a core lifeline after disasters occur, as the aircraft are used to drop supplies and/or rescue survivors. As a result, passenger aircraft may be an alternative remote sensing platform in emergency response due to the high revisit rate, dense coverage, and low cost, i.e., photographs from the people on the aircraft. A more operational use, for example, could be for wildfire detection and monitoring, with thermal sensors being particularly useful. The initial characterization of the fire's properties (e.g., location, size, proximity to water or inhabited areas) is critical to mounting an initial response.

Uncrewed Aerial Vehicles (UAVs), often termed drones, can also provide local situational understanding in terms of what is currently happening and/or the immediate aftermath.

Looking towards the near-term future, High Altitude Pseudo Satellites (termed HAPS) which are high altitude balloons, or constellations of micro-satellites, will increasingly offer sensor-dependent persistent coverage.

4.1.3. Citizen Science Data

Sensors can also be found in smartphones and other devices, plus social media offers potential to collect data. As a result, any person, device, or sensor is a potential data generator and can create complex datasets, termed Big Data. The location of the sensor is expressed in a standard and readily understood form, such as latitude-longitude, street address, or position in some coordinate system. But these data may also include indirect information about location or unstructured data, where methods and tools for extracting the required information are needed. Also, although mobile applications can be a key element in improving situational awareness, a post-event observation may not provide important information on the pre-event structures and so different sources for pre- and post- event awareness must be combined. Also, any new technological 'solution' would tend not be used during a disaster unless the stakeholder community had already adopted and trained with the solution pre-event.

4.1.4. Real time sensor data

While citizen science data tends to be intentionally submitted, mobile devices and other systems can collect data more automatically. Producing a continuous stream of data which can be leveraged to observe patterns and detect anomalies, and in turn detected patterns can help drive hazard indicators. These data can be collected from sensors, instruments, or devices in the environment (Internet of Things IoT).

4.1.5. Model Data

While real time sensors give a better situational awareness of what is happening in the world today, models provide a better understanding of what could be happening given a range of assumptions. These assumptions are used to feed a model calibrated to behave in ways that approximate to some aspect the natural world. Increasingly, the importance of incorporating the results of climate models to gain a better understanding of future possibilities and hazards associated with climate change is being realized.

4.1.6. Challenges of Using Geospatial Data

While the idea of using geospatial data within disaster and emergency situations is positive, there are several practical issues that can prevent the data being used to the greatest advantage. These challenges include the following.

For First Responders

- Geospatial maps and data can be useful to give situational awareness, but are not comparable to having experienced boots on the ground determining what needs to be done.
- Sharing data is challenging for first responders:
  - lack of mobile coverage and service is a big issue; and
  - data often have to be shared physically, such as via AirDrop on Apple devices.
- Speed of update is critical in fast moving situations.
- Offline options for data management and visualization are vital in rural areas.

For Operational Managers:

- Data acquired are not always useful as availability can be limited by meteorological and geographical factors.
- Emergency management agencies want value-added products such as decision support information, thematic data/images, etc., as these can be quickly integrated into the decision-making process.
- The area impacted by an event, or within which the rescue teams operate, varies considerably from a few square kilometers for local events (landslides, earthquakes, etc.) to thousands of square kilometers for very large area events such as tsunamis, tropical storms, and floods in low-lying areas. So, data need to be at a spatial resolution that can help and support decision making.
- Tendency to go with the tried and tested approach for data sharing and mapping applications, and a conservative approach to trying new technology.

For Data and GIS Analysts

- Obtaining, downloading, and integrating data into local GIS systems can take too long, i.e., before the data are useful for disaster response.
- Increases in the amount of data potentially available can be overwhelming and can inhibit the ability to efficiently manage, use, and share data.

For Satellite data operators/value adders

- Satellite data response time is often not considered rapid enough for real-time monitoring.
- Delivery of first crisis satellite products within 23 hours remains challenging, due to the characteristics of the satellites, their orbits, cloud cover, and “true operational” revisit time.
- The lack of a framework to quickly supply satellite images free of charge in an emergency, which needs to include data providers (space agencies and commercial organization), data analysts (universities, research institutes, etc.), and users (disaster management organizations), can make it difficult to obtain data where credit card or financial approval is needed. These issues are partly addressed through international efforts, but activities need to continue to improve satellite data to fulfill the potential for the data to be used throughout the value chain.

For Citizen Science Data

- Social media data have improved the efficiency and scope of disaster information communication, but at the same time, social media data also bring some misinformation. Therefore, filtering and cleaning is an important part of the disaster information and representation process. Also, social media companies are starting to monetize data and other offerings and so access may no longer be free.
- Social engagement and participation in data sharing and reliable information are lacking in developing disaster GIS maps and 3D representation.

5

HOW TO USE THIS GUIDE?

5 HOW TO USE THIS GUIDE?

The OGC Disaster Pilot 2023 (DP23) technical solution built on the success and outcomes of Disaster Pilot 2021 (described in Clause 7.2) and other OGC Collaborative Solutions and Innovation Program (COSI) initiatives.

This Guide is for existing and potential data and technical application providers, data collectors, processors, publishers, emergency management information technology support personnel, and other supporting stakeholders.

This Guide gives the detailed technical requirements of each of the tools and data workflows, together with links to persistent demonstrators showing the operating details and the benefits available to disaster and emergency communities. This information should give enough detail to enable the tools and workflows to be operated, and also give tool developers the standards needed to participate in this ecosystem.

5.1. Tools to Support Use of Geospatial Data

Within Annex A there are a series of potential tools that can help disaster and emergency communities to gather, find, and visualize data for any type of disaster. For each tool there are:

- a description of the tool, and what it can offer;
- details of the benefits the tool offers, how it can support decision making, and the job roles of who would use this tool; and
- details of how to find the online demonstrations for the tool and any collaborations undertaken as part of DP23.

5.2. Data Workflows to Support Disaster Management & Response

A series of specific data workflows have been developed by DP23 & DP21 participants covering the following.

- Droughts in Annex B
- Wildfires in Annex C
- Flooding, including landslide and pandemic impacts, in Annex D

- Integration of Health & Earth Observation Data for Pandemic Response in Annex E

These data workflows will produce either Analysis Ready Datasets or a Decision Ready Indicator, which are described in more detail below.

Each of the data workflows within the Annexes include the following.

- Introduction to the workflow and the risk or issue it aims to support.
- Indicator recipe, which describes the input data used, the processing and transformations undertaken, the output data produced, and details on the technical requirements and standards used by the workflow.
- Details of the benefits the workflow offers, the types of decisions it can support by these data, and the job roles that would use the output.
- Details of how to find the online demonstrations for tool and any collaborations undertaken as part of DP23.

5.2.1. Types of Users

The Pilot has identified the following four user groups.

1. Data Analysts working for the responding organizations providing insights and information for the disaster planners or field responders. These may include data analysts, GIS analysts, and logisticians.
2. Disaster Response Planners or Managers who lead the disaster readiness and response activities for the responding organizations.
3. Field Responders who are on the ground responding to the disaster and reporting to the responding organizations.
4. Affected public and communities who want direction and guidance on what to do.

Each of these user groups requires different types of data or information, at different levels, and presented in different ways.

5.2.2. Data Set Types

The data workflows take raw data (which could be any form of geospatial data such as geographic data, satellite, or airborne data) fixed gauges or instruments, demographic and social data, health data, field observations, or citizen science data, and then undertake some processing to create one of two types of datasets; either an Analysis Ready Dataset or a Decision Ready Indicator as shown in Figure 3.

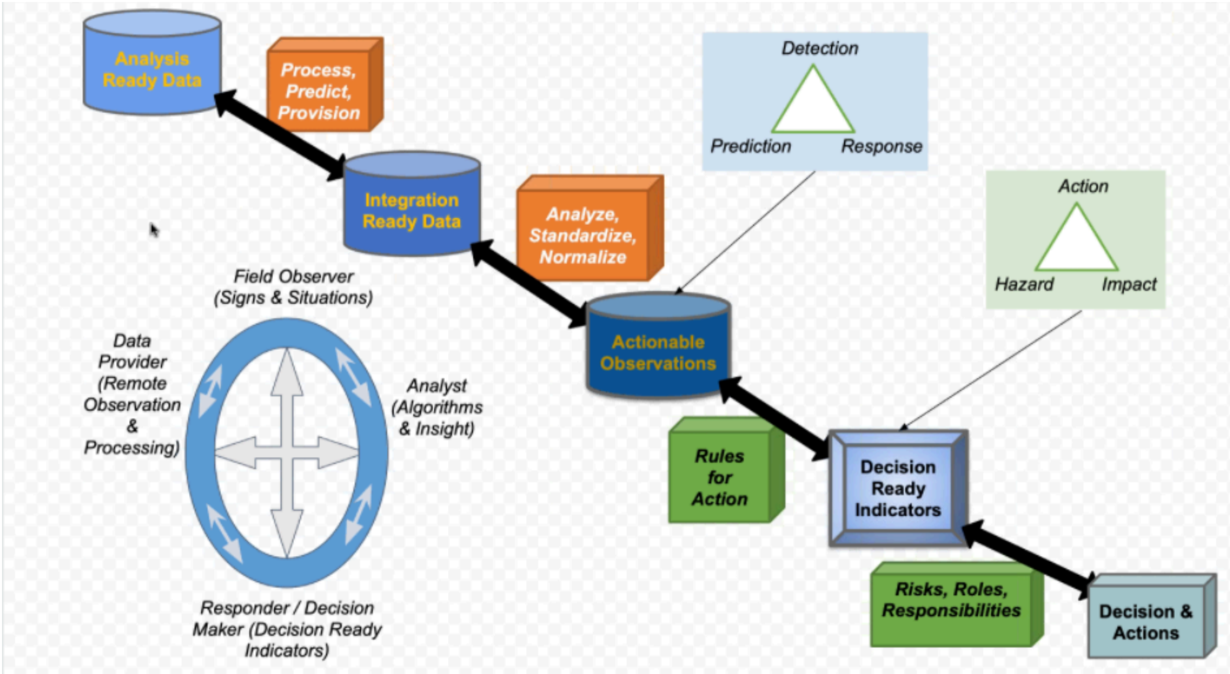

Figure 3 — Relationship between ARD to DRI, courtesy of Josh Lieberman (OGC).

- **Analysis Ready Datasets (ARD)**

Analysis Ready Datasets are raw geospatial data to which initial processing has been undertaken to create a dataset in a format that can be immediately integrated with other information and used within a Geographic Information System (GIS) and can be interrogated by people with the right skills to gain greater insight. These data can be either visualized or further analyzed, interrogated, and/or combined with local knowledge to create information upon which decisions can be made.

+ ARD is most likely to be used by Data Analysts but could also be used by Disaster Response Planners and Managers.

- **Decision Ready Indicators (DRI)**

Decision Ready Indicators are ARDs that have undergone further processing to create information and knowledge in a format that provides specific support for actions and decisions that have to be made about the disaster.

+ This information will be useful for Disaster Response Planners and Managers, Field Responders, and the Affected Public and will be able to be used without any specialist knowledge, skills, or software. DRI datasets may also be useful to Data Analysts in order to build composite or multi-stage indicators.

Note: Although these are the two main types of data envisioned throughout the Pilot it was acknowledged that datasets might exist between ARD and DRI. For example, some datasets may be considered to be actionable observations: more refined and richer than basic ARD, but without the clearly defined rules or parameters as to what action should be taken that would be necessary to consider them DRIs. The type of dataset offered by each participant should include a clear indicator recipe and/or output type in the Annexes.

6

WHAT IS PROVIDER READINESS?

6 WHAT IS PROVIDER READINESS?

Readiness is the state of being fully prepared and in this case, it is the state of being fully prepared to provide information to support a disaster response activity. More specifically, in terms of the OGC Disaster Pilot activities, Readiness is determining what is needed for developed tools and workflows to be operationalized by a disaster and emergency community ecosystem.

The overarching aim of DP23 was to develop flexible, scalable, timely, and resilient information workflows, together with applications and visualization tools to promote a wider understanding of how geospatial data can support emergency and disaster communities and critical disaster management decisions. To be part of the envisaged Pilot ecosystem, both data providers and users need to be prepared to take part, which means making a series of agreements. However, this cannot simply be a set of agreements between individual data providers and users, nor can it be one single solution that everyone has to fit within. Instead, it requires a set of agreed operating approaches and standards such that, for example, the data providers need to know the format the data needs to be provided in that users can immediately integrate within the data system being operated.

Ideally, this activity would be undertaken before a disaster occurs, as starting this process once a disaster is underway will simply take time and slow down getting the geospatial data to the people that can put it to use to support the response. The elements that need to be agreed run from license agreements through to data formats, geospatial systems used, analysis skills, data aggregation and transformation methods, and even the symbols and colors to be used in the visualization, and so on.

This section of the Guide describes the four steps that providers should complete in order to be in a position to achieve readiness and fully participate in the disaster response ecosystem.

6.1. Step 1: Understand and Implement Common Standards

As discussed, the driving force of these initiatives is to enhance the access, sharing, use, reuse, and exploitation of geospatial information and applications across, and between, organizations within disaster and emergency communities. Common standards are fundamental, as are the underpinning foundations that are needed to support data interoperability.

Using agreed technical standards alongside common data formats will ease the process of integrating data, not only within the disaster and emergency community, but also across boundaries, which will also help any new data providers wanting to offer new datasets to be clear as to what the requirements would be for any new data flows.

Without standards, the potential for wasted time on data wrangling and preparation is high, and even worse, the potential for inefficient, incorrect, or even wrong disaster response decisions increases.

6.1.1. FAIR Principles

OGC promotes, and encourages, the FAIR principles for data management to improve the Findability, Accessibility, Interoperability, and Reuse of digital assets; these are as follows.

- **Findable**

The first step in (re)using data is to find them. Metadata and data should be easy to find for both humans and computers. Machine-readable metadata are essential for automatic discovery of datasets and services, so this is an essential component of the FAIRification process.

- **Accessible**

Once the user finds the required data, she/he/they need to know how the data can be accessed, possibly including authentication and authorization.

- **Interoperable**

The data usually needs to be integrated with other data. In addition, the data need to interoperate with applications or workflows for analysis, storage, and processing.

- **Reusable**

The ultimate goal of FAIR is to optimize the reuse of data. To achieve this, metadata and data should be well-described so that both can be replicated and/or combined in different settings.

6.1.2. Geospatial Standards Within Disaster Pilot 23

The geospatial standards for each of the elements from data discovery to visualization include the following.

- **Discovery**

Service(s) and associated application(s) support near-real-time registration, search, and discovery of Analysis Ready Datasets (ARD) and Decision-Ready Information and indicators (DRI), alongside contextual social-political-health datasets and local observations within impacted areas. This element includes implementations of OGC API Standards that provide structured geospatial data to support web-based searching with JavaScript Object Notation — Linked Data (JSON-LD) and include generation of metadata catalogs and self-describing datasets to aid data access and processing, e.g., SpatioTemporal Asset Catalog (STAC) and GeoPackage.

- **Data Storage and Processing in the Cloud:**

Cloud-based storage, processing, and service elements support the loading, preparation, and access to individual satellite-based datasets alongside complementary geospatial datasets. Then, further application elements are deployed near to source datasets and support agile, rapid, and scalable generation of decision-ready (e.g., indicator) information products.

- *Registry and Search Catalog generation* has utilized STAC
- *Processing* has utilized Jupyter Notebooks
- *Storage formats* included the transition of imagery to formats that support cloud-native geospatial processing, e.g., Cloud Optimized GeoTIFF (COG) and GeoPackage
- *Storage locations* such as Amazon Simple Storage Service (S3).
  - **Visualization:**

- *Mobile client applications* able to discover, request, and download DRI products as GeoPackages in support of disaster response field personnel, operations, and decision making during connected-disconnected operations
- *Web/desktop client applications* able to interact with cloud-based server components to access both ARD and DRI products for analysis and visualization by analysts and decision-makers
- *Delivery standards* for these clients include GeoRSS, Web Coverage Service (WCS), Web Feature Service (WFS), and Web Map Tile Service (WMTS)
- *Platforms to serve the geospatial data and visualize it*, e.g., GeoServer and GeoNode, with transmission standards such as Web Coverage Service (WCS), Web Feature Service (WFS), and Web Map Tile Service (WMTS)

Having these pre-agreed and understood in advance can ensure consistency and an efficient processing/delivery of the needed disaster-related information.

6.2. Step 2: Develop Dataset Recipes or Tools to support the access, sharing, use, reuse, and exploitation of geospatial data

To be part of the OGC Disaster Pilot ecosystem, providers need to develop a value chain as shown in Figure 7, whether this is a non-proprietary tool to help access, share, or visualize data, or the development of an indicator recipe to create either an ARD or a DRI value chain that produces a dataset that can be used directly, or combined with other information in a GIS.

Examples of the tools and indicators developed by Pilot participants can be seen in the Annexes to this Guide, with details of the indicator recipes, collaboration possibilities, and persistent demonstrators.

A number of tools can be used to implement these recipes in a way that is readily interchangeable and reusable in different contexts. One approach is the use of open-source web-based scripted tools like Jupyter Notebooks, often involving Python and other languages such as Java or R. Another approach is to use model-based spatial Extract, Transform, and Load (ETL) tools to support data integration and automation. Either approach can support rapid recipe development to generate the data products necessary to support disaster responders, and examples of both approaches were tested in the context of Disaster Pilot activities.

An example of working through the process of understanding what is needed were the discussions within the ARD and DRI working groups in Disaster Pilot 21, with the OpenStreetMap (OSM) conversion undertaken by Safe Software using FME as follows.

- Areas of interest extents or polygons were shared in GeoJSON format allowing all participants to be sure discussions were about the same geographical extent.
- Basemap data was extracted from OSM and shared via a GeoPackage as foundation layers. Although this may sound like a trivial exercise, it was not because:
    - there was an interpretation process when extracting information from OSM and 'flattening' it for use in a GIS; and
    - a further complexity was that the original OSM data use geodetic coordinates and the Coordinate Reference System (CRS) 'EPSG:4326', where latitude is specified before longitude, while a GeoPackage defines co-ordinates according to the OGC Well-Known Text (WKT) standard of x,y,z,t that will override any CRS axis order, i.e., longitude would come first.

In DP23, a similar focus was placed on the climate projections from models that are often distributed in formats such as NetCDF (Network Common Data Form), a community standard for sharing scientific data. NetCDF has advantages such as being self-describing and appendable with climate community agreed standards such as the CF Metadata Conventions. However, it can be difficult to use/understand alongside data being stored in large files. One solution is to create virtual Zarr interfaces (a format designed for cloud storage and access) while another is to just extract the data of interest and reformat the data into a simpler format, e.g., serving point/polygon data via a Features server.

6.3. Step 3: Determine the Method For Delivering Outputs

Receiving a large amount of data, and then analyzing, processing, and visualizing the data is only the first half of the work. The second half is getting the outputs of that work to the people managing the disaster response, including the field responders on the ground via their mobile phones or similar devices.

There are a variety of solutions for this and so the Pilots do not recommend one, nor do the Pilots suggest that the solution would be based around a single technology. Instead, using a set of standards for data sharing, as described in Clause 6.1 will enable data to be interoperable and reusable across any platform. Solutions could be provided that are open source, commercial, or even using existing internal infrastructures.

The key element is that the receiving organization has a solution where the decision-ready indicators can be uploaded for users to access. The preferred solution will depend on the organization's infrastructure, financial pressures, technical skills, etc.

Within the Pilots, several external platforms were tested, including the following.

- **Immersive Indicator Visualizations**

Immersive Indicator Visualizations were developed by USGS-GeoPathway which offers ARD and DRI to enhance comprehension of drought and wildfire management across varied spatial-temporal scales. It has two elements: **Disaster Augmented Reality Simulation Table (DARSIM) — DARSIM modernizes traditional simulation tables, replacing bulky sand models with a portable, data-integrated solution, designed in response to wildland firefighter needs; and** Single Pane of Glass (SPoG) — The SPoG provides a unified view of multiple data sources, promoting synchronized decision-making using DRIs and ARD.

- **Geocolloborate**

Geocolloborate is a platform developed by StormCenter Communications under the U.S. Federal SBIR program, which offers an option for an expert to lead the analysis and sharing of trusted data with a series of followers receiving the data in real-time on the same screen. This approach offers the potential for a lot of people to interact with the same information at the same time leading to collaborative decision-making with the latest data available, some of which could be updated in real-time.

- **GeoNode Platform**

GeoNode, developed by GeoSolutions, is a web-based application and GIS platform for displaying spatial information. A GeoNode controlled by HSR.health has been used to display various data layers that were then accessible using open standards.

If an external platform is chosen, it is important to ensure that it can comply and adhere to the Standards highlighted in Clause 6.1. In addition, it will be necessary to ensure the following.

- Licenses have been agreed with the external provider for the use of the platform, including sufficient licenses being available for everyone who might need access to data during a disaster.

- All possible users have and know any username and passwords required to access the external system. In addition, this could also include additional security to allow only certain users to see specific datasets — this approach was tested through encrypted GeoPackages.
- All possible users have received training in the use of the system for disasters.

It is acknowledged that similar points will be relevant to in-house solutions. The key element is that the chosen platform itself should support the data standards which will be used by the data providers to ensure that the indicator and data sets will be portable between platforms.

6.4. Step 4: Operationalize the Disaster Response Tool or Workflow

Step two focused on developing datasets workflows, applications, and visualization tools, but to prevent these tools from being proof-of-concept examples or a short-lived demonstration, the tools need to be able to be operationalized to promote the wider understanding of how geospatial data can support emergency and disaster communities.

Providers need to maintain persistent demonstrators of applicable data workflows or tools, and offer disaster and emergency communities the opportunity to test workflows and tools in controlled environments to experience how the workflows and tools work. In the Annexes to this Guide are descriptions of all the data workflows and tools which should give an understanding about what the provider is offering, but it is the use of the tool or workflow in practice or within disaster exercises that will determine whether it works for that community, whether changes are needed, or whether it is a success.

Finally, it will be important for the users of the datasets, indicators, and tools to understand what the impact will be, and what specific decision trees will be enacted when an indicator reaches a certain level. For example, in a flood or wildfire situation, at what point is an evacuation order issued? This will be necessary to give the decision-makers confidence in data-driven decisions and knowing how they should respond.

In summary, the workflows and tools need to be established for the long term, not just for the project, otherwise there is no point in any of the disaster and emergency communities testing and using workflows and tools, if the communities cannot be sure the workflows and tools will be available when a disaster situation strikes.

Although not developed within the Pilots, one suggestion was to develop a series of Operational Readiness Levels (ORLs), similar to those developed by Earth Science Information Partners (ESIP) for making Earth science data more trusted, which will identify the steps and operating standards that both data providers and users will need to take to be able to fully participate.

7

DESCRIPTIONS OF CASE STUDY AREAS AND HAZARDS

7 DESCRIPTIONS OF CASE STUDY AREAS AND HAZARDS

The vision of the Disaster Pilot 2023 (DP23) initiative revolved around bringing the technological pieces together and increasing stakeholder engagement, in order to reduce the preparation time and accelerate the ability to transform data from observations into decisions. To achieve this goal required bridging the divides between providers, responders, and other stakeholders, forming a connected ecosystem of data and technologies, and developing the capacity to produce Decision Ready Indicator (DRI) products that answer decision makers' questions almost as fast as the questions can be posed.

Previous work delineated multiple phases of cycles of activity within disaster management, see Figure 4, all of which depend on getting the right information to the right people at the right time.

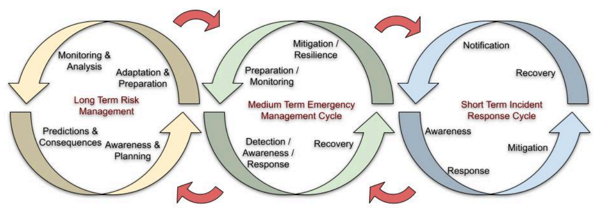

Figure 4 — Cycles of activity

Within the longer-term, risk management and emergency management cycles are shorter term incident response phases for which the ability to move fast and adapt is particularly important. Disaster Pilot 2021 (DP21), found in Clause 7.2, focused on supporting these shorter-term activities such as the following.

- Risk and vulnerability assessment and preparation
- Threat prediction from hazards
- Severity assessment of disaster occurrences
- Impact awareness
- Response and mitigation

DP2023 expanded its focus to activities across a wider range of timescales, such as adaptation and planning, because drought and wildland fires occur on very different timescales, and there is a need to support the balancing of resources between immediate and longer-term needs. This balancing is also relevant to resilience in the face of broader climate change effects.

In developing tools and workflows, the DP23 & DP21 participants have used several case study areas and hazards as the basis for demonstrators. In DP23, it was Manitoba in Canada and the south western United States, while DP21 focused on the Red River Basin in Canada and the United States, the Rimac and Puira Rivers in Peru, and Louisiana in the United States.

7.1. 2023 Disaster Pilot

Details of the case study areas and the hazards for DP23 include the following.

7.1.1. Manitoba: Drought Hazards

Manitoba in Canada has been used in DP23 as the case study area looking at hazards associated with drought. Specifically, the area covered is the provincial boundary of Manitoba, covering an area from 49 to 52 degrees North.

Canada's Changing Climate Report projected a substantial increase in the number of hot days for the region, highlighting the potential increased risk of droughts which will affect many aspects of Manitoba's landscape. Droughts not only affect agriculture. Water-sensitive areas, such as power generation, fisheries, forestry, drinking water supplies, wildfires, manufacturing, recreation, wildlife, and aquatic ecosystems, can also be severely affected due to recurring droughts (Manitoba Green Plan, 2020).

For example, in Manitoba, from 1988 to 1990 and 2002 to 2003, drought in the Churchill/Nelson River Basin reduced agricultural production to 60% below average, caused an $80M CAD loss in reduced hydropower exports, a massive loss of wetland habitat, and an increased incidence of disease (Manitoba Green Plan, 2020). A 2012 drought caused wildfires to break out near the communities of Badger and Vita, leading to the declaration of local states of emergency. Manitoba's recent extreme drought of 2021-22 throughout most agricultural regions reduced hydropower exports by $400M CAD (Manitoba Hydro, 2021) and decreased crop yield by 37%, equivalent to an estimated $100M CAD in revenue, and caused the loss of an estimated 270 jobs.

The individual workflows for this Case Study can be found in Annex B.

7.1.2. Southwestern United States: Wildfire hazards

There are three southwestern states selected as the case study areas for wildland fires.

- **Utah**
  - *Fish Lake with a 50-mile radius.*

    Fish Lake is a high alpine lake in south-central Utah, which lies within the Fishlake National Forest. The lake is five miles long and one mile wide and the surrounding forest covers 1.5 million acres. The forest is home to Pando, a huge cluster of 40,000 aspen trees covering over 100 acres, that all share the same root system. Fishlake

National Forest was the site of Utah's largest wildfire of 2023, which began with a lightning strike and burnt almost 8,000 acres during August.

- *Brian Head with a 25-mile radius.*

  Brian Head is a small town in Iron County, Utah, with a population of around 100 people. It sits at 3,000 meters above sea level and is the highest elevation town in Utah. Given the town's altitude, it has an alpine climate with cold winters and annual snowfall of around 9 meters, while the summer provides frequent thunder storms from the monsoons. Brian Head sits within the Dixie National Forest, which covers almost 2 million acres. The vegetation in the Dixie National Forest ranges from desert-type plants at lower altitudes, through to pine and juniper, and finally aspen and coniferous trees at the higher altitudes.

- *Parley's Summit with a 25-mile radius.*

  Parley's Summit is a mountain pass at the top of Parley's Canyon, to the east of Salt Lake City in Utah. The summit has an elevation of 2,170 meters and is the highest elevation point of the I-80 highway in the state. In 2021, a wildfire burned almost 550 acres in the Canyon and led to thousands of evacuations.

- **Arizona**

  - *Tucson with a 25-mile radius.*

    Tucson is the second largest city in Arizona and has a population of over a half a million people. It is situated between Saguaro National Park to the east and west, and the Coronado National Forest to north and south. Tucson is surrounded by five minor mountain ranges and has a hot desert climate, with the summer average daily high temperatures between 98 and 102°F. The wildland fire risk in Tucson, on the most dangerous fire weather days, is very high and expected to increase with climate change.

  - *Sedona with a 50-mile radius.*

    Sedona is a small city in the north of Arizona, within the Verde Valley region. The city sits within the boundaries of the Coconino National Forest and borders four wilderness areas and two state parks. Sedona is surrounded by 1.8 million acres of mostly coniferous woodland and has a semi-arid climate with mild winters and hot summers where the average temperatures approach 100°F during July. Increasing temperatures coupled with low levels of precipitation mean the forest is ideal fuel for any wildfires. In early 2023 lightning caused the Miller Fire, which covered around 30 acres before being bought under control.

- **California**

  - *South Lake Tahoe with a 25-mile radius.*

    South Lake Tahoe is the most populated city in El Dorado County, California, and is based within the Lake Tahoe basin. The city itself covers a total area of 43 square kilometers and lies along the southern edge of Lake Tahoe in the Sierra Nevada mountains surrounded by forest wilderness areas. South Lake Tahoe has a climate featuring chilly winters, and summers with warm to hot days and cool nights with very low humidity. The city can have temperatures reaching up to 90°F in July and August. The June 2007 Angora Wildfire was the worst forest fire in Lake Tahoe history, which burned more than 3,000 acres destroying more than 250 homes and a large area of forest. Since then, the Tahoe Fire and Fuels Team has treated tens of thousands of acres of forest around Lake Tahoe and is using forest management to reduce the threat of catastrophic wildfires. In 2021, the Caldor Fire went around the populated areas due to the treated forest and firefighting effort.

The individual workflows for this Case Study can be found in Annex C.

7.2. 2021 Disaster Pilot

Details of the case study areas and the hazards for DP21 include the following.

7.2.1. Rimac and Piura Rivers: Landslide & Flooding Hazards

Peru's Piura region in the north and the Rimac river basin near Lima are both impacted by difficult to predict El Niño related flooding. The El Niño/Southern Oscillation (ENSO) is a naturally occurring phenomenon in the tropical Pacific coupled ocean-atmosphere system that alternates between warm and cold phases called El Niño and La Nina, respectively.

The Piura climate is arid but can experience very heavy rainfall associated with the high nearby Sea Surface Temperature (SST) during El Niño phases. When heavy rain occurs, severe floods can occur, which in turn can cause mudslides called *huaycos*. Figure 5 shows an index that indicates the El Niño phases in red and La Nina phases in blue.

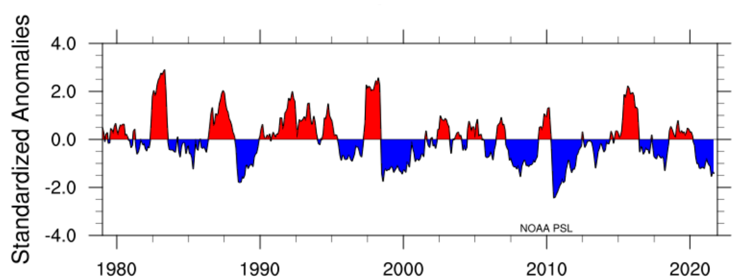

Figure 5 — ENSO index with red indicating El Niño periods, Multivariate ENSO Index Version 2 courtesy of NOAA, USA

As an example of the relationship between ENSO and flooding, El Niño brought rains that caused severe flooding in 1982-1983 and again in 1998 but then, for several years, droughts and extreme heat were the main worries for these communities. Then the flooding returned again in 2002-2003 and 2017-2019. In 2017, ten times the usual amount of rain fell on Peru's coast, swelling rivers, which caused widespread flooding and triggered huge landslides that tore through communities (Collyns, 2017).

The individual workflows for this Case Study can be found in Annex D.1.

7.2.2. Red River Basin: Flooding hazards

One of the most common types of flooding is river flooding, where the river (or rivers) overflow due to high rainfall or rapid melt upstream that causes the river to expand beyond its banks. The Red River flows north from Northeast South Dakota and West Central Minnesota into Manitoba Canada, and eventually out into Hudson Bay. The relatively flat slope of the Red River valley means that the river flow is slow, allowing water runoff from the land to backfill into tributaries, particularly when the downstream river channel remains frozen. In addition, localized ice jams may impede the water flow, resulting in higher river levels.

Therefore, conditions that determine the magnitude of a spring flood include (Anatomy of a Red River Spring Flood):

1. the freeze/melt cycle;
2. early spring rains increase melting of the snow pack or late spring snow storms add to the existing snowpack;
3. the actual snow pack depth and water equivalency;
4. frost depth;
5. ground soil moisture content; and
6. river ice conditions.

A typical spring thaw occurs from the middle of March across southern portions of the basin and mid or late April across the north.

An unusually wet fall and winter, combined with spring melting, drove the water levels up in April 2020. Figure 6 shows the April 2020/2021 water level comparison for the City of Winnipeg's main gauge (James Avenue).

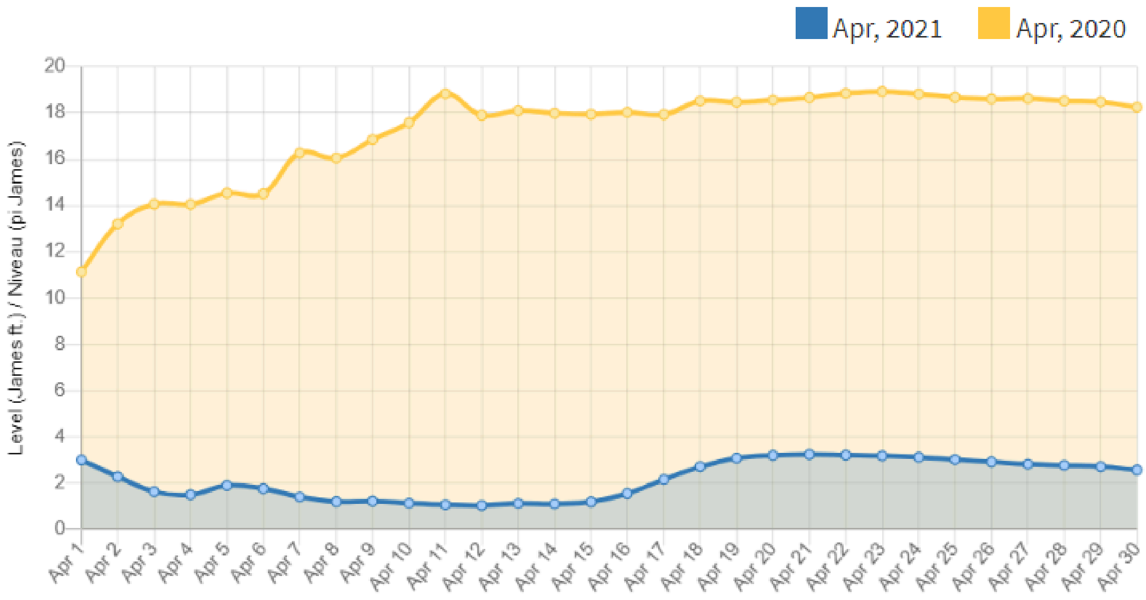

Figure 6 — Red River water level April 2020/2021 comparison, Winnipeg river levels

Winnipeg does have a 48 km floodway (long excavated channel) to reduce flooding within the city, but the floodway can only be opened when there are no ice jams. The floodway successfully protected Winnipeg from flooding during the high-water levels of 2020, and it is estimated the floodway resulted in around 930 million m3 of water being diverted around the City of Winnipeg (Manitoba, 2020 — PDF).

Unfortunately, ice jam events impacting the lower reaches of the Red River, between Winnipeg and Lake Winnipeg, have increased in both severity and frequency over the last century, a trend which is expected to continue and worsen in the future (Lindenschmidt, 2010).

The individual workflows for this Case Study can be found in Annex D.2.

7.2.3. Integration of Health and Earth Observation (EO) data and services for pandemic response in Louisiana in the United States

The State of Louisiana is located on the coast of the Gulf of Mexico, between Texas and Mississippi and covers a geographical area of just over 43,000 square miles. Louisiana is divided into 64 individual parishes and was estimated to be home to over 4,600,000 people in 2019 (US Census, 2019). Almost 16% of the population are over the age of 65, and just over 23% of the population are under the age of 18. Like the rest of the planet, Louisiana has suffered with COVID-19. By the middle of October 2021, over 750,000 cases of COVID-19 had been confirmed in the State, with over 14,000 deaths reported to date.

The climate within Louisiana is considered to be subtropical, and the physical geography of the area includes the Mississippi floodplain, coastal marshes, Red River Valley, terraces, and hills. Louisiana's largest city, New Orleans, lying five feet below sea levels and protected by natural levees, is prone to flooding and hurricanes. During the pandemic, the area was hit by its second-most damaging and intense Hurricane, Ida, the most damaging being 2005's Hurricane Katrina that flooded 80% of New Orleans.

The individual workflows for this Case Study can be found in Annex E.

7.2.4. Technical Architecture for Disaster Pilot 21

The technical solution aimed to bring together multiple providers into an ecosystem that transformed input data into actionable information by developing prototypical components and services. These components aimed to utilize modern cloud architectures and next-generation technologies to optimize collaborative workflows and scale solutions rapidly. An overview of the architecture for the Pilot is shown in Figure 7.

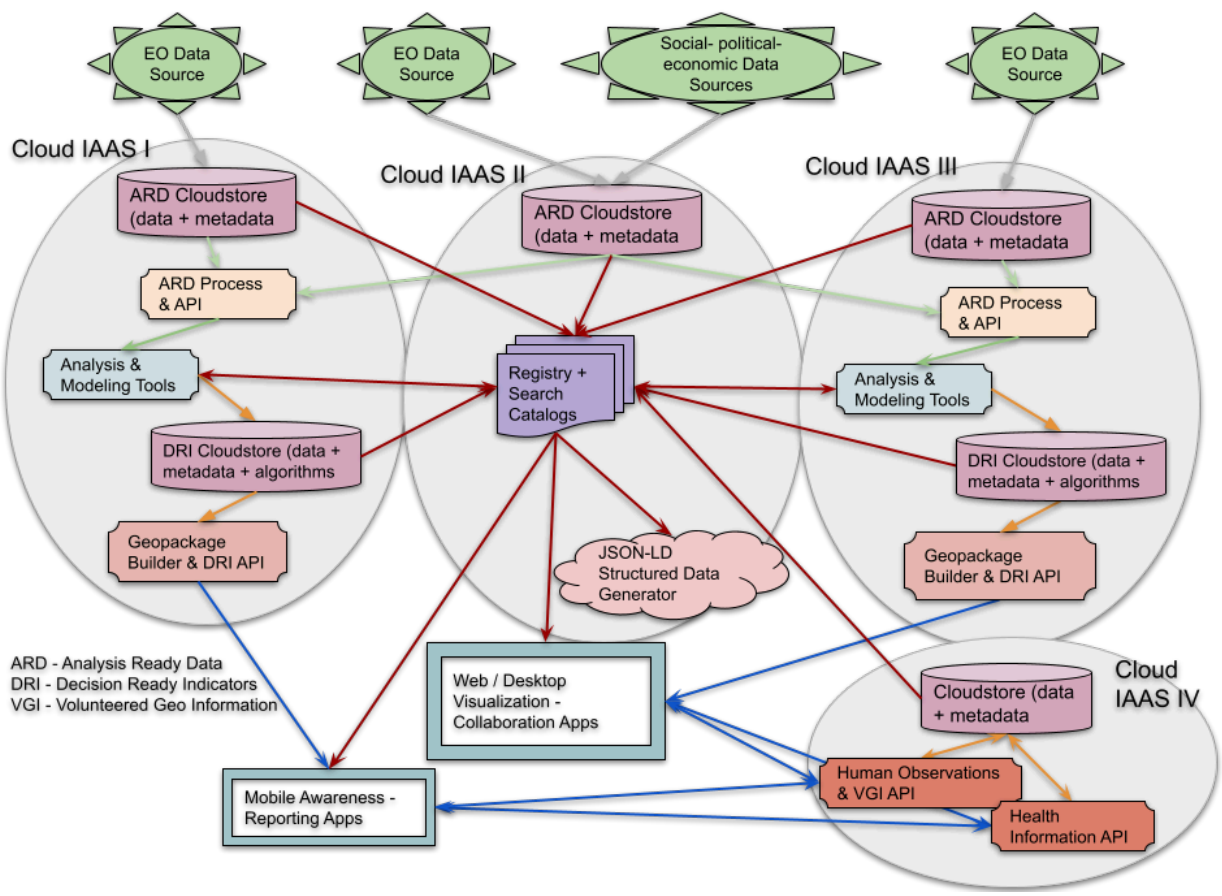

Figure 7 — Pilot architecture overview

At the top of Figure 7 are the data sources, which included Earth Observation (EO) and social-political-economic data alongside ancillary geospatial sources. The sources of data were seen as both being free-to-access and paid-for, and the availability could be restricted depending on the source and sensitivity of the data.

Sources considered or used within the Pilot included the following.

- **Satellite Earth Observation**
  - _Copernicus Sentinel Missions is operated by the European Union, with data acquired by constellations of global missions focused on specific technologies. For example, Copernicus Sentinel-1 are two Radar missions (A&B) that operate at the C-band frequency. Since the Pilot, Sentinel-1B was lost.
  - _Landsat-8 is a high resolution (30 m spatial resolution) mission that carries the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) instruments. Landsat 9 is the most recently launched Landsat satellite, but was not launched in time for the Pilot.
  - _NewSat was a Satellogic constellation that consisted of 17 commercial NewSat satellites in sun-synchronous Low Earth Orbit (LEO).
  - _PeruSat-1 is a National Commission for Aerospace Research and Development's (CONIDA) small (~ 430 kg) satellite launched in September 2016 which carries NAOMI (New AstroSat Optical Modular Instrument) that has a panchromatic band and four multispectral wavebands: Blue, green, red, and Near-InfraRed (NIR). The panchromatic band has a spatial resolution of 0.7 at nadir, while the multispectral bands have a spatial resolution of 2.5 m at nadir.
  - _RADARSAT includes three RCM (RADARSAT Constellation Mission) satellites that operate at the C-band frequency, with a spatial resolution from 1 to 100 m depending on the acquisition mode.
- **Health data**
  - *Tracking*
    - Locations of interest, e.g., specific and black markets.
    - Large gatherings
    - People and items going into and out of any facility to access disease spread risk.
    - Land Use Change, e.g., change in air quality, coastline, the water table, access to water, deforestation, animal, insect, human habitats, and many others.
    - Migration of Animals and Insects
  - *Measuring*
    - Point-in-time population density
  - *Monitoring and monitoring*
    - Evacuation routes and development of alternate evacuation routes
    - Health resource utilization within a medical facility.

        - Volume of traffic at discrete points in transportation infrastructure, e.g., bridges, key intersections, train/light rail stations, etc.

    - Assess distance, travel time between population centers & medical facilities (based on traffic, land cover, storm, etc.).

- **Social-political-economic**

    - Administrative boundaries

    - Census micro data

- **Ancillary geospatial**

    - *OpenStreetMap (OSM):* Buildings and road network.

    - *Meteorological Data:* For example, storm tracking alongside information on weather conditions such as precipitation and wind speed.

    - *Digital Elevation Model (DEM):* Shuttle Radar Topography Mission (SRTM) @ 30 m spatial resolution provides global coverage and several enhanced DEM versions thereof (e.g., http://hydro.iis.u-tokyo.ac.jp/~yamadai/MERIT_Hydro/), while airborne lidar data can provide sub-meter resolution locally.

    - Other *in situ* observations such as stream gauge data.

The input data, ideally in an ARD format, were ingested into cloud-based storage areas from where the data could be transformed into DRI. Users interacted through Mobile and Web/Desktop Applications (Apps), shown in the boxes at the bottom, which interacted with the DRI through a Registry and Search Catalog and GeoPackages. In addition, users provided Volunteered Geographic Information (VGI) into the overall ecosystem to support real-time insights into what was happening.

A key output was recognition and acknowledgment of the need to address:

- stakeholder collaboration on data-to-decision workflows,

- readiness, resilience, and timeliness of data collection and processing to support critical disaster management decisions;

- flexible and scalable deployment of workflows and applications necessary to support disaster practitioners in their day-to-day and minute-to-minute responsibilities; and

- publication and visualization tools to promote a broader understanding of the wide range of scales in both geography and time over which coordinated actions are needed for disaster resilience.

8

COLLABORATING WITH WORKFLOW AND TOOL DEVELOPERS

8 COLLABORATING WITH WORKFLOW AND TOOL DEVELOPERS

As described in Clause 6.2, a key focus for this Pilot was the development of data workflows and tools that can be operationalized by emergency and disaster communities.

The Pilot tried to enhance interoperability of critical connections where a lack of interoperability is particularly likely to derail data sharing. Figure 8 illustrates several pivotal points within a data to decision pipeline involving ARD and DRI, together with the feedback loops.

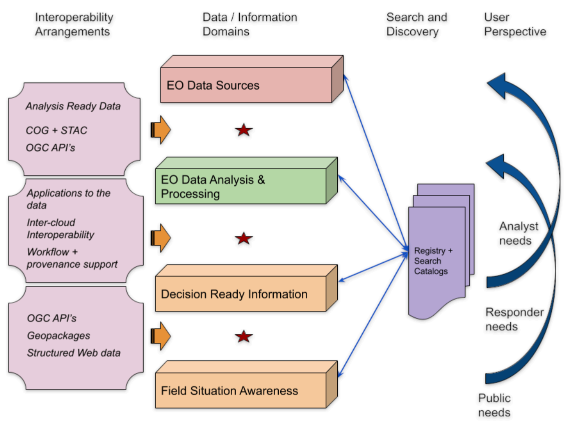

Figure 8 — Pivotal points of interoperability between distinct components of a data-to-decision pipeline

Within the Pilot activities, the developed workflows and tools often involved collaboration between participants, including:

- using the outputs of one workflow/tool as an input to a different workflow or tool; and
- collaborating with each other to try and use tools developed to help users find, access or visualize the data workflows that were developed.

As described in Annex A, Annex B, and Annex C, participants in the Disaster Pilot 23 aimed to provide persistent demonstrators to allow the disaster and emergency communities the opportunity to test workflows and tools in controlled environments to experience how the workflows and tools work. The participants will be happy to assist and support any community that needs further information on data workflow or tools, and the contact details for each participant will either be in the Guide and/or within the persistent demonstrators.

9

NEXT STEPS & RECOMMENDATIONS FOR FUTURE DISASTER PILOT INITIATIVES

9 NEXT STEPS & RECOMMENDATIONS FOR FUTURE DISASTER PILOT INITIATIVES

The Disaster Pilot initiatives made considerable steps towards improving the understanding, accessibility, and demonstration of what is possible with geospatial data for disaster and emergency communities. However, there was still a significant way to travel to ensure communities utilize and benefit from geospatial data solutions.

The following areas were highlighted as worth further exploration during future Pilots.

9.1. User Centric Approach

Greater involvement from the first responder and emergency manager stakeholders in defining the themes and deliverables would help the work have a more user centric approach, and ensure work undertaken directly addresses stakeholder needs. Pilots must begin with stakeholder's wants and needs, an issue which was highlighted both in Disaster Pilot 23 (DP23) and in the associated Climate Resilience Initiative.

During DP23 a talk was given by an active firefighter who highlighted the geospatial data flows that would be must useful:

- better detection of new wildland fires;
- near real time information regarding what a wildland fire is doing, including the identification of hotspots through thermal detection, and anticipated wind direction and strength predictions; and
- providing offline delivery of information within rural locations.

Interestingly, none of the DP23 participants were actively working on any of these data flows. The challenge for future Disaster Pilots is that participants are often focused on what is possible technically, demonstrating the cutting edge of geospatial data and/or their current area of interest and expertise rather than what users want and need.

A similar conclusion was reached by the first OGC Climate Resilience Pilot whose recommendations include to *'design OGC Pilots with activities addressing potential stakeholders … to understand their requirements and access data products and tools related to their needs'*.

While working with users needs is critical, it should be alongside continuing to look to the future and pushing the boundaries on the use of geospatial data.

9.1.1. Recommendations

- Increase the involvement of first responder and emergency manager stakeholder community before the start of OGC Pilots to help define themes and deliverables to ensure the Pilots meet the stakeholder community's wants and needs.
- Ensure Pilots retain work to push the boundaries of the use geospatial data in the areas the users require help and support.

9.2. Artificial Intelligence & Machine Learning

Artificial Intelligence (AI) and Machine Learning (ML) are rapidly developing technologies and both need to be brought into future Pilots for development and assessment activities.

For example, simply during this Pilot, a number of developments were reported in the use of AI & ML for wildfires as follows.

- Historically, Californian firefighters relied on a network of mountain top cameras and spotters to detect wildfires. In 2023, the firefighters were training an AI system to do the monitoring. In early results, the AI has delivered a faster indication of a fire around 40% of the time, improving response times, and identified fires where no 911 calls were ever made. Currently, the program still requires people to make sure the AI is detecting smoke and not something else. This work began in June 2023, and is expected to be rolled out across all 21 command centers later this year.
- In Australia, fire agencies require fire updates every two minutes, especially for remote incidents, to improve situational awareness. The current XPRIZE Wildfire innovation contest aims to give firefighters a resilient advantage in accurate fast detection using AI.
- One of the DP23 participants, HSR.health, is working on a solution to develop training data for a ML solution focused on the early identification of wildland fires and fuel sources by using NASA satellite data.
- OGC approved the standard for OGC Training Data Markup Language for Artificial Intelligence (TrainingDML-AI) Part 1, which defines the conceptual model for standardized geospatial training data for ML which is used to train, validate, and test AI/ML models.

These examples show a small sample of current activities within one specific disaster scenario. It is important that Disaster Pilot initiatives keep up with this advancing trend, and work should cover areas such as those listed below which is not an exhaustive list.

- Development of AI/ML solutions using various data from the diverse data sets available

- Creation of high quality disaster-specific ML training data sets to enable providers to test their solutions and enable comparisons to be made
- Provide an assessment of the accuracy of different data sets to determine which ones are most useful and beneficial

9.2.1. Recommendations

- Include AI/ML activities as part of future Disaster Pilots, including solution development, training data sets, and an assessment and comparison of solutions.

9.3. Operationalizing Geospatial Data

The use of geospatial data to support decision making varies within disaster and emergency communities, with many communities currently using minimal geospatial data, tools, and applications. Some first responders need to meet face-to-face to enable the sharing of information, as robust technical solutions are not available.

From such a low starting point, it may be difficult to convince disaster and emergency decision makers to implement a disaster specific Analysis Ready Data and datasets (ARD) or Decision Ready Information and indicators (DRI) as a first foray into operationalizing and using geospatial data. Therefore, there needs to be a focus on developing geospatial capacity and quick wins for the benefits of geospatial data.

Cutting edge geospatial applications, tools, and data flows are interesting, but the goal of the Disaster Pilot initiatives needs to be the real time operationalization of the data flows and tools developed. Otherwise, the Pilots are simply demonstrators and are not providing real-life benefits. Quick wins might not be cutting edge, but would provide a stepping stone to operationalizing other data flows and tools.

Another opportunity would be greater use of real-time sensor data within future Pilots. Producing indicators providing a real time view of the current disaster situation, hazards, or risks would offer an alternative way of operationalizing the work. This would sit alongside the existing practices used by the first responding community and may highlight the advantages and benefits of geospatial data and information. Any real time sensors should leverage OGC sensor web enablement standards such as SensorThings API to make the data services involved modular, interchangeable, and readily consumable by downstream applications.

Similarly, the Operational Capacity Guide received positive feedback from the Manitoba Emergency Community which was keen to use it to develop and enhance the geospatial readiness of Manitoba communities. Further work on specific elements within this Guide — such as developing example Geospatial Operating Procedures templates or providing a Geospatial Disaster Guide for Emergency Managers — could provide a useful and positive step in furthering the use of geospatial data.

9.3.1. Recommendations

- Working with first responders and emergency managers in the stakeholder community to identify quick wins for geospatial data and ensure these form part of the deliverables for future Pilots
- Encourage the inclusion of real time, sensor-based indicators, and/or dashboards in future Pilots
- Promote the use of OGC SWE — sensor web enablement standards for sensor communications and OGC APIs for the publication of indicators
- Continue working on the specific elements of the Operational Capacity Guide to provide further support to help disaster and emergency communities to improve their geospatial readiness

9.4. Disaster and Climate Resilience

The frequency and severity of disasters are increasing as climate change causes weather and climate variations to become more extreme. Using climate services to inform indicators such as drought in terms of what future possibilities may be expected is going to be increasingly valuable. The ability to add the future dimension to forecast scenarios to better understand both possible threats and mitigation options will support improved resilience.

To fully exploit the opportunity of using climate services, the data need to be made more accessible and available to the disaster and emergency planners and managers who can use it. Two current approaches that show promise, although there may be others, are publishing data cubes via open standards (OGC APIs) and making ARD available in something approaching a gaming environment. Getting this information to those directly responsible for managing and mitigating natural hazards should help to better mitigate the issues and find practical solutions at the local level.

Future Disaster Pilots will benefit from having more direct integration between indicators and climate variables and services with the intention of bringing together the Disaster & Climate Pilots enabling this.

9.4.1. Recommendations

- Ensure some type of climate services or variables are made available early in the Pilot to participants building indicators and data workflows to promote future climate projections becoming part of the outputs alongside the past/present/real-time perspective. Ideally, future looking indicators should support multiple scenarios, so that a variety of climate scenarios can be assessed.

- Ensure climate services are available via open standards such as OGC APIs.
- Further development of the concept of ARD in terms of climate services. ARD in terms of observations or measurements is well understood, but it is less defined for forecasting and future looking datasets due to the various potential scenarios available. Making climate ARD more easily understandable, accessible, and usable for disaster and emergency planners and managers will be critical in developing datasets and indicators that will offer future benefits.
- Developing climate DRI's will also benefit from more engagement with local and domain experts to help interpret and visualize potential climate impacts, including better engagement with indigenous peoples who, given their traditional knowledge, are often the leading local experts in terms of what local resources are most valuable and potentially vulnerable. This will be particularly important in terms of helping define the business rules of the indicators, i.e., if flooding is getting more severe, by how much does the timing of the evacuation order need to be altered. The challenge will be to ensure that indicators are not developed in such a way that the indicators are so locally tuned to only be valuable in one specific area.

9.5. Standing on the Shoulders of OGC Work

One of the strengths of OGC initiatives is the ability to build on and develop existing work to enhance, develop, or improve the work, whether the development of standards or Innovation Programs. However, it might be possible to develop this further.

Each Disaster Pilot has individually produced excellent work, but there is still a philosophical approach where each Pilot starts again from scratch. While previous documents and engineering reports are used, the specific data flows and tools are often left behind. While it is understandable that new ideas and disaster scenario's are examined, providing continuity and availability of previous work would be valuable as well.

This Pilot aims to deliver persistent demonstrators from each of participants, as described in the Annexes, which is a positive step. This can go further, with a series of catalogs/registries listing developed data flows; supported by relevant documentation. The data flows themselves should be available and maintained for the long term and applications and tools should be available (license and fees dependent).

This is not to say previous work should not be further developed. For example, if catalogs can be improved then the catalogs should be. However, does each Pilot need to start by establishing a catalog?

Similarly, the Disaster Pilots could do more to support the development of standards, particularly in terms of supporting the development of standards such as those relating to ADR and DRI, testing standards with implementations, or establishing disaster-specific training data.

There is an opportunity for the establishment of an OGC based disaster planning and response ecosystem providing disaster and emergency communities with a plethora of ARD/DRI data flows, applications, and tools to support the communities' activities. This would provide multiple benefits, including the following.

- Disaster and emergency communities would have a place to go to see a wide variety of data flows and tools that could support the communities. The tools would have a level of authority, being based on OGC standards.
- Providers looking to enter the ecosystem would have examples to review to understand what is required.
- OGC Standards used in Disaster Pilot activities would have greater visibility.
- Future OGC Disaster Pilots would have a place where the work the Pilots develop can be showcased and offered to disaster and emergency communities for future benefit.

As highlighted earlier, there is a need to make geospatial data and tools more accessible for disaster and emergency communities. The communities may not begin to use the data and tools today, but who knows what the communities will do tomorrow? It is certain that if the tools are not easily accessible, the tools will not be used.

9.5.1. Recommendations

- Establish a long term persistent OGC disaster ecosystem where current, past, and future geospatial data flows and tools to support disaster planning and response can be made easily available and accessible to communities and organizations who might want to operationalize them.
- Explore how persistent demonstrators can provide examples of how to use already available services, including the use of indicator displays and visualizations.
- Involve the OGC Disaster Pilots in a greater manner in supporting the development and implementation of OGC Standards.

A

ANNEX A (NORMATIVE) TOOLS DEVELOPED

A ANNEX A (NORMATIVE) TOOLS DEVELOPED

There are many types of emergency disaster events and the tools described in this Annex can provide support to a range of events. The tools cover the following.

- **Gathering data**

There are two examples of citizen science projects that use apps on smartphones to gather information for disaster planning or responding to an event in progress.

- **Finding datasets**

The number of geospatial datasets available can vary. Some events will have a lot of datasets, while others may be more limited. Emergency Managers need quick and straightforward methods of finding what datasets may be able to help in terms of disaster planning or responding to unfolding events. Below are tools that offer catalogs and registry functions that could help identify available datasets.

- **Visualizing data**

Taking advantage of the developing technology in terms of augmented reality, as shown below, can offer new ways for first responders and emergency managers to look at situations in a different way and can offer new insights.

It should be noted that data generated by a disaster event itself from sensors, observations, etc., exceed the data generated through normal day-to-day business by a degree of magnitude. Sorting through this massive quantity of data, a significant proportion of which will be from new, or less familiar sources, means that data catalogs and registry services are critical for helping to find and access the right data at the right time.

The tools developed by the Disaster Pilot 23 (DP23) participants are a follows.

- Annex A.1.1 Registry & Catalog Functions developed by Compusult
- Annex A.1.2 Climate Data Catalog, Data Service & Registry Tool developed by Safe Software
- Annex A.1.3 Geospatial Data Registry Services developed by USGS-GeoPathways
- Annex A.1.4 Emergency Location & Language Application developed by GISMO-Basil Labs

- Annex A.1.5 FLORA Wildfire Mobile App developed by USGS-GeoPathways
- Annex A.1.6 Wildfire & Drought Immersive Indicator Visualizations developed by USGS-GeoPathways
- Annex A.1.7 GeoCollaborate Tool Visualization developed by StormCenter

The detailed technical information about each of these tools can be seen below:

A.1. Data/Workflow Service Registry and Discovery Tools

A.1.1. Catalog Services Developed by Compusult

A.1.1.1. Introduction

Compusult has enhanced its catalog to support OGC API records and other OGC APIs.

The Compusult Web Enterprise Suite application provides a means to carry out scenarios that include adaptation and planning in wildland fire situations, using the available data and workflows designed by all participants.

A.1.1.2. Description

A.1.1.2.1. Input Data

- Files
    - The area of interest (bbox) and datetime parameter can be used to select only a subset of the records in the collection (the records that are in the bounding box or time interval). The bbox parameter matches all records in the collection that are not associated with a location, as well. The datetime parameter matches all records in the collection that are not associated with a time stamp or interval.
    - The limit parameter may be used to control the subset of the selected records that should be returned in the response, the page size. Each page may include information about the number of selected and returned records (numberMatched and numberReturned), as well as links to support paging (link relation next).
- bbox

    - Only records that have a geometry that intersects the bounding box are selected. The bounding box is provided as four or six numbers, depending on whether the coordinate reference system includes a vertical axis (height or depth):
        - Lower-left corner, coordinate axis 1
        - Lower-left corner, coordinate axis 2
        - Minimum value, coordinate axis 3 (optional)
        - Upper-right corner, coordinate axis 1
        - Upper-right corner, coordinate axis 2
        - Maximum value, coordinate axis 3 (optional)
    - The coordinate reference system of the values is WGS 84 long/lat unless a different coordinate reference system is specified in the parameter bbox-crs.
    - For WGS 84 longitude/latitude, the values were, in most cases, the sequence of minimum longitude, minimum latitude, maximum longitude and maximum latitude.
    - However, in cases where the box spans the antemeridian, the first value (west-most box edge) was larger than the third value (east-most box edge).
    - If the vertical axis was included, the third and the sixth number were the bottom and the top of the 3-dimensional bounding box.
    - If a record had multiple spatial geometry properties, it was the decision of the server whether only a single spatial geometry property was used to determine the extent or all relevant geometries.
- filter
    - Filters features in the collection using the query expression in the parameter value. Filter expressions are written in the Common Query Language (CQL2), which is a candidate OGC standard. The current API implements the draft version from February 2022, which is a release candidate. The language for this query parameter is CQL2 Text (filter-lang=cql2-text).
    - CQL2 text expressions are similar to SQL expressions and also support spatial, temporal, and array predicates. All property references must be queryables of the collection and must be declared in the Queryables sub-resource of the collection.
- filter-crs
    - Specify which of the supported CRSs to use to encode geometric values in a filter expression (parameter 'filter'). Default is WGS84 longitude/latitude.
- filter-lang

- Language of the query expression in the ‘filter’ parameter. Supported are ‘cql2-text’ (default) and ‘cql2-json’, specified in the OGC candidate standard ‘Common Query Language (CQL2)’. ‘cql2-text’ is an SQL-like text encoding for filter expressions that also supports spatial, temporal and array predicates. ‘cql2-json’ is a JSON encoding of that grammar, suitable for use as part of a JSON object that represents a query. The use of ‘cql2-text’ is recommended for filter expressions in the ‘filter’ parameter.

- limit
  - The optional limit parameter limits the number of items that are presented in the response document. Items are only counted that are on the first level of the collection in the response document. Nested objects contained within the explicitly requested items shall not be counted.
- properties
  - The properties that should be included for each feature. The parameter value is a comma-separated list of property names.
- sort by
  - Specifies a comma-separated list of property names by which the response shall be sorted. If the property name is preceded by a plus () sign it indicates an ascending sort for that property. If the property name is preceded by a minus (-) sign it indicates a descending sort for that property. If the property is not preceded by a plus or minus, then the default sort order implied is ascending ().
- Example Query of the CSW Catalog is https://ogc.compusult.com/wes/webservices/wescatalog/record/collections/CSW/items?f=json&lang=en&bbox=49,-144,68,-54&limit=10&offset=0

A.1.1.2.2. Output Data

The response was a JSON document consisting of records in the collection. The records included in the response were determined by the server based on the query parameters of the request. To support access to larger collections without overloading the client, the API supported paged access with links to the next page if more records were selected than the page size.

A.1.1.2.3. Technical Requirements & Standards

The WES Catalog is an OGC-based integrated services registry/catalog and repository. The application provided comprehensive, standards-based catalog creation and management modules, enabling data and service discovery, publishing, access, and maintenance.

WES Catalog was initially implemented using the OGC Catalog Service for the Web (CSW) standard and was recently upgraded to support the new OGC draft specification OGC API —

Records. Backward compatibility has been maintained so that clients that only support CSW are still able to interact with the REST service. The application has a configurable metadata harvest process that will automatically ingest service metadata from remote services, servers, and other applications/catalogs. WES Catalog easily manages metadata about services (e.g., WMS, WFS, WCS, and WPS) OGC APIs (Features, EDR, Processes, Coverages, Tiles, and Maps), and repository items (e.g., XML documents, text documents, images, and sound) contained in the catalog.

- The Web Enterprise Suite client has been enhanced to provide visualization in both 2D and 3D of the following OGC API standards:
  - OGC API Features
  - OGC API Coverages
  - OGC API Processes
  - OGC API EDR
- WES Catalog supports multiple OGC API standards, each of which can be published and discovered via Catalog Services: CS-W and OGC API – Records for discoverable registries of geospatial data:
  - OGC API – Common
  - OGC API – Features — Part 1: Core and Part 2
  - OGC API – Environmental Data Retrieval (EDR)
  - OGC API – Processes
  - OGC API – Coverages
  - OGC API – Records
  - OGC API – Styles
  - OGC API – Maps
  - OGC API – Tiles
  - OGC SensorThings API
- An OGC API Process will allow users to submit services and files to the catalog. The OGC API Records currently supports access to collections:
  - CSW Catalog

A.1.1.3. Benefits

Compusult's catalog, with the support of OGC API records and processes, allowed external users to have access to register, search, and discover products and services.

This improved access and sharing of data and services, provided easy-to-use GUI and REST interfaces to publish, discover, and use data services using standards-based APIs for interoperability.

A.1.1.4. Collaborations

Compusult's catalog was made available to all participants to contribute and share data. Content from other participants was harvested into the catalog and an account provided to others to allow them to query for data.

A.1.2. Climate Data Catalog, Data Service, and Registry Tool Developed by Safe Software

A.1.2.1. Description

Safe Software's Climate Data Catalog, Data Service, and Registry component is implemented using the FME platform to support cataloging, referencing, and access to climate model data and related web services and metadata. The service also makes climate model data cubes available as FAIR Analysis Ready datasets (ARD) for search, access, downstream analysis, and decision support. In addition, the service has the capacity to incorporate base map, earth observation, and a wide range of other datasets. Whatever the type of natural disaster, whether fire, flood, drought, or other hazards, increasingly the severity of natural disasters is exacerbated by the effects of climate change. The challenge to manage and mitigate these effects poses difficulties for spatial and temporal data integration. One challenge is translating the outputs of global climate models into specific impacts at the local level.

The FME spatial data integration and automation platform, produced by Safe Software, can help explore options for bridging this gap given its ability to read datasets produced by climate models such as NetCDF or OGC WCS and then filter, aggregate, interpolate, and transform the data as needed. The platform is configured using no code data transformation models that can bridge the gaps between disparate systems using its support for hundreds of different spatial and nonspatial data formats and services. FME can also inter-relate climate data with higher resolution local data, and then output the data to whatever format or service is most appropriate for a given application domain or user community. This component supports the consumption of climate model output data cubes such as NetCDF or ZARR, transforming the data into a relational spatial database and making the database available by OGC API services.

Safe's data service component has a particular emphasis on incorporating and serving climate model output ARD, which is essential to support disaster management in the changing world. While ARD has traditionally been applied in the context of earth observation data, ARD approaches can be equally applied to the development of data products related to climate scenario time series making the data products easier to consume for a wider range of applications and users.

This data service component also explored approaches to support data search and cataloging. The metadata harvest component allows users to provide a dataset in the form of a url or uploaded file. The service then auto-generates an ISO 19115 spatial metadata which can then be used to support cataloging. Safe Software has also implemented a basic OGC Records API service which provides a metadata catalog of Safe Software's climate ARD services and lists the various items available via our services.

A.1.2.2. Description

A.1.2.2.1. Analysis Ready Data (ARD) Service

The challenge was to take climate model results and use them to feed forecast and impact models related to the hazards of interest such as drought, fire, or flood. This workflow transforms climate services data cubes such as NetCDF to a form of ARD — analysis ready data — more easily consumable by GIS applications, via publication of this via vector themes on OGC API Feature services. The underlying goal related to the wider pilot architecture is to feed the data value chain from raw source data — in this case climate model data cubes, through to ARD in order to feed a variety of DRI or decision and impact indicator workflows.

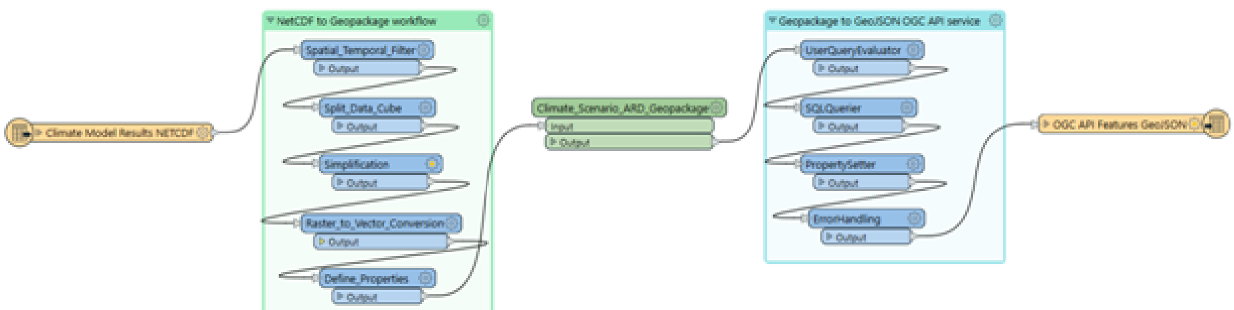

Figure A.1 — High level component FME workflow from climate data cube NetCDF to spatial database geopackage to OGC API Feature service GeoJSON

In terms of processing, this component takes the climate scenario model results from climate data services and transforms this into ARD. Making this data available via commonly accessible open standards is key to making this crucial data more widely accessible and usable by those who are likely to be affected by potential impacts.

In this example, the climate model data cube below was downloaded as NetCDF v4 using NetCDF conventions CF v1.4 with 960 bands representing monthly time steps. This was downloaded from Environment Canada, using the Environment and Climate Change Canada Climate Extraction tool.

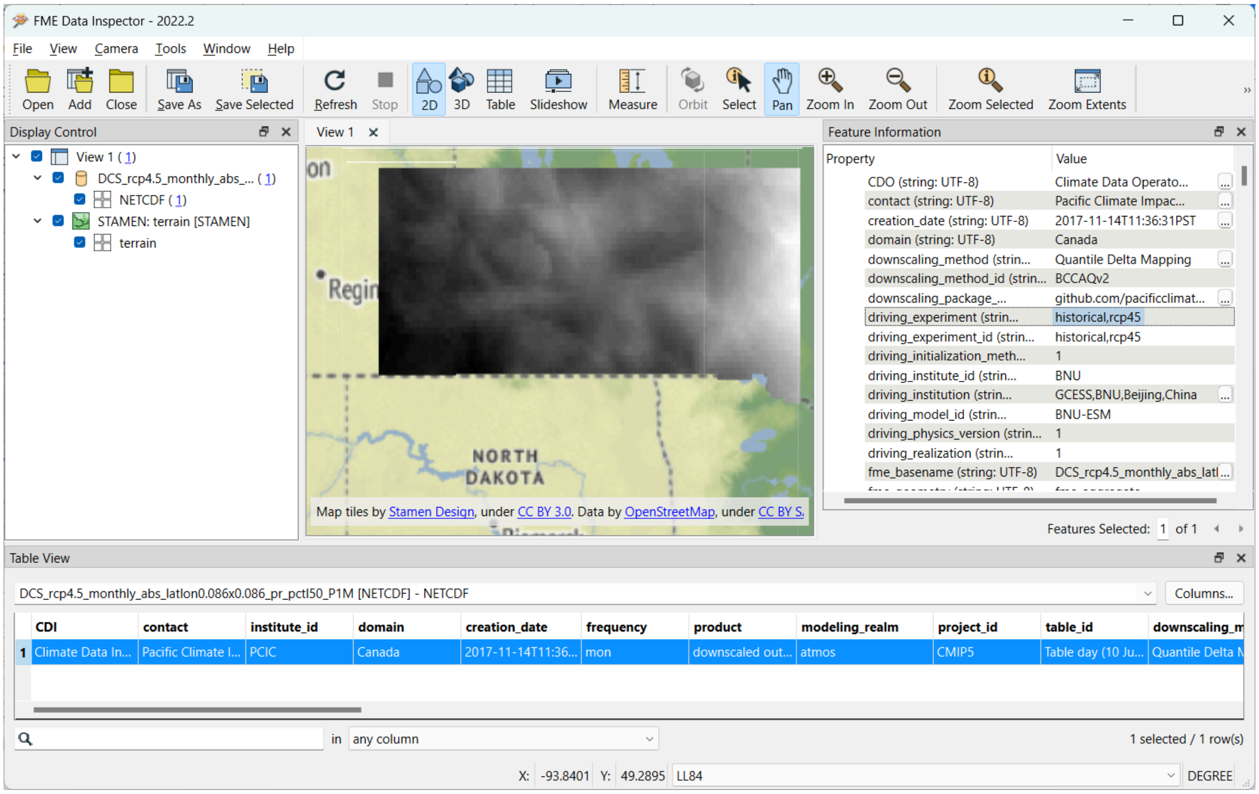

Figure A.2 — Source NetCDF data cube from Environment Canada's climate data extraction tool shown in FME

The data are then converted into a relational form and stored in a spatial database — in this case OGC Geopackage — shown in the FME NetCDF to Geopackage workflow below:

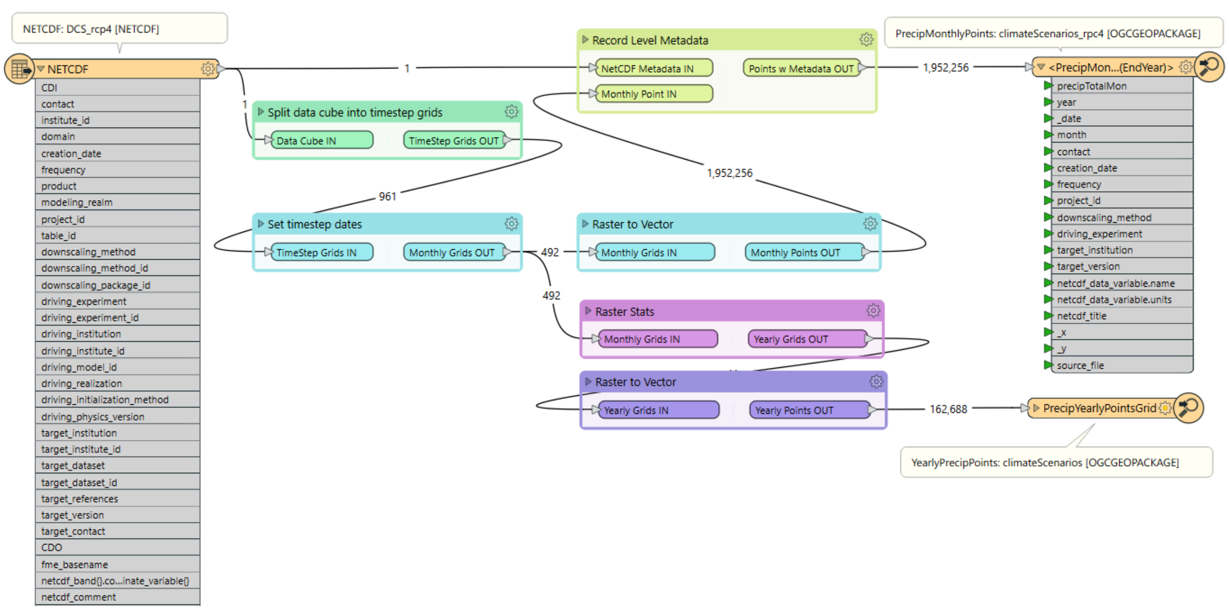

Figure A.3 — Mid level component FME workflow from climate data cube NetCDF to spatial database - Geopackage

Then, a spatial database to GeoSON workflow is used to make the data available by an easily accessible via an OGC API Feature service shown below:

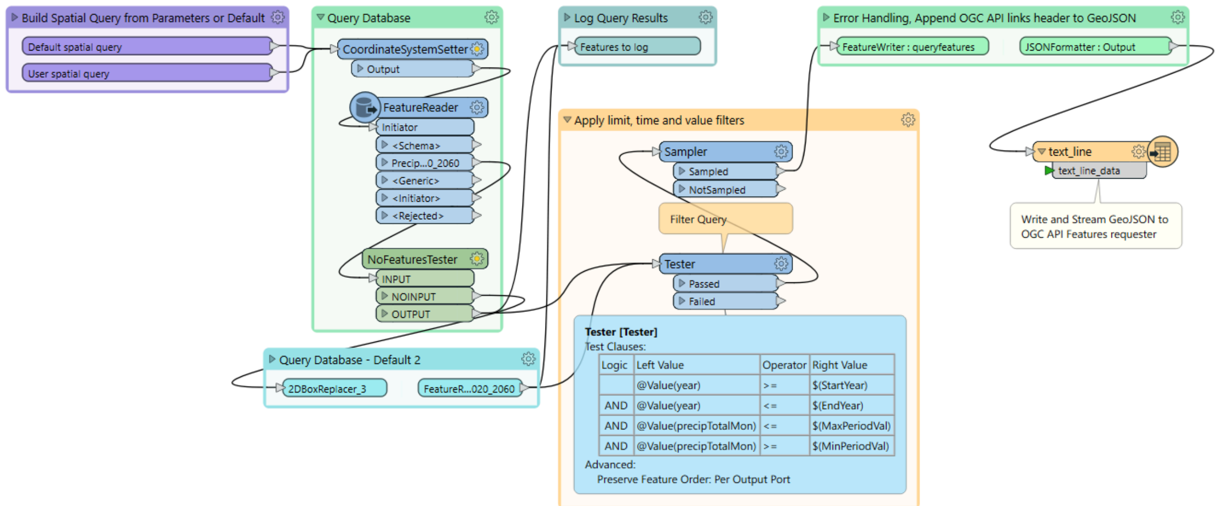

Figure A.4 — Mid level component FME workflow from climate data cube NetCDF to spatial database - Geopackage

Note that the Geopackage to GeoJSON workflow is published to FME Flow / FME Server which in turn is hosted on the FME Hosted environment (FME Cloud) that runs on AWS — Amazon Web Services. This allows a workflow developed on the desktop using FME Form to run as a continuously accessible web service — in this case configured to support the OGC API Features protocol. One key aspect of this is parsing the OGC API feature requests and translating the parameters from them into database queries. This ensures that the feature queries only process the data actually needed to fulfill the request and is key to scaling performance given that the database stores several million records of point data.

For the selected climate scenarios, this supported the analysis of estimated drought risk impacts over time via simple feature queries that could be translated to SQL queries on the underlying spatial database and also fed drought related environmental factors to other DP23 indicator components such as Pixalytics drought model for more refined drought risk analysis. For the purposes of DP23, it was recognized that more complex indicators such as drought risk are likely driven by multiple environmental and physical factors. As such, the initial goal was to select and provide primary climate variable data such as precipitation and temperature that would be useful for deriving drought risks in combination with other inputs. The ARD data flow extracted total precipitation and mean temperature per month and made this available as OGC API features of time series points streamed as GeoJSON. These climate scenario primary drought data were provided for the province of Manitoba study area and was the dataset consumed by the Pixalytics drought model component. For more information on this refer to the Annex B impact and indicator components.

The data service also allows end users to use an OGC API client to access the climate data using queries and retrieve the environmental variables and statistics for their specific geographic extent and time period of interest. The service itself supports a range of query parameters which can allow users to explore various value ranges and extremes inherent in the climate scenario projections. Multiple environmental variables such as temperature, precipitation, and change in precipitation relative to historic values are available on the time series points. Users can then ask questions to look for times and places of concern relative to specific natural hazards such as drought, fire, heat, or flood.

As an example, the following OGC API Features client request can be made to the service: *"Find all time step points over the next 40 years for southern Manitoba where projections indicate > 25% dryer and mean monthly temperature > 23C."* The OGC API Features Query Parameters would be:

- Start Year: 2020
- End Year: 2060
- BBox: -100.0,49.0,-96.0,50.5
- Limit: 2,000,000
- MinPeriodValue: 0 (PrecipDelta)
- MaxPeriodValue: 0.75 (PrecipDelta)
- MinTemp: 23C (Min Mean Monthly Temp)

This would produce the out below, displayed in Safe Software's Data Inspector client using the OGC API Features reader. This result shows climate model points derived from the RCP4.5 business as usual scenario that result from the query above. That is, these points from August 2048 and 2058 represent the hot and dry areas and times that satisfy the query above and could constitute increased drought and fire risk. The ultimate goal is to make climate model outputs more accessible in a form and structure easy to consume by those used to working with GIS tools.

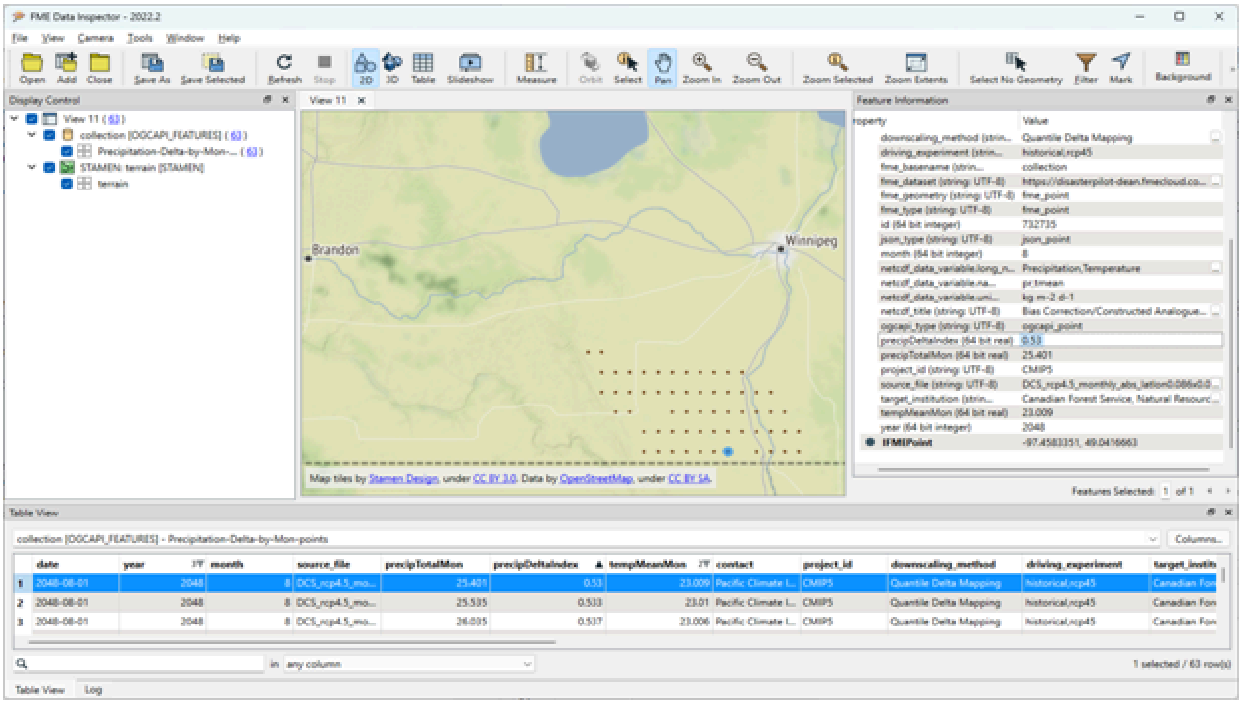

Figure A.5 — OGC API Features response to above query: 63 temporal points with associated temperature and precipitation values, as shown in FME Data Inspector client.

A.1.2.2.2. Metadata Harvest Service

The Metadata harvest service allows users to provide datasets or data service links which it then reads and automatically extracts key properties and information metadata. This metadata can be supplied to data catalogs to enable the metadata to be discovered by users searching for data. In particular, the Metadata Harvest workflow reads the source data and dynamically extracts properties such as table and field names, extents, ids, and time stamps and then fills out an ISO 19115 template with those values.

The metadata harvest process has the following steps:

- Read feature type name
- Capture cumulative extents for all feature type records
- Extract all feature type attribute names
- Generate time stamp and unique id
- Write properties to ISO 19115 metadata template

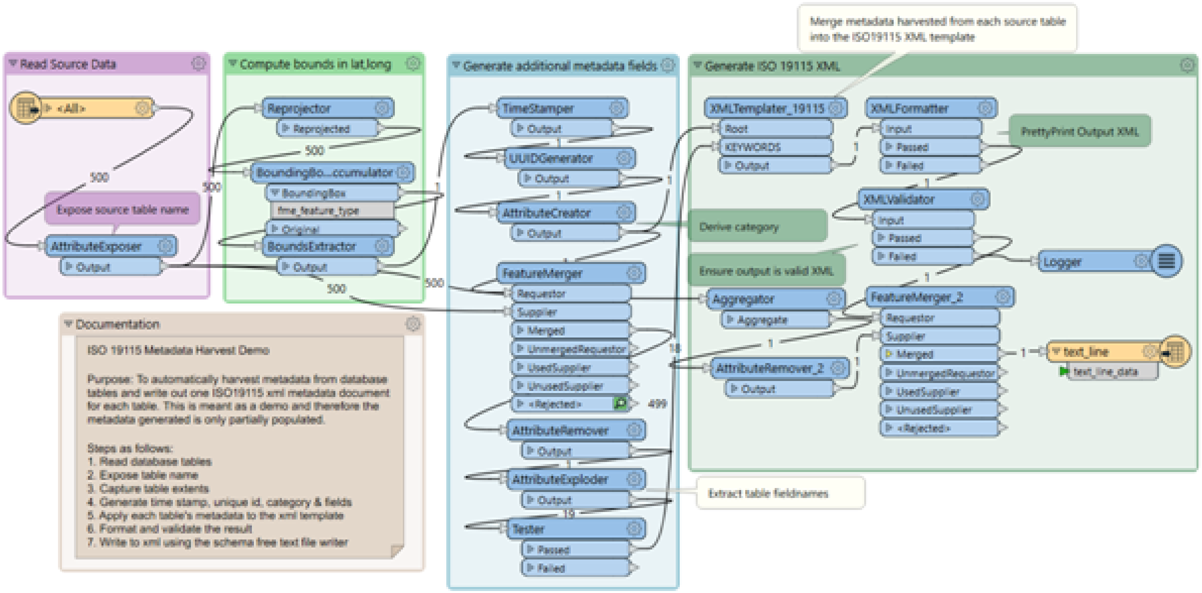

Figure A.6 — Metadata harvest FME workflow

This workflow is a standalone service. In the future it would be good to integrate this workflow with the OGC API services currently available. For example, when publishing new datasets to an OGC API Features service and registering the datasets with an OGC API Records service, this metadata harvest service could be used to auto-generate a description which could include the feature types and properties contained in the dataset.

This metadata harvest service could also be enhanced to add support for coordinate systems, auto-detect date fields to extract temporal range, and perhaps detect other data types, ranges, and statistical information.

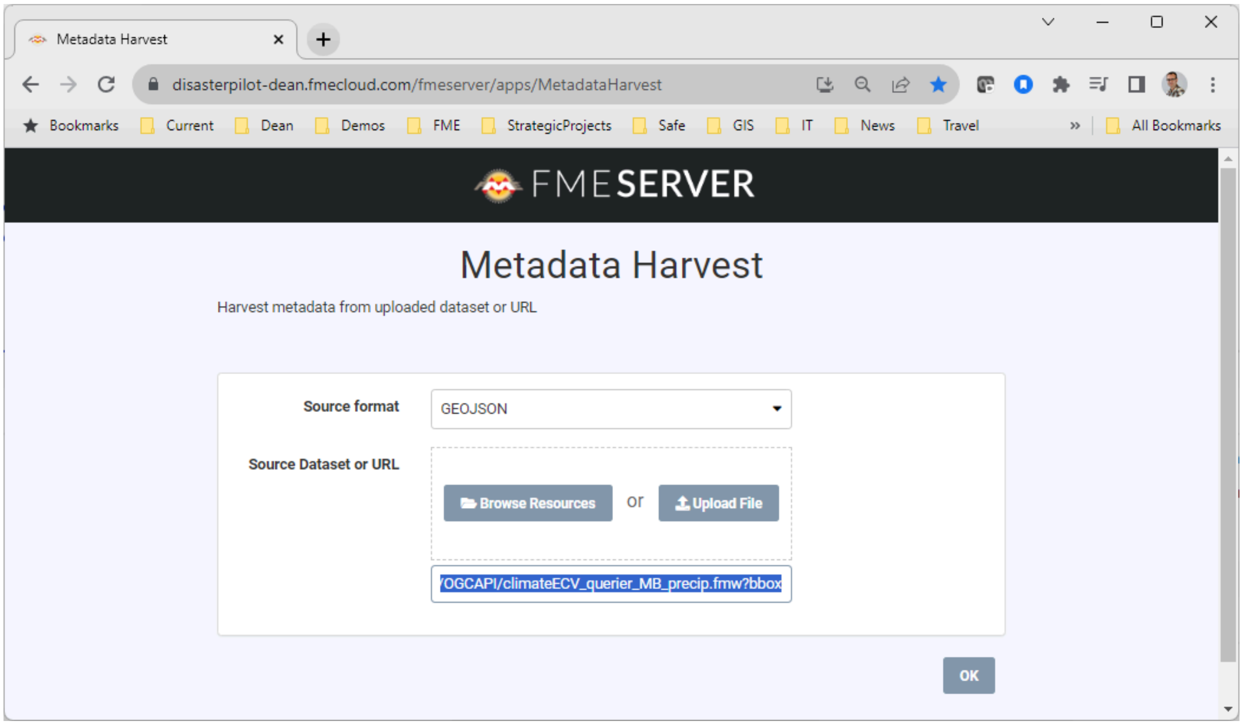

Figure A.7 — User form for specifying dataset service link or dataset upload to harvest metadata from. This can also be invoked via an API call.

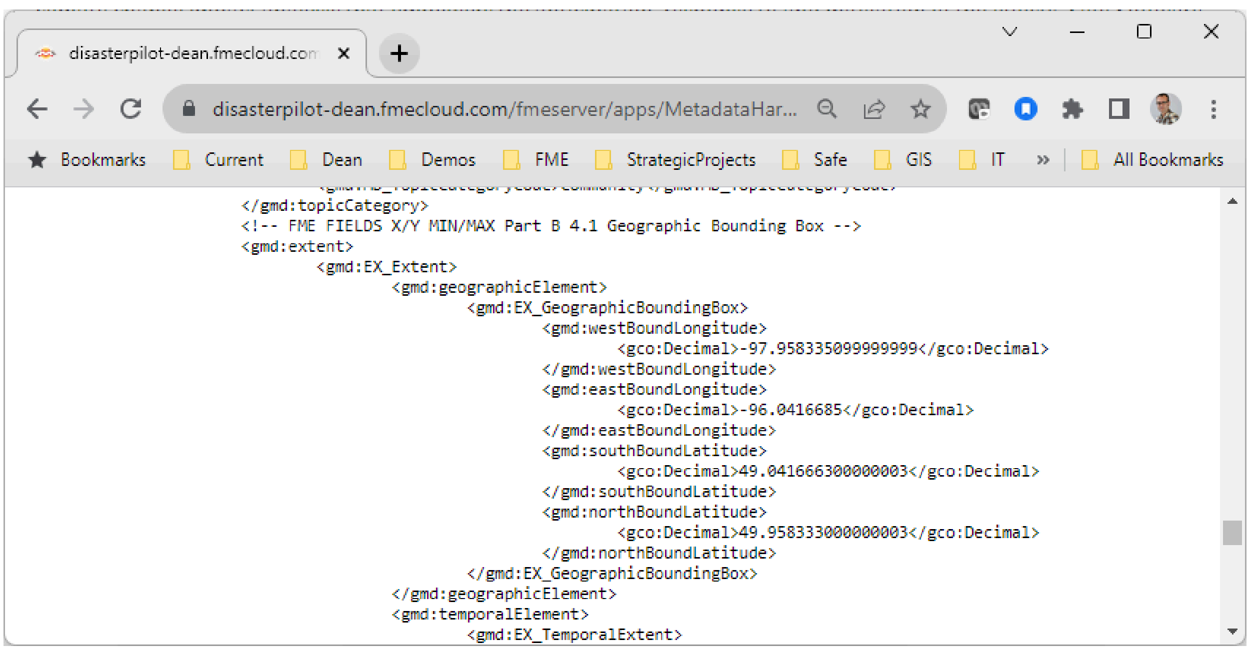

Figure A.8 — Metadata result harvested from user specified data service showing the data extents.

A.1.2.2.3. OGC API Records Service

Safe Software implemented a basic, experimental OGC API Records service which provided metadata on the climate data services and datasets delivered by the ARD component described above. The service was a basic implementation in that it simply provided the standard landing page, collection, conformance, and item information depending on the REST request made by the Records client allowing other components in DP23 to interrogate the catalog service and use the resulting metadata to assess and query other feature data services.

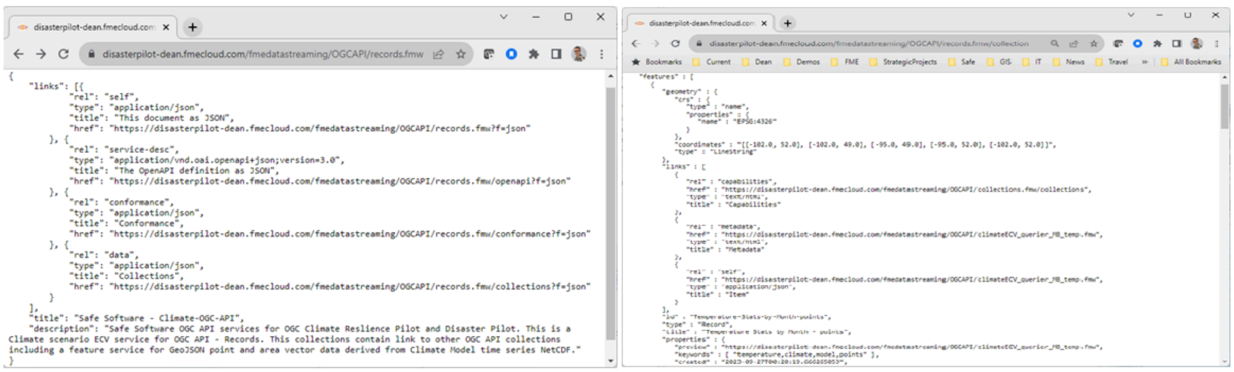

Figure A.9 — Safe's OGC API Records Service: landing page on the left, and item collection page on the right

Safe's OGC API Records Service is a read-only catalog service that serves to publish metadata on the datasets and services Safe Software has contributed to DP23. It should also be emphasized that this is an experimental limited implementation of the OGC API Records standard that only implements a selected subset of the methods described in the standard sufficient to offer the basic catalog and collection information mentioned above.

As limited as this implementation was, it did illustrate the way in an FME workflow can be designed to implement message handling in order to support a REST API such as this one based on OGC API Records. A typical FME workflow or transformation pipeline is designed to translate from one dataset type to another, such as CAD to GIS. This implementation showed that FME workflows can also be designed to handle message pipelines such as those associated with an OGC API. Instead of a source dataset, the input was simply a client request message. The data transformation workflow became a message handling workflow, which ultimately produced a response message instead of a response dataset. When run on FME Form on the desktop this simply reads one input URL or JSON message and outputs another, writing to an output text file. When published to FME Form (Server) this results in a service that continually monitors an endpoint, accepts GET or POST messages, and produces the appropriate JSON responses via a data streaming service.

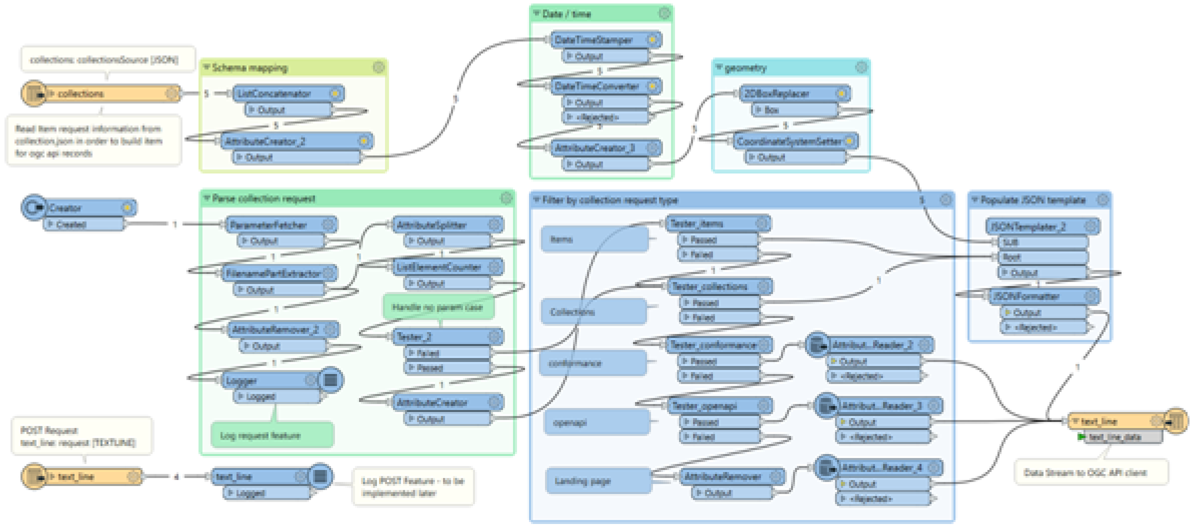

Figure A.10 — FME message handling workflow published to FME Flow

In the case of the OGC API Features workflow, a get capabilities or collection request produced the collection JSON response listing the available layers that include embedded get feature request URLs. When the API client selected a specific dataset and layer, a get feature request associated with that called a specific FME workflow which was configured to query the requested data based on the user request parameters. This Geopackage to GeoJSON FME workflow then streamed GeoJSON features back to the client. So it was possible to have a message driven FME workflow published to FME Flow (FME Server), which ultimately streamed features back to the client based on the parameters of the initial request message. The ultimate goal was to make climate model outputs more easily accessible in a form and structure easy to consume by those used to working with GIS tools.

Also, by using OGC API interfaces, the data services were provided with sufficient parameterization such that end users could compose queries in order to retrieve the environmental variables and statistics for the specific spatial and temporal ranges of interest. In this way a query against potentially gigabytes of time series data may generate a query response of a few kilobytes of environmental variable point data that satisfies the composite query.

For example, consider the query looking for all time step points where mean monthly temp > 23.5C and precipitation has dropped > 25%. The initial implementation would require posing 2 queries: 1) mean monthly temperature is > 23C and 2) precipitation dropped more than 25%. Each of these queries might yield tens of thousands of points or more, and combining them would require joining the results of both queries together by location and time, which can be very process intensive. By appending these environmental variables by time step point, a composite query can filter on both value ranges at the same time and produce only a few hundred points as the result with no client side joins required. The principle here is to let the database do the work which keeps the client side traffic much lighter.

A.1.2.3. Benefits

The data services developed by Safe Software for DP23 provide a range of crucial capabilities to disaster responders, managers, planners, and analysts. The ARD data service allows planners and analysts to combine historical and current natural hazard risk assessments with models of future risk in order to better evaluate the resilience of their infrastructure and mitigation strategies. Composite query capabilities allow users to interrogate a combination of environmental variables for different value ranges and changes relative to past norms using OGC APIs meaning that analysts can experiment with different business rules and tolerances to explore trends in the data that may correspond to increased natural hazard risks over time, whether for heat waves, drought, flood, or fire.

Specifically, this ARD data pipeline is able to consume climate model outputs and use the outputs to feed forecast and impact models related to the hazards of interest such as drought, fire, or flood. The workflow transforms climate services data cubes such as NetCDF or ZARR to a form of ARD — analysis ready data — more easily consumable by GIS applications, via publication of this via vector themes on OGC API Feature services. The underlying goal is to feed the data value chain from raw source data — in this case climate model data cubes — through to ARD in order to feed DRI or decision and impact indicator workflows.

Because of the automated nature of the underlying FME workflows, it was also relatively easy to process different climate scenario inputs from data cube to geopackage, to support a range of scenario analyses downstream. The ability to evaluate a range of climate scenarios from low to mid to high emissions is crucial to testing the resilience of communities. Ultimately the goal of incorporating climate model outputs in disaster management planning is not so much to predict the specific level and type of natural hazards at a particular place and time, but rather to better understand the range and probabilities of hazard risks that can be expected, and what overall trends are likely.

Disaster planners can use the ARD service associated with a climate model future projections service to query for temperature and precipitation anomalies in order to give the planners a better understanding of environmental extremes that might be expected in the future. One key capability is to allow users to directly interact with and interrogate climate projection data, so that the users can see what type of environmental variable value ranges might be expected in the future and what trends to be aware of.

Note that the FME Data Inspector tool shown above also supports consumption of more than 500 spatial and non spatial data formats and services including more than 30 OGC standards, other open standards such as Open Street Map, as well as vendor proprietary standards. This includes a wide range of data types from metadata catalogs (CSW, STAC, OGC APIs) to tabular or databases and CAD / GIS to satellite imagery and 3D point clouds. This can help disaster analysts rapidly review any available data in a rapid response situation and quickly determine which datasets are most useful to support assessment and response efforts.

The metadata harvest service was useful to support auto-generation of metadata records which in turn can streamline the process for publishing and updating dataset metadata to data catalog services. One of the biggest challenges with any disaster response effort is which sources provide the most relevant data for the appropriate temporal and spatial context. Accurate and up to date metadata makes this search process a lot easier.

Finally, the OGC API Records service provided metadata on the climate data services and datasets delivered by the ARD component allowing users to interrogate the catalog service and use the resulting metadata to assess and query other feature data services.

A.1.2.4. Collaborations

Safe Software's climate scenario drought impact component generated output as an OGC API Features service, delivering GeoJSON point features with associated climate properties. This enabled any other DP23 participant to consume this climate time series data for use in DRI components. In particular, properties include monthly mean temperature, total precipitation, and change in precipitation compared to the historical baseline (mean precipitation from 1950 to 1980 for that same location). This allows any end user to submit queries to the climate drought variable service. These data can then be used to drive downstream drought analysis or as a rough estimate of general drought risk. For example, Pixalytics was able to query for precipitation estimates for specific locations and feed that into near future drought model runs. In this way, Pixalytics wa able to compile a continuous summary of observed and projected drought severity for specific locations in Manitoba from approximately 2020 to 2024.

Further information on Safe Software's contributions to OGC Disaster & Climate Pilots can be found at https://community.safe.com/s/article/OGC-Disaster-and-Climate-Resilience-Pilots

Safe Software's persistent demonstrators for the services can be found at:

- OGC API Features Service (accessible 9am — 5pm EDT, M-F)
- OGC API Records Service (accessible 9am — 5pm EDT, M-F)

A.1.3. Geospatial Data Registry Services Developed by USGS/ GeoPathways

A.1.3.1. Introduction

USGS/GeoPathways created a catalog, workspace, and workflow to index datasets, information, and apps. This supports researchers, citizen scientists, and policy makers in developing workflows for decision-ready disaster resilience indicators.

A.1.3.2. Description

There are a series of registries and one catalog in this community of resources. These are as follows.

- **Terria Disaster Risk Resilience Registry (Open Source)** — This uses the web-based TerriaJS application to provide 3D visualizations of disaster-related datasets, for fire, drought, and more, with terrain elevation context.
- **ArcGIS Disaster Risk Resilience Registry (Proprietary)** — This Esri ArcGIS Hubsite includes apps, data catalogs, and external resource links on disaster risk and resilience. This includes:
  - *Knowledge Hub* — This is a digital repository within ArcGIS Experience Builder containing explanations, multimedia, and key disaster information. Accessible via the 2023 GeoPathways Disaster Risk Resilience Hub, it features an ArcGIS 123 Survey for collecting and defining wildfire terms, apps, tools, and data. As the project grows, the aim is to expand the repository, allowing external contributions.
  - *Extended Reality Immersive Spatial Market Catalog* — A web-based ArcGIS Dashboard showcasing key metrics on the world's best virtual reality and augmented reality headsets and can be used by anyone interested in metaverse technology to determine which extended reality (XR) headset will work best, including country, price, and company. Metrics can be sorted by various data types.

- **https://ogc-dp23.voyagersearch.com/navigo/search?disp=D187992491DF&view=card&filter=true&basemap=ESRI%20Street%20Map&q=&sort=score%20desc [Voyager Search Disaster Risk Resilience Registry] (Hybrid)**

This web-based application by Voyager Search provides an indexed registry of disaster-related datasets. It facilitates the visualization of data across various map viewer software and enables the integration of AI/ML workflow models with indexed data. Voyager's advanced indexing encompasses millions of datasets from commercial, organizational, and government data. Voyager's software includes a powerful search function, exposing API data without complicated API requests. Voyager doesn't store data but reveals endpoints and uses metadata for optimal searchability and data accessibility. Voyagers efficient API connector framework processes entire government and organizational data APIs in minutes for quick data extraction, enrichment, transformation, and deliverability.

+ As part of the partnership with Voyager Search, work was undertaken on indexing and testing Esri's Living Atlas and USGS models with workflows that detect, extract, and assess ARD. Workflows were critical to automate repeated tasks that would increase overall efficiency as well as reduce the risk of data errors. Moreover, models operating on indexed data generate fresh data that are automatically integrated into the registry, thereby expanding the volume of data accessible to users.

A.1.3.3. Benefits

Users will receive updates on tech capabilities, response strategies, breaking news, and relief resources. The dashboard dynamically updates metrics based on selected queries or locations. It links each data record to a geographical location, enhancing analysis of XR hardware and allowing DP23 participants to share workflow information.

A.1.3.4. Collaborations

To develop these resources USGS/GeoPathways worked with USGS, US Forest Service, Federal Geographic Data Committee, NASA, ESRI, AmeriGEOSS, NOAA, GeoPathways Peru, Google, USDA, Microsoft, and Voyager Search.

Further information and demonstrations of this work can be found at:

- Terria Disaster Risk Resilience Registry
- ArcGIS Disaster Risk Resilience Registry
  - *Knowledge Hub* .
  - *Extended Reality Immersive Spatial Market Catalog*
- Voyager Search Disaster Risk Resilience Registry

A.1.4. Emergency Location and Language Application developed by GISMO-Basil Labs

A.1.4.1. Introduction

The Emergency Location and Language Application (Ella) is a mobile crowdsourcing survey and reporting application that aims to give a client the opportunity to design a survey script to collect information direct from individual citizens via a smartphone. The goal is that Ella would supplement the 9-1-1 system when it was overwhelmed and important information was being missed.

A.1.4.2. Description

Ella was designed to capture information and use it for a variety of outputs that could be quickly reviewed by the response community and made available to responders in the field. Ella can also provide up-to-the-minute status reports of conditions within the disaster zone, and — unlike the way 9-1-1 is utilized — could be modified and redeployed whenever there were changes in the nature of the disaster.

Data are inputted via users filling out surveys that administrators create. Administrators have options to add text, voice, dot placement on map, and geolocation questions. Voice questions are transcribed and translated into English, and all responses are viewable in charts and maps on the platform in the “Summary” section. If the administrator wishes, topic word bins can be created to classify text and voice responses into specific categories. Administrators can export data in CSV format as well as generate API keys to access data via REST API. Regarding geolocation, administrators can select one of two options: collecting the general geolocation via IP address of the respondent's device, or precise geolocation via mobile phone geolocation access.

Operational capabilities that can be designed into Ella to be captured through a smartphone include the following.

- Rapid survey design using application template: Ella can be designed so that non-programmers can rapidly modify a survey, or quickly create wholly new surveys through the use of simple pull down menus. The surveys can offer:
  - Multiple choice questions;
  - Location Capture by GPS via satellite and/or cell tower triangulation;
  - Photo and/or video capture to highlight input (can be multiples); and
  - Voice Capture — transcribe voice notes into written text in language spoken, and translation services into a common language.
- Analytics and the use of artificial intelligence tools to identify key words and common themes, and levels of urgency if utilized when 9-1-1 systems are overloaded or unavailable.
- Ability to re-issue surveys as the situation on the ground changes, or when a data refresh is required.
- Collect information and intelligence from people within a disaster zone or other area of interest.
- Support communications between first responders in the field, disaster response managers, and people caught within a disaster zone: Ella can allow response managers to transmit guidance to all those within a disaster area, or to specialized groups such as those evacuating using vehicles or those identified to be in immediate threat.
- Support communications between different teams of responders dispatched to the same or adjoining areas for improved coordination.

A.1.4.2.1. Manitoba Ella (M-Ella)

A specific version of Ella tool was developed for the Manitoba Case Study for DP23.

At the request of the Manitoba team, Ella was aimed at capturing information about businesses that were affected by drought, with a specific interest in understanding the effects of drought on business revenue and employment. The Manitoba Drought Survey aimed to capture key information about the effects of drought on Manitoba businesses by structured questions, photos, voiced responses, and generalized location. Team Manitoba hopes to use this information to document both quantitatively and qualitatively the effects of drought on local businesses and employment to better inform the government about local needs and to design improved support services. It is hoped that the M-Ella application will also be adapted to a wide variety of survey and information exchange needs, each with its own benefits profile.

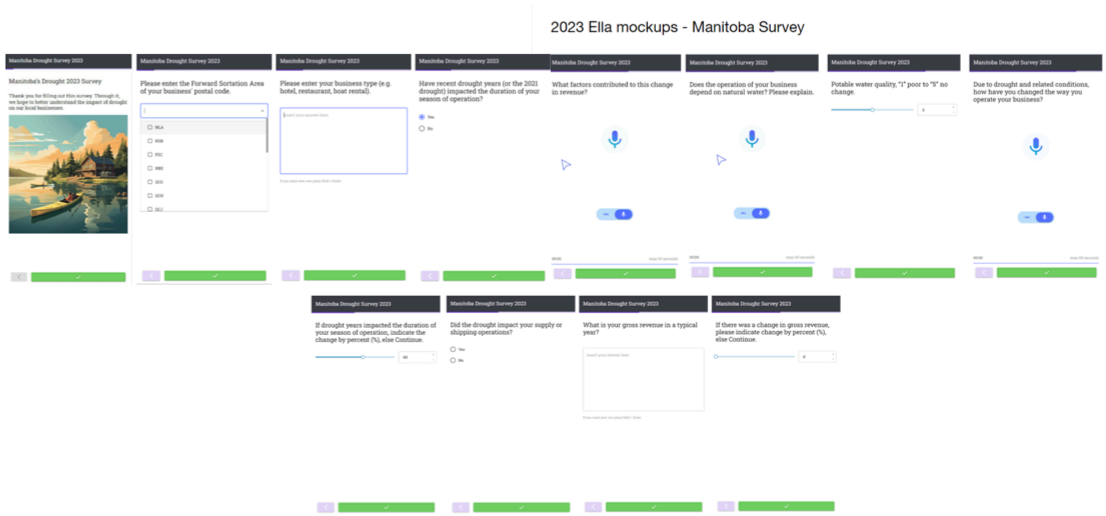

Figure A.11 — Example mock-ups of the Manitoba-Ella survey

The draft M-Ella Drought survey can be examined in detail here.

- At the request of Manitoba, for privacy, respondents were requested to choose their location by one of a list of Forward Sortation Areas instead of using the GPS capabilities of the smartphone.
- Photo(s) were requested of natural areas that were important to the business being surveyed.
- Voice responses were requested relating to:
  - factors contributing to changes in revenue noted in previous structured questions;
  - explanation of the importance of natural water to business; and
  - description of business changes due to drought.
- Use of voice translation and AI: Voice responses would be translated into English and converted into text. The responses would then be analyzed by AI for common words and themes which could then be grouped by business type, postal location, and other factors.

A.1.4.3. Technical standards and infrastructure

The platform survey responses are accessible via REST API for individuals who wish to view and explore the data in other platforms. For individuals who are not interested in external viewing, all data are viewable in the “Summary” tab of the platform, allowing individuals to quickly explore responses in real-time without external software.

To access the survey creation page (administrators) as well as the surveys themselves (respondents), internet access is required. Surveys are mobile responsive and can be accessed via desktop or mobile. All user information and data are housed in Firebase (the exception being the pilot in Canada, in which the data are housed on a server instance that is geographically located in Canada).

There are some constraints and considerations for use of the Ella tool.

- Persistent Communications: For Ella to be effective in collecting data, it requires wireless communications which can be a challenge in a disaster situation as telecommunication infrastructures can be limited or destroyed.
- Smartphone Battery Life: Similarly, if disaster areas do not have access to electric power due to the disruption, there could be limitations to using the phones without recharge facilities.
- Standardized Smartphone Capabilities: It would be important to make sure that all smartphones adhere to standards which would ensure that the data collected would be compatible and easily integrated for analysis.

A.1.4.4. Benefits

The Ella application was designed to be user friendly and easily modifiable by non-technical personnel. Individuals who are comfortable using smartphones for conversations, texting, and photographing should have no difficulty becoming comfortable with the application. Ella applications should be easy to use by citizens caught within a disaster area, responder teams within a disaster area, by disaster managers at operations centers, or from vehicles. User friendly dashboards and analytics can be designed for use both by citizens and by responders, while more technical personnel can be provided with more sophisticated outputs.

There are many ways of using an Ella-type applications to track individuals and groups of citizens threatened by a disaster event and leverage response teams and resources to protect them, whether the individuals or groups remain at home, traveled to a safe place, or are still on the road. Information can be regularly re-calibrated if there is a significant shift in fire direction and speed of spread. Other newly arising conditions impacting safety can also be included.

All individuals within the disaster zone, responding to the disaster, or managing the disaster, can make use of the information and communications enabled by an Ella-type application. Conducting pre-event exercises will be essential to ensure that Ella can be used with maximum effectiveness. Separate Ella groups can be formed among specialized teams of responders including medical personnel, fire fighters, and those responsible for coordinating evacuation.

A.1.4.5. Collaborations

The GISMO/Basil Ella Team was in touch with a number of other DP23 participants including:

- *USGS GeoPathways Team* to discuss the citizen science solutions they were both developing within DP23;
- *HSR.health Team* to explore the potential of using Ella to support measuring population vulnerabilities to fire and smoke conditions; and
- *StormCenter's GeoCollaborate* although not a participant in DP23, discussions continued with StormCenter as StormCenter offers tools useful for the sorting, combining, analysis, and distribution of data and data products across the entire response community including citizens caught within the disaster area.

Information about Basil Labs can be obtained from their website. NYC GISMO can be contacted by emailing Alan Leidner at leidnera@nyc.rr.com.

A.1.5. Wildfire Mobile App Developed by USGS/GeoPathways

A.1.5.1. Introduction

Combining in-situ data and EO through citizen science, this mobile app collects field data, refining EO validation for wildfire-prone areas. This enhances decision-making using machine learning for wildfire mitigation.

A.1.5.2. Description

The **FLORA Wildfire Mobile App** integrates crowdsourced and EO data to understand wildfire vulnerability. The cross-platform application invites users, like hikers and homeowners, to provide on-the-ground imagery of vegetation.

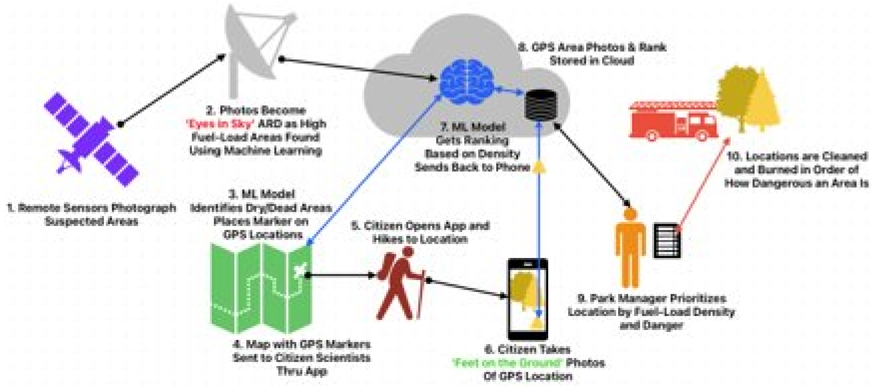

Figure A.12 — Example of how the FLORA Wildfire mobile app operates

Processing the input imagery data, the app identifies potential wildfire fuel based on the 0-5 scale provided by the National Fire Danger Rating System.

- Users send imagery through Esri's ArcGIS QuickCapture for further processing in Amazon Web Services, where the partner's APIs, i.e., Pl@ntNet, PlantID, and Trefle.io, are all used to calculate the fire rating.
- Once the vegetation is processed, the tree imagery is pipelined to community-supported OpenStreetMaps (OSM) as tree nodes insides changesets to better visualize the real world.

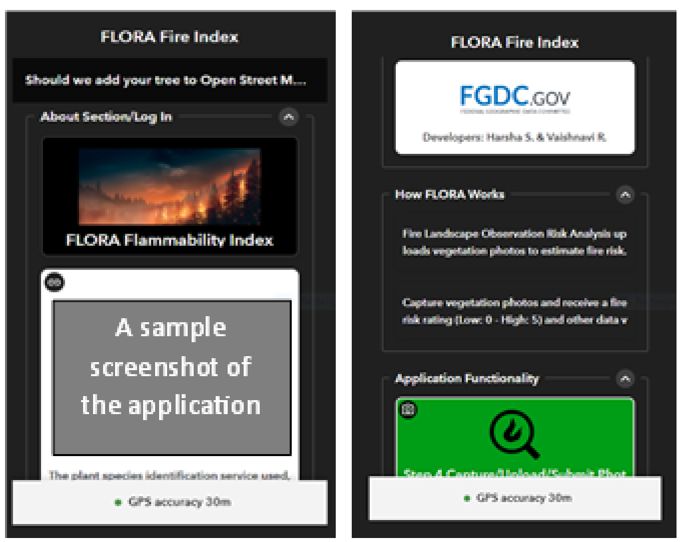

Figure A.13 — Sample screenshots of the front end of the FLORA Wildfire mobile app

- AmeriGEO Mapathon

Set for late 2023, this event will be hosted virtually and invites community data input, augmenting wildfire risk data. Users will use OpenStreetMap US Task Manager for the mapping projects and will navigate to machine-identified areas, capturing photos assessing fire risk.

These photos will be processed through a cloud-based machine learning model which evaluates ignition risks.

For accuracy, the app uses the NASA MODIS sensor and ArcGIS geolocation, designating areas for citizen documentation.

A.1.5.3. Benefits

This approach refines decision models by merging satellite and ground data. Validated data assist professionals in targeted wildfire mitigation during droughts, guiding actions, and safe zone identification.

A.1.5.4. Collaborations

To develop these resources USGS/GeoPathways worked with US Forest Service, Federal Geographic Data Committee, NASA, ESRI, AmeriGEOSS, NOAA, GeoPathways Peru, Google, USDA, Microsoft, Voyager Search, Pl@ntNet, PlantID, and Trefle.io.

The links to the app and event described here are:

- FLORA Wildfire Mobile App
- AmeriGEO Mapathon

A.1.6. Wildland Fire and Drought Immersive Indicator Visualizations Developed by USGS/GeoPathways

Work on this component is at an early stage and this section outlines what is planned to be delivered.

A.1.6.1. Description

This deliverable offers ARD and DRI to enhance comprehension of drought and wildfire management across varied spatial-temporal scales. It has the two following elements.

- Disaster Augmented Reality Simulation Table (DARSIM) — DARSIM modernizes traditional simulation tables, replacing bulky sand models with a portable, data-integrated solution, designed in response to wildland firefighter needs.

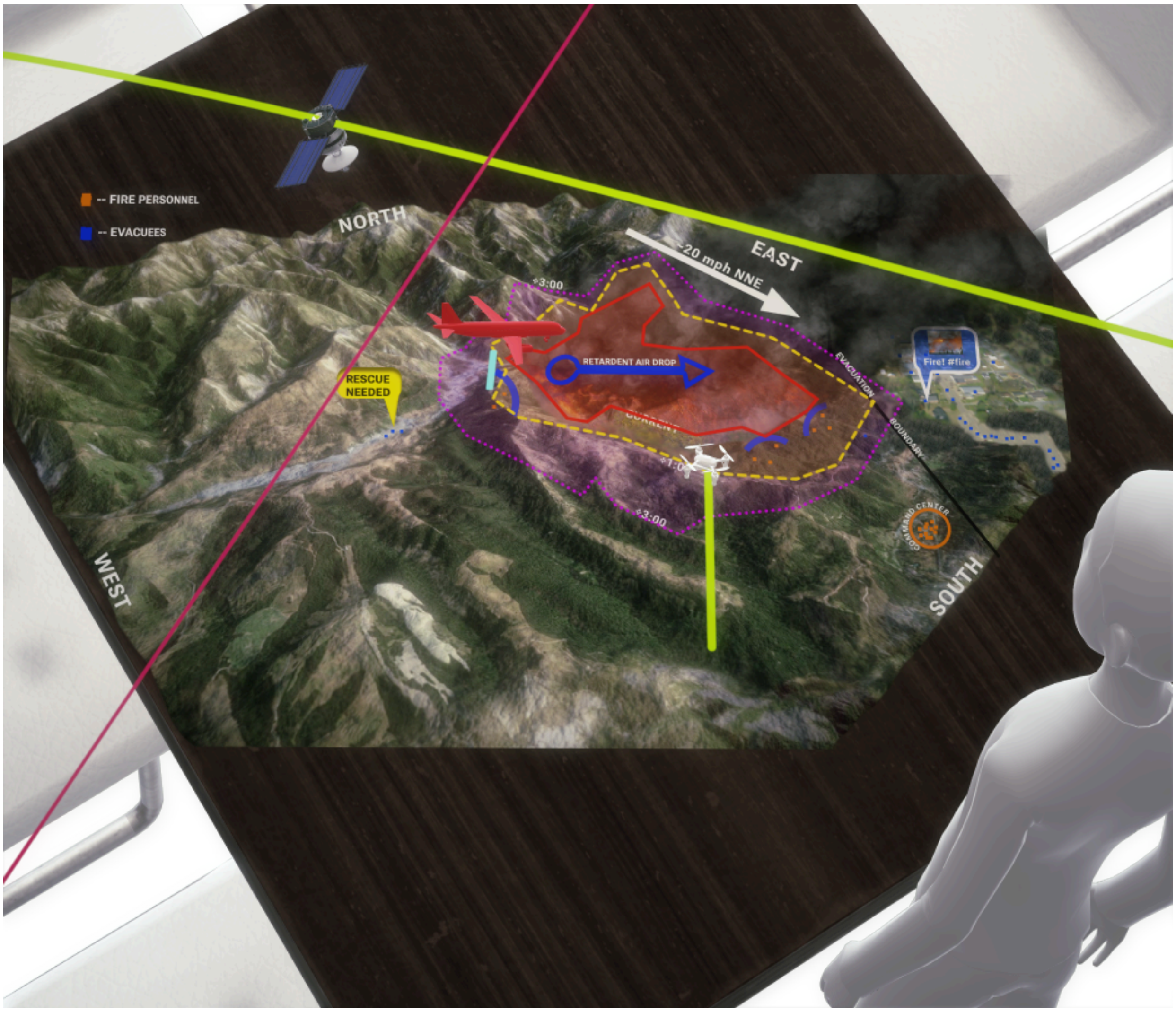

Figure A.14 — Example of the DARSIM output

- Single Pane of Glass (SPoG) — Provides a unified view of multiple data sources, promoting synchronized decision-making using DRIs and ARD. SPoG utilizes XR visualization, data from the geospatial data registry services, and other components. Together with DARSIM, SPoG streamlines the dispatch of crucial ARD and decisions, leveraging both cloud and local networks.

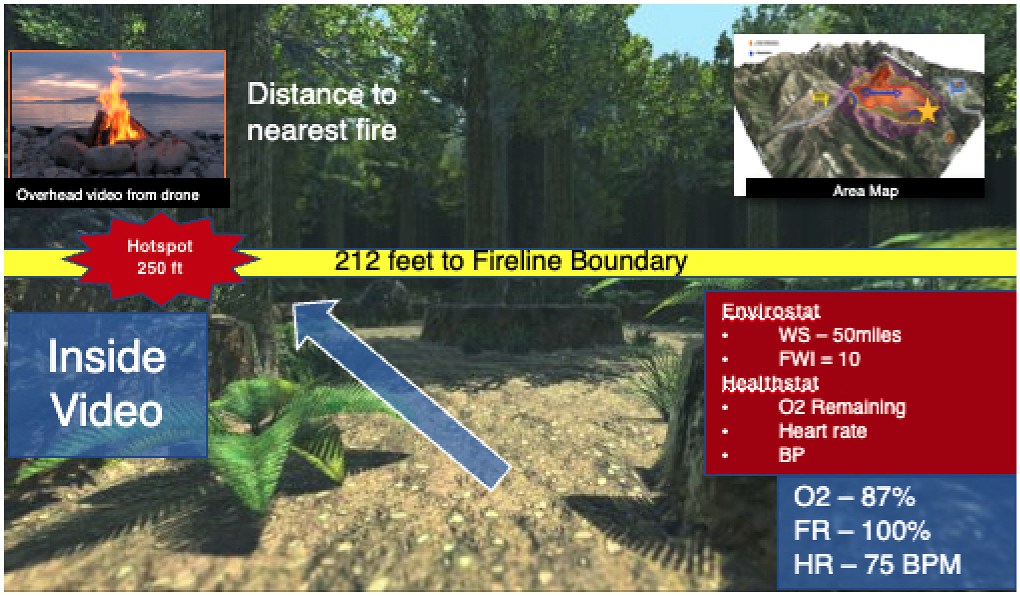

Figure A.15 — Example of the Single Pane of Glass view

A.1.6.2. Benefits

An indicator framework enhances the efficiency of disaster planning and response products/ services. Collaborating with the other DP23 Participants, the aim will be to create immersive wildfire and drought visualizations that sync with their workflows. Two main deliverables are as follows.

- DARSIM (Virtual Sand Table/SIM Table):
  - represents a digital twin of wildland and wildland-urban interface (WUI) areas for data and workflow layering;
  - facilitates on-the-spot deployment and integration of ARD & DRI, speeding up decision-making and meeting information needs;
  - requires just a flat surface and an AR-compatible device for visualizing a 3D/4D metaverse environment, offering a collective view for practitioners; and
  - targets stakeholders like park managers, forest service, and fire commanders and is versatile across AR, VR, mobile, and desktop platforms, providing varying immersion and flexibility degrees.
- SPoG:
  - customizable for practitioners in diverse settings, from ground units to command centers;
  - aids firefighters by displaying crucial geospatial information like fire perimeters, weather, personnel locations, and fire hotspots; and

- incorporates a mix of open-source, commercial, and interactive apps, and is available through AR, VR, and desktop platforms.

A.1.6.3. Collaborations

To develop these resources USGS/GeoPathways worked with USGS, US Forest Service, Federal Geographic Data Committee, NASA, ESRI, AmeriGEOSS, NOAA, GeoPathways Peru, Google, USDA, Microsoft, and Voyager Search.

A.1.7. GeoCollaborate Tool Visualization developed by StormCenter

A.1.7.1. Introduction

GeoCollaborate is a tool to help both the visualizing and disseminating of geospatial data. GeoCollaborate was demonstrated and developed during Disaster Pilot 21.

A.1.7.2. Description

The concept of GeoCollaborate is that there is a lead author of a geospatial map, and other people can follow the map of the leader in real-time, offering an opportunity to provide everyone following the leader to be looking at precisely the same up-to-date information within minutes of a disaster impacting an area.

Figure A.16 shows an example of how visualization and dissemination can occur. The screenshot shows the leader's screen on the left and the followers' screen on the right. A flooded area is overlaid with a geospatial service provided by the NASA SEDAC (Socioeconomic Data Applications Center) at Columbia University, giving details of the demographic breakdown of the people in that area that can support both responders and decision-makers. The leader controls the screen, and everyone else follows, so all of the people involved are getting the same information simultaneously. As this approach only requires an internet-connected device, the lead can operate the solution with minimal bandwidth.

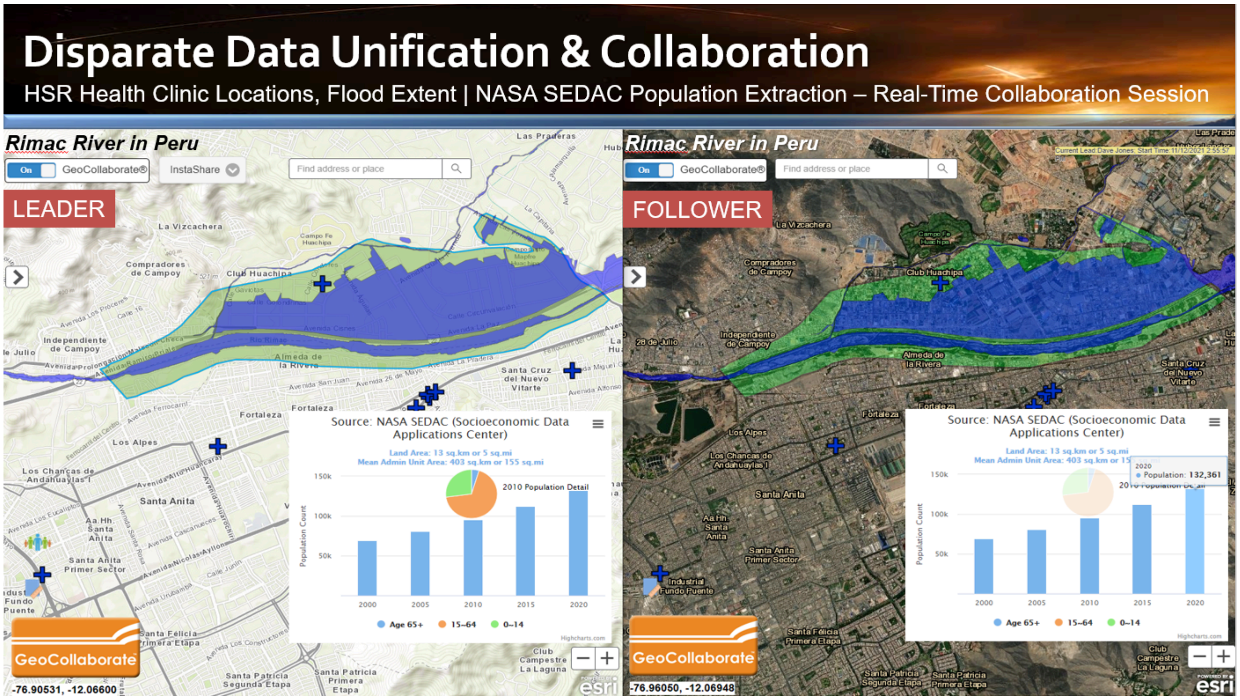

Figure A.16 — Data for Rimac River in Peru, including flood extent and demographic breakdown of the area, together with clinic locations from HSR.health, visualized via GeoCollaborate

GeoCollaborate can offer a way of communicating and collaborating on the information available to help speed up situational awareness and decision-making. GeoCollaborate offers an approach to access and share the datasets across multiple followers or users from its dashboard, including any datasets or layers that have been provided, giving a way of connecting decision-makers together in a collaborative environment.

B

ANNEX B (NORMATIVE) DROUGHT WORKFLOWS/CAPABILITIES DEVELOPED

B

ANNEX B (NORMATIVE) DROUGHT WORKFLOWS/CAPABILITIES DEVELOPED

Drought is a disaster that can impact a wide range of sectors, such as agriculture, health, and, particularly in Manitoba, energy production through hydropower.

Listed below are a series of indicators that focus on the overall severity of drought alongside the impact on individual sectors, which were developed in Disaster Pilot 2023 (DP23). While these workflows were built as standalone indicators, the participants also worked together to combine indicators to develop workflows that tell a more complete story of the impact of droughts. For example, the Drought Severity Indicators were used by the Drought Health Risk Impact to help better understand what the impact of a drought occurring in a particular area would be on the health of that population.

These workflows are available to be seen as a demonstration and could provide help and support to communities planning for and responding to drought scenarios.

- Annex B.1.1 Drought Severity Indicator Assessment Framework developed by United Nations University
- Annex B.1.2 Drought Severity Workflow developed by Pixalytics Ltd
- Annex B.1.3 Drought Severity Indicator developed by Safe Software
- Annex B.2 Drought Crop Suitability Indicator developed by 52 North
- Annex B.3 Water Supply Indicator developed by RSS Hydro
- Annex B.4 Energy Climate Indicator developed by GECOsistema
- Annex B.5 Drought Health Risk Indicator developed by HSR.health
- Annex B.6 Direct & Indirect Health Impact Indicators of Drought developed by IIT Bombay.

The detailed technical information about each of these workflows can be seen below.

B.1. Drought Severity Indicators

This series of drought severity workflows aim to enhance the implementation of interoperability, that is, the ability of data/applications/tools created independently by different individuals and organizations to be understood, integrated, and function consistently regardless of user knowledge and technology suites. This helps ensure that diverse information can be quickly brought together to support decision-making in the context of disasters.

B.1.1. Drought Severity Indicator Assessment Framework Developed by United Nations University

B.1.1.1. Introduction

To ensure interoperability of the systems for drought severity and vulnerability analyses, it is essential to bring the right group of people to the table and provide them with adequate data to make fair, efficient, and informed decisions about drought risk and severity. Drought severity workflow knowledge encompasses several aspects of environmental (e.g., precipitation), economic (e.g., income level), and social data (e.g., health and chronic condition data). The summary of steps for an interoperability assessments includes:

- bringing experts in environmental, economic, and social impacts of drought together with adequate data relevant to interoperability capacity;
- assessing drought direct and indirect impacts and then ranking impacts;
- assessing vulnerability; and
- developing a "to-do" list and identifying actions.

B.1.1.2. Indicator Recipe

Figure B.1 shows an example of how to set up a table to prioritize the impacts of drought severity relevant to Manitoba, Canada.

Rank	Impact	Cost	Area extent	Trends over time	Public priority?
1	Manitoba Hydro exports				
2	Farming and crops				
3	Wildfires fighting				

Figure B.1 — Example of how to set up a table to prioritize the impacts of drought severity relevant to Manitoba

The table also ranks the "current" impacts according to the priorities that should be considered. The general public, community advisory committees, and groups of relevant scientists and policymakers can be included in the ranking for informed and equitable impact assessment.

The final step (and the output) would be a vulnerability assessment. For example, as the drought impact assessment from the example establishes that mitigating and adaptation strategies for agriculture and crop damages are a priority, Figure B.2 can identify the underlying conditions. The logic behind vulnerability assessment is finding key entry points and adaptation strategies to mitigate the impact of drought in a region. Many agricultural regions in the world can be impacted adversely by drought, but not all of the impacts are equal. Therefore, finding the root causes of the impacts is a step toward recovering from its assessed severity.

Impact of drought	Underlying causes	Possible actions	Mitigation (M), Response (R), Accepted Risk (AR)	Feasible ?	Cost	To do?
Crop failure	Variable climate	Weather modification	M			
		Weather Monitoring	M			
	No irrigation	Haul water during a drought	R			
		Provide government assistance for irrigation projects	M			
	Expensive seeds	Subsidize seeds sales	M			
	Farmers preference to plant specific seeds	Conduct workshops	M			
		Conduct research	M			
		Enhance communication	M			
	Government preference to plant specific seeds	Lobby for new incentives	M			
	No drought warning	Provide weather monitoring	M			
	High cost of crop insurance	Government Subsidies	R			
	Lack of research on the efficiency of drought relief efforts	Identify target groups and conflicting relief programs	M			
	Lack of drought relief program coordination	Streamline relief application on funding	M			

Figure B.2 — Example vulnerability assessment for crop failure

In designing a drought severity workflow, it is essential to differentiate between the impacts of drought severity versus the underlying reasons (i.e., vulnerability) for drought. The impacts of drought are usually associated with reduced crop yields, livestock losses, and reservoir depletion. Drought impacts can also be traced to social consequences such as the forced sale of household assets or lands or physical and motivational malfunctions. Understanding the underlying drought severity differs from mentioned direct and indirect drought impacts. It is also essential to evaluate what drought impacts will recur in a region under climate change, as well as population and water demand changes.

B.1.1.3. Benefits

This workflow highlights how a collaborative drought severity workflow can identify vulnerable populations in drought-affected areas. The benefits of UN Univeristy's contribution is a workflow for prioritizing impacts and vulnerabilities relevant to a particular region or activity and supporting scientific researchers, policymakers, and the public.

A drought impact and vulnerability assessment guideline as a prerequisite for enhancing the ability of web services to integrate and exchange spatial data to ensure consistent decision-making results. Having interoperable systems in place becomes especially important during wide-scale emergencies like drought responses and firefighting.

B.1.1.4. Collaborations

Within the DP23 work, the workflow from Pixalytics aims to look at the impact of drought, while the workflow developed by Safe Software looks at drought vulnerability. In addition, the participants are working together to produce a version of the Pixalytics indicator which combines the two elements.

B.1.2. Drought Severity Workflow Developed by Pixalytics Ltd

B.1.2.1. Introduction

The Drought Severity Workflow (DSW) was begun in the Climate Resilience Pilot, and was updated and further developed in the DP23.

B.1.2.2. Indicator Recipe

The DSW is used to create a Decision Ready Combined Drought Indicator. Its components are as follows.

- ***Input Data:***

The input data are a combination of modeled and/or Earth Observation (EO) derived products that can act as indicators of drought. Within the Combined Drought Indicator the user selects the indicators of m ost interest and the inputs used vary according to what is chosen and include precipitation, soil moisture, and the Fraction of absorbed light by the plants (FAPAR). These parameters are retrieved from multiple sources that may be combined or used individually:

- Copernicus Climate Change Service (C3S) through the Climate Data Store (CDS);
- Copernicus Global Drought Observatory (GDO);
- NOAA through their Climate Environmental Data Retrieval (EDR) API; or
- Safe Software through their Features Server API.
  - ***Processing & Transformations:***

Individual drought indicators are calculated for the three chosen input parameters: for precipitation the Standardized Precipitation Index (SPI) is calculated, for soil moisture it's the Soil Moisture Anomaly (SMA), and for vegetation health FAPAR is used. These drought indicators can also be downloaded in a pre-calculated form from the GDO. The three individual indicators are then combined to generate the Combined Drought Indicator (CDI), the detailed methodology behind this is described by Sepulcre-Canto et al (2012).

- ***Output Data:***

The data are provided through an API, which provides a point time-series, bounding box or polygon extraction into output files in CSV, GeoJSON, CoverageJSON or NetCDF format. The API access were set up following the Building Blocks for Climate Services Web Processing Services (WPS) approach, with the front-end supported by Nginx, which is an open-source web server, and Certbox for HTTPS certification.

- ***Running the Indicator:***

The code is held within several GitHub repositories and, to make it easier to install, the code was also transitioned to a Docker container uploaded to Pixalytics' Amazon Elastic Container Registry. Using the OGC provided Amazon Web Service (AWS) credits, testing of the container on the AWS infrastructure was conducted.

B.1.2.3. Benefits

The aim for this indicator was to support an understanding of whether a location is suffering from drought and what the indication of drought is referring to, i.e., is it a lack of rain, lack of soil moisture, or stressed vegetation? Multiple individual indicators may be triggered and there is a temporal dependency to this. An example of the multi-parameter inputs to the combined indicator (CDI) is shown in Figure B.3. The top plot shows the SPI, middle plot SMA, and bottom plot FAPAR. The colored (yellow to orange) vertical bars show the CDI moving from watch to warning when one of the indicators is triggered — when the CDI moves to alert there is a *reddish* bar with Alert 1 showing two indicators are triggered while Alert 2 is all three individual indicators triggered.

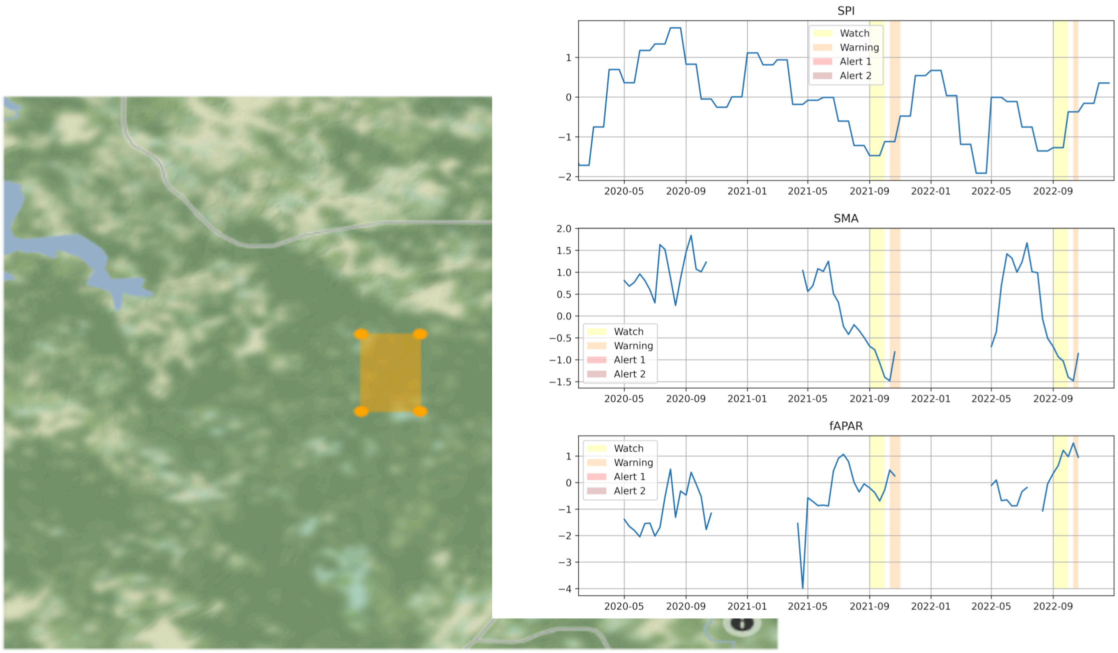

Figure B.3 — Plot of the CDI for a point location in Canada (Latitude: 55.5 N Longitude: 99.1 W); generated using Copernicus Emergency Management Service information [2023]

The job roles that would be supported include a Decision Ready Indicator (DRI) Analyst and DRI Decision Maker. The individual indicators and CDI indicate whether drought is occurring and what the current impact is. It would be helpful for farmers, if there was a lack of soil moisture identified, then irrigation or early crop harvesting might be appropriate actions; especially when the vegetation indicator is also triggered. In future, the aim is to expand the indicators to also be suitable for forested areas and include health effects on the population through temperature.

B.1.2.4. Collaborations

There were collaborations with ECMWF, NOAA, and Safe Software in terms of the input datasets (carried over from the Climate Resilience Pilot). Also, HSR Health used the DSW as an indicator ingested into their Health Impact Indicator.

The API runs on a webserver owned by Pixalytics, with testing undertaken to transition the API to an OGC permanent demonstrator as the cloud computing infrastructure becomes available.

B.1.3. Drought Severity Indicator Developed by Safe Software

B.1.3.1. Introduction

The Drought Severity Indicator developed by Safe Software supports the modeling and analysis of drought impacts in southern Manitoba. This component takes the climate scenario environmental variable summary ARD (Analysis Ready Data) from Safe Software's Data Service component and applies the service to drought analysis using appropriate queries to derive preliminary drought risk impacts over time based on selected climate scenarios. Given resource constraints, there was not have time to integrate other drought environmental factors such as hydrology or watershed data. However, other participants such as Pixalytics were able to incorporate Safe's climate scenario environmental variables into Pixalytics' richer drought models in order to provide a more accurate projection of potential future drought risk.

Central to this is the identification of key drought risk impact indicators required by decision makers and the business rules and datasets needed to drive them. The workflow includes data aggregation and statistical analysis of precipitation over time, taking into account deviation from historical norms and cumulative impacts by time period which should provide a starting point for the assessment of drought risk by region and time. The workflow also represents an important example of how global and regional climate model outputs can be used to support disaster and climate resilience planning at the regional and local scales, by translating scenario model outputs into specific natural hazard risks and impacts at local levels.

Safe Software gained valuable experience working with water flow time series models in the context of the DP21 working with RSS Hydro and Dartmouth Flood Observatory to ingest the time series results from flood models and flood extents. Drought is about water scarcity rather than excess. However, the modeling to drive impact analysis for both have similar requirements — that is, to evaluate water budgets including component rainfall and flows over time and interrelate this with topography and hydrology to estimate where the impacts of water surplus or scarcity are likely to occur.

In DP23, the primary focus has been drought impact in southern Manitoba. This area, historically, has not tended to experience as much drought as other regions of the prairies to the west. However, as shown in the Figures below, more recently, with the effects of climate change, this area has shown increasing drought stress which has implications for the need to manage and model drought more closely there.

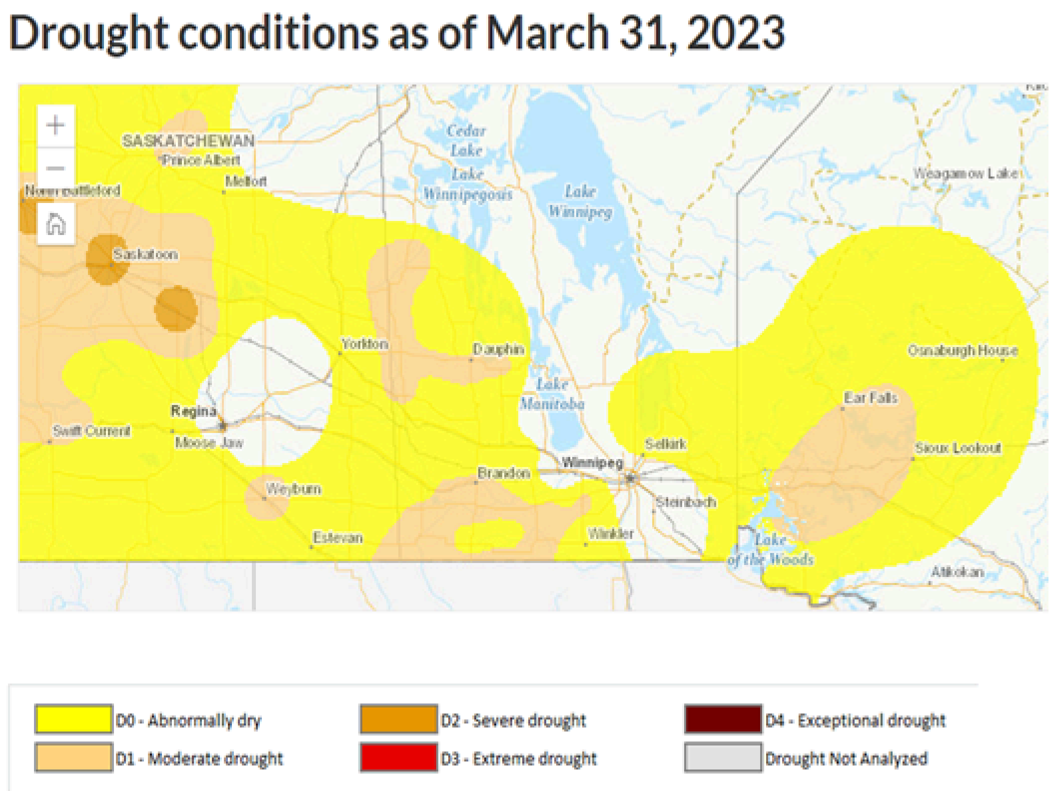

Figure B.4 — Canadian drought monitor showing areas of the eastern prairies experiencing various degrees of drought as of March 2023 (Agriculture Canada)

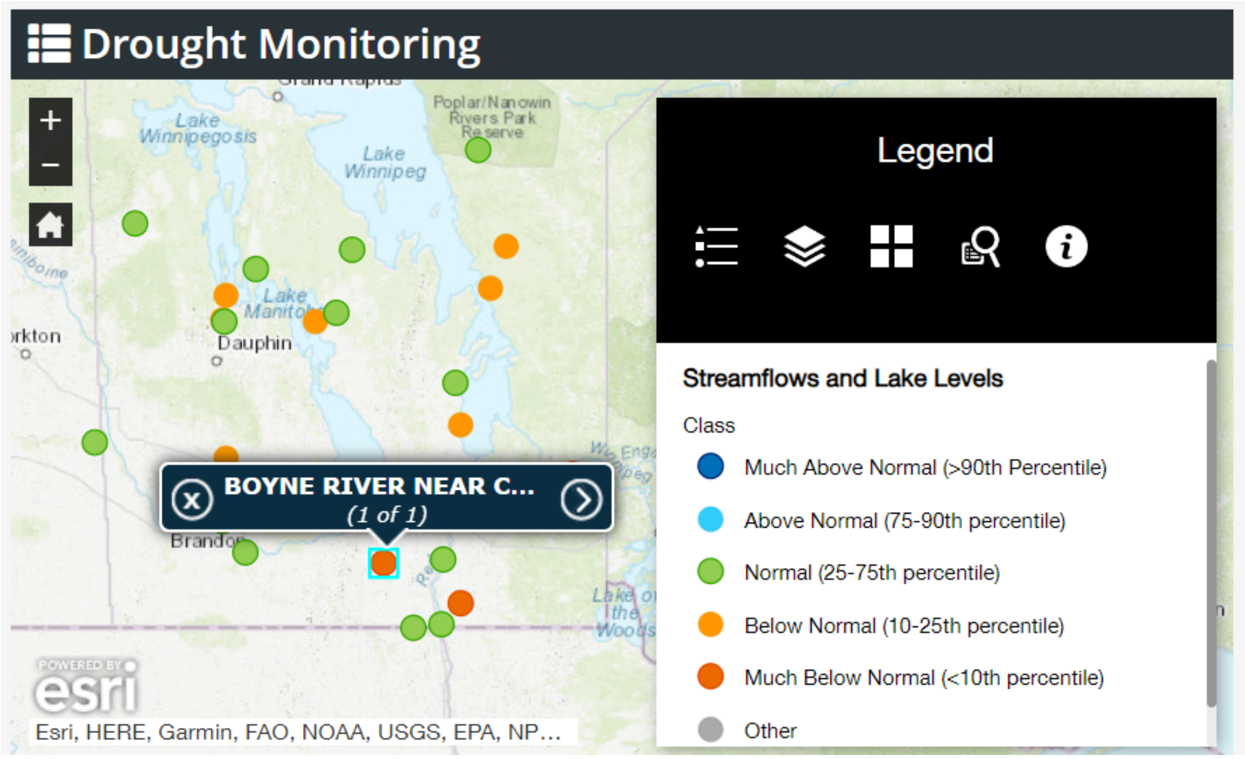

Figure B.5 — Manitoba drought monitor showing degrees of drought for lakes and rivers in Manitoba, fall 2023 (Manitoba Environment)

Workflows developed for Manitoba drought impact analysis were designed in such a way that the workflows can be readily transposed to other contexts and scenarios, given adequate provision of equivalent source data. The process recipes were implemented using Safe Software's FME platform, which is a no-code, model based, rapid prototyping environment that supports data integration and automation with a special focus on spatial data support (more than 500 formats and services supported). With this model driven approach it is relatively easy to rerun or automate the same dataflow based on new inputs. In this way new results can be generated based on different climate scenarios such as those based on low, medium, or high emissions.

B.1.3.2. Indicator Recipe

The drought indicator analyzes climate model outputs, including environmental variable time series, to derive estimated drought risk impacts over time based on selected climate scenarios for the Manitoba study area. It does this by taking the climate scenario summary ARD results from Safe Software's Data Service ARD component described in Annex A, and analyzes the results to derive estimated drought risk impacts over time for the climate scenario and also feeds drought related environmental factors to other pilot DRI components for more refined drought risk analysis.

B.1.3.2.1. Input Data

The climate model data used in this pilot were obtained from the climate data services published by Environment and Climate Change Canada. From the perspective of the Drought Indicator component process, the main input is Safe Software's Data Service ARD component described in Annex A.

The Manitoba Regional Climate Model scenario selected for the purposes of DP23 was:

- Spatial Extent: Lat 49 N to 52 N, 102W to 95W
- Spatial Resolution: 10km x 10km grid cells
- Temporal Extent: 2020-2060
- Model generation: CMIP5
- Model scenario: RCP45
- Downscale approach: bias-corrected and spatially downscaled (BCSD)

This provided future total monthly precipitation and mean monthly temperature from RCP45 CMIP5 for 2020-2100 Statistically downscaled climate scenarios from Environment Canada Climate Data Portal (BCSD: bias-corrected and spatially downscaled) RCP4.5: 'Business as usual'.

RCP 4.5 is the most probable baseline scenario (few climate mitigation policies) taking into account the exhaustible character of non-renewable fuels. CMIP5 describes the RPC run version or generation (Phase 5 2012-2014), and BCSD is a statistical term about the method of downscaling used (bias-corrected and spatially downscaled). This NetCDF dataset used 'Bias Correction/Constructed Analogue Quantile Mapping version 2.0 (BCCAQ2) downscaling model output for Canada.' CMIP5 and BCSD are technical terms that may not be meaningful to readers not familiar with climate models, but are necessary parameters to be aware of in order to achieve the same results. For more information on climate model parameters can be found here.

- Climate Model Projections — Other Sources
  - Environment Canada Climate Scenarios
  - Climate Data Canada (Limited download)
  - Copernicus CDS
  - Earth System Grid
  - USGS THREDDS Data Service
  - Climate Mapping for Resilience and Adaptation U.S. Global Change Research Program (USGCRP) and with U.S. Federal Geographic Data Committee (FGDC). Funded by DOI and NOAA, implemented by Esri:

B.1.3.2.2. Processing & Transformation

The workflow involved developing a transformation workflow on the FME platform to extract, transform, and load climate model results from data cubes into a relational spatial database and then provide OGC API services to deliver GeoJSON to end-client applications. Safe Software's ARD component generates climate model outputs as an OGC API Features service, delivering GeoJSON point features with associated climate properties. In particular, properties include monthly mean temperature, total precipitation, and change in precipitation compared to the historical baseline (mean precipitation from 1950 to 1980 for that same location) allowing the end user to develop business rules that define climate scenario based drought impacts by submitting the appropriate queries to the ARD climate variable service. So, in a very real sense, the drought model is essentially a set of queries submitted to Safe's climate ARD component that ask for a set of time series points that pass a combination of drought related environmental variables business rules. The output of this is the same as that of the climate ARD component, but applied to drought risk estimation.

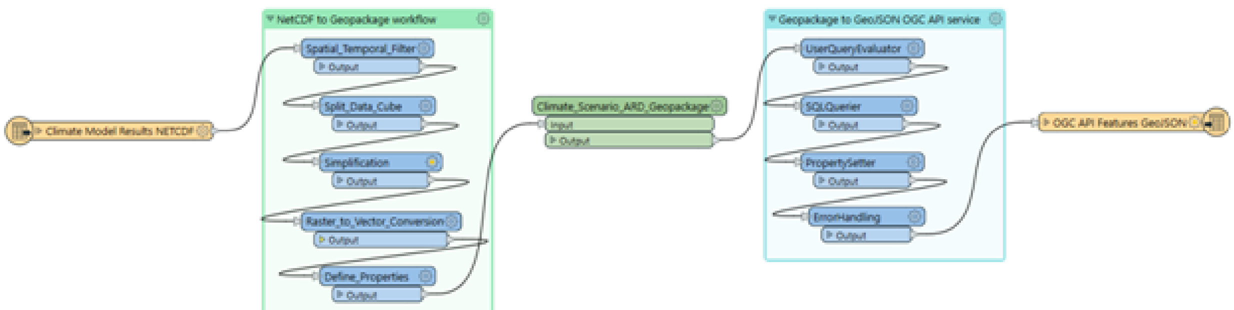

Figure B.6 — High level component FME workflow from climate data cube NetCDF to spatial database geopackage to OGC API Feature service GeoJSON

The basic workflow for precipitation and temperature:

1. download and read the data cube for the selected climate scenario and environmental variable type of interest;
2. split the data cube into separate grids for each time step;
3. set timestep parameters;
4. compute timestep stats by band;
5. convert grids to vector points;
6. map geometry and feature properties and load features to a relational database data model in Geopackage;
7. upload the geopackage staging database to the FME cloud instance; and
8. publish the client feature query workflow to the FME cloud-hosted OGC API Feature Service, which extracts features as GeoJSON layers for the

environmental variables of interest (precipitation, precipitation delta, and temperature).

For the precipitation delta drought proxy indicator, the following steps were also performed:

1. read data cube for selected climate scenario environmental variable types of interest;
2. split the data cube into separate grids for each time step;
3. set timestep parameters;
4. dompute timestep stats by a band;
5. compute average historical precipitation per cell from 1950-1980;
6. combine future and historical bands for each environmental variable type into a multiband raster for each time step;
7. divide future precipitation by historical mean for that location to compute precipitation delta;
8. convert grids to vector points, preserving environmental properties for each point including precipitation total, precipitation delta, and temperature mean;
9. map geometry and feature properties and load features to a relational database data model in Geopackage;
10. upload the package staging database to the FME cloud instance; and
11. publish the client feature query workflow to the FME cloud-hosted OGC API Feature Service, which extracts features as GeoJSON layers for the environmental variables of interest (precipitation, precipitation delta, and temperature).

Parameters for each of the environmental variables of interest are also set at publication. This gives the end user the ability to execute composite queries (environmental value ranges, spatial, and temporal filters).

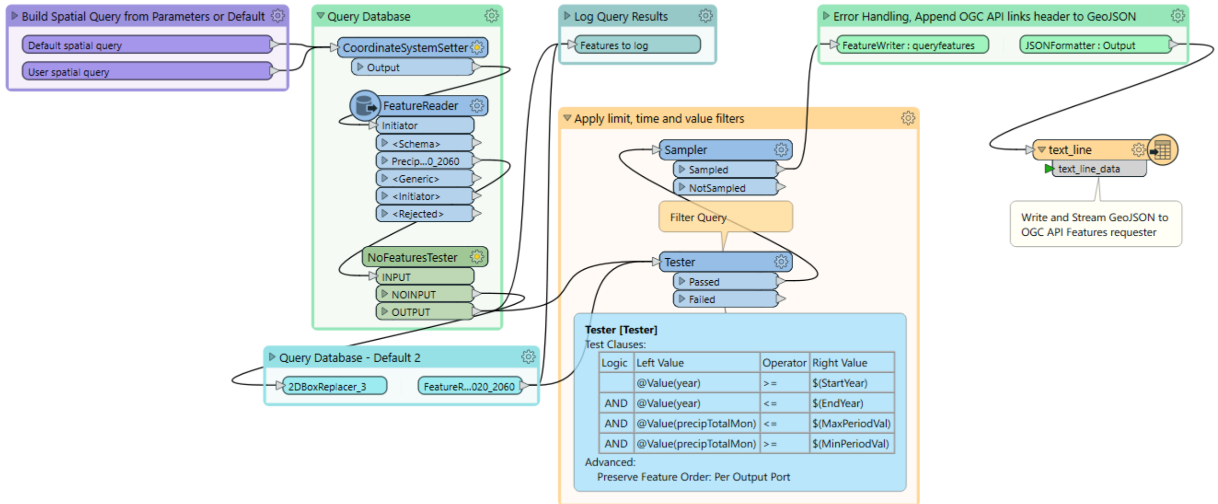

Figure B.7 — Climate service data FME transformation workflow from NetCDF data cube to Geopackage relational database.

Calculations were made using the division between time series grids of projected precipitation and historical grids of mean precipitation per month. These precipitation deltas were then divided by the historical mean per month to derive a precipitation index. The goal was to provide a projected value between 0 and 1 where 1 = 100% of past mean precipitation, for that future month at that location. Naturally this approach can generate values that exceed the range of 1 if the projected precipitation values exceed the historic mean. The goal was not so much to predict future absolute precipitation values but rather generate an estimate for precipitation trends given the influence of climate change. For example, this approach can help answer the question — in 30 years for a given location, compared to historical norms, by what percentage is precipitation expected to increase or decrease?

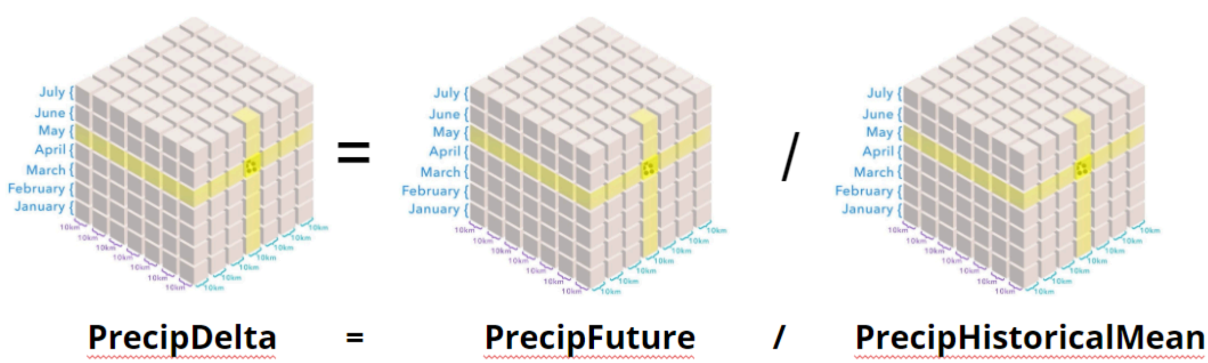

Figure B.8 — Calculation of precipitation delta by dividing future projected precipitation by historical for each point in the time series.

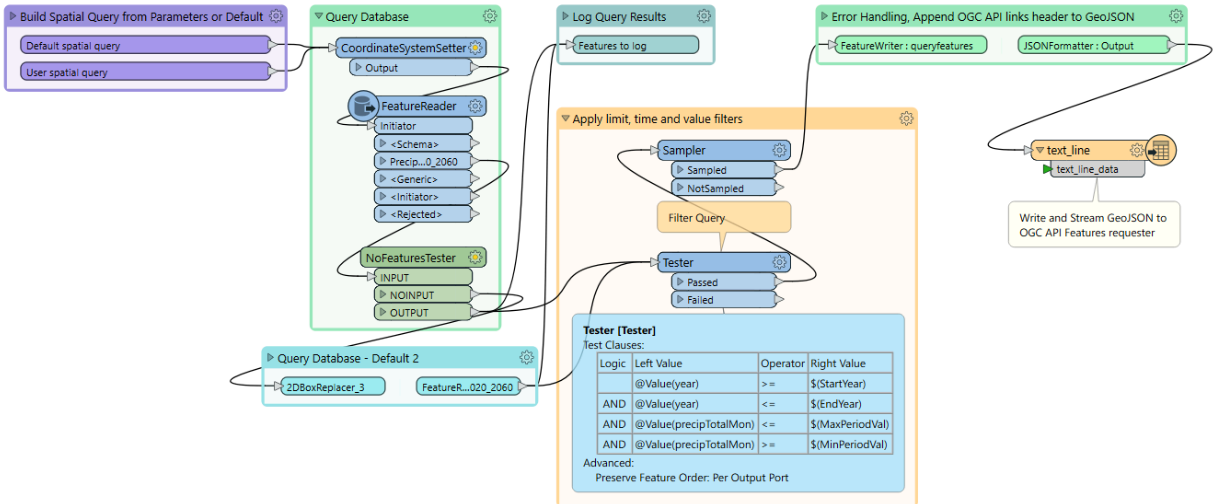

Figure B.9 — OGC API Feature Querier: Geopackage to GeoJSON. Published parameter based filters and queries are embedded in the FeatureReader WHERE clause and Tester filters.

B.1.3.3. Outputs

As stated above, the drought model is essentially a set of queries submitted to Safe's climate ARD component that ask for a set of time series points that pass a combination of drought related environmental variables business rules. The output of this is the same as that of the climate ARD component, but applied to drought risk estimation. So the drought model is ultimately a drought targeted OGC API Feature request and the output is the associated OGC API Features GeoJSON response that specifies the time series points along with their environmental variables that meet the conditions of the drought query.

The service response data can then be used as a rough estimate of general drought risk, or to drive downstream drought analysis. For example, Pixalytics submitted a query for precipitation estimates for a specific location and time range, and fed that into the near future drought model runs. In this way, Pixalytics was able to develop a continuous summary of observed and projected drought severity for specific locations from approximately 2020 to 2024.

For the selected climate scenarios, this supports the analysis of estimated drought risk impacts over time via simple feature queries that can be translated to SQL queries on the underlying spatial database and also feeds drought related environmental factors to other pilot indicator components for more refined drought risk analyses. While drought risk is driven by multiple environmental and physical factors, the DP23 goal was to select and provide primary climate variable data such as precipitation and temperature that would be useful for deriving drought risks in combination with other inputs. This climate scenario primary drought data were provided for the province of Manitoba study area and was the dataset consumed by the Pixalytics drought model component

It is important to underline that this particular indicator is more of an interactive service than one meant to yield one specific result or prediction. As such, it is up to the end user, whether drought domain experts or local farmers or administrators, to develop the business rules for drought that are deemed most appropriate. This indicator service provides a means of interacting with the relevant environmental variables from the climate model projections, such as precipitation and temperature, to see when and where problems might occur. What is defined as problematic will naturally differ depending on whether the end user is concerned about a specific agricultural crop, water supply for a city, or hydroelectric power for the province. This drought indicator service then provides an access point where end users can explore the climate scenario data as it relates to southern Manitoba. The cases shown here are just examples and are only meant to serve as a starting point for further testing and exploration.

In order to better support drought related queries, the indicator component service was enhanced to support multiple environmental variables on each of the time series points. This includes values such as temperature, precipitation, and change in precipitation relative to historic mean. Users can ask questions to look for times and places of concern relative to specific natural hazards such as drought, fire, heat, or flood. As example, the following request was made to the service: “Find all time step points over the next 40 years for southern Manitoba where projections indicate > 25% dryer and mean monthly temperature > 23C.”

Query:

```
bbox=-100.0,49.0,-96.0,51.0, StartYear=2020, EndYear=2060
MaxPeriodVal=0.75, MinPeriodVal=0, MinTemp=23
```

Listing B.1

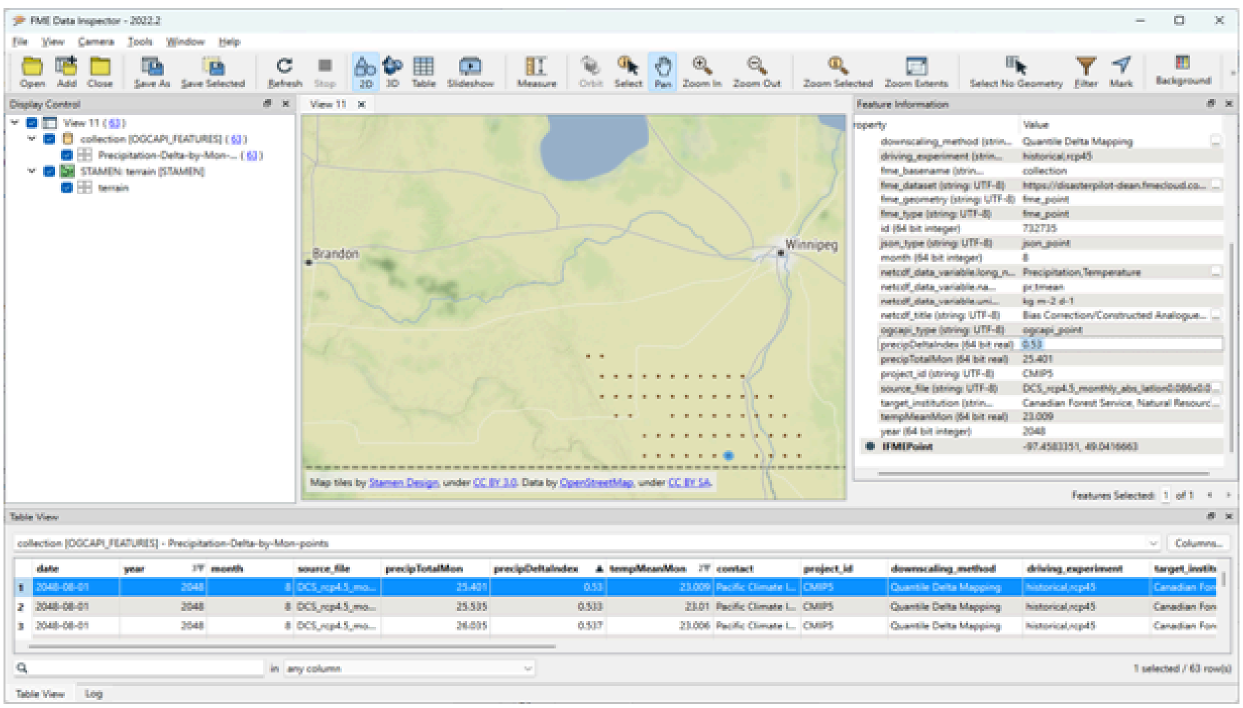

Figure B.10 — 63 temporal points with associated temperature and precipitation values, as shown in FME Data Inspector client

Result: Points as above for the timesteps Aug 2048 and Aug 2058

These data are displayed in Safe Software’s Data Inspector client using the OGC API Features reader. This result shows climate model points derived from the RCP4.5 business as usual scenario that result from the query above. That is, these points represent the hot and dry areas and times (August 2048 and 2058) that satisfy the query above and could constitute increased drought and fire risk. This illustrates one approach for making climate model outputs more accessible in a form and structure easy to consume by those used to working with GIS tools.

B.1.3.4. Benefits

The benefits of this workflow can help disaster management and planners evaluate the resilience of plans against a range of possible future climate scenarios. By making climate model outputs, such as NetCDF data cubes, more accessible to common analytics platforms typically used by planners, such as GIS, this indicator component helps shed light on what local trends to expect in the future based on various climate model scenarios and should help the stakeholders responsible for managing disaster and climate impacts more easily access and interpret the potential risks associated with climate change in their local context.

From a planning perspective, it can be expensive to build comprehensive drought models, either at the local scale or across an entire province. So it may be useful to make basic environmental variable projections available such as precipitation over time. It is usually not obvious to a non-domain expert how much precipitation is enough, excessive, or inadequate. There are many factors that come into this in terms of the type of impact involved. On the other hand, a simple normalization of changes or trends in key environmental variables is a good first step in looking for regions and times where drought or flood risk may be increasing. For example, knowing where and when precipitation is 20% lower or higher over a given time period might warrant an investigation in the resilience of those areas for drought or flood respectively. Naturally these trends need to be examined in the context of existing drought risk factors and historical drought. Different impact types such as agricultural, drinking water, recreation, or hydropower will all have different thresholds of concern. Still, the general trends can at least serve as a first step in terms of locating those of areas and times of interest for closer management and more thorough investigation.

In a similar vein, another important benefit of this drought primary indicator is that it can be used to support downstream analysis. This indicator is a rough proxy for drought risk since at present it only includes values for precipitation, change in precipitation from historical baseline, and temperature. On the other hand, more sophisticated drought models such as that developed by Pixalytics can use the precipitation and temperature values as inputs to drive more refined models. Future forecast scenarios for precipitation and temperature can be combined with localized detailed models that include other drought risk factors like soil type, geology, hydrology, land use, and vegetation. In this way, climate projection data can allow the more sophisticated drought models to make projections about possible future drought risk which neither model or indicator could do on its own. This type of indicator synthesis is crucial in order to build comprehensive views of disaster and climate risks over time at the regional and local scale. Also, the concept of primary indicators that can be used to drive secondary indicators is also important in that it allows a wider range of indicators to be developed without each indicator recipe having to build the entire analytical workflow on their own.

B.1.3.5. Collaborations

To support future drought risk estimates for Manitoba, Pixalytics was provided a precipitation forecast time series as an input to Pixalytics' drought analytics and DRI component described in Annex B.1.2. The Pixalytics component provides a much more sophisticated indicator of drought probability since in addition to precipitation it also takes into account soil moisture and vegetation. Pixalytics then ran the drought model based on these precipitation estimates in order to assess potential future drought risk in southern Manitoba, as shown below.

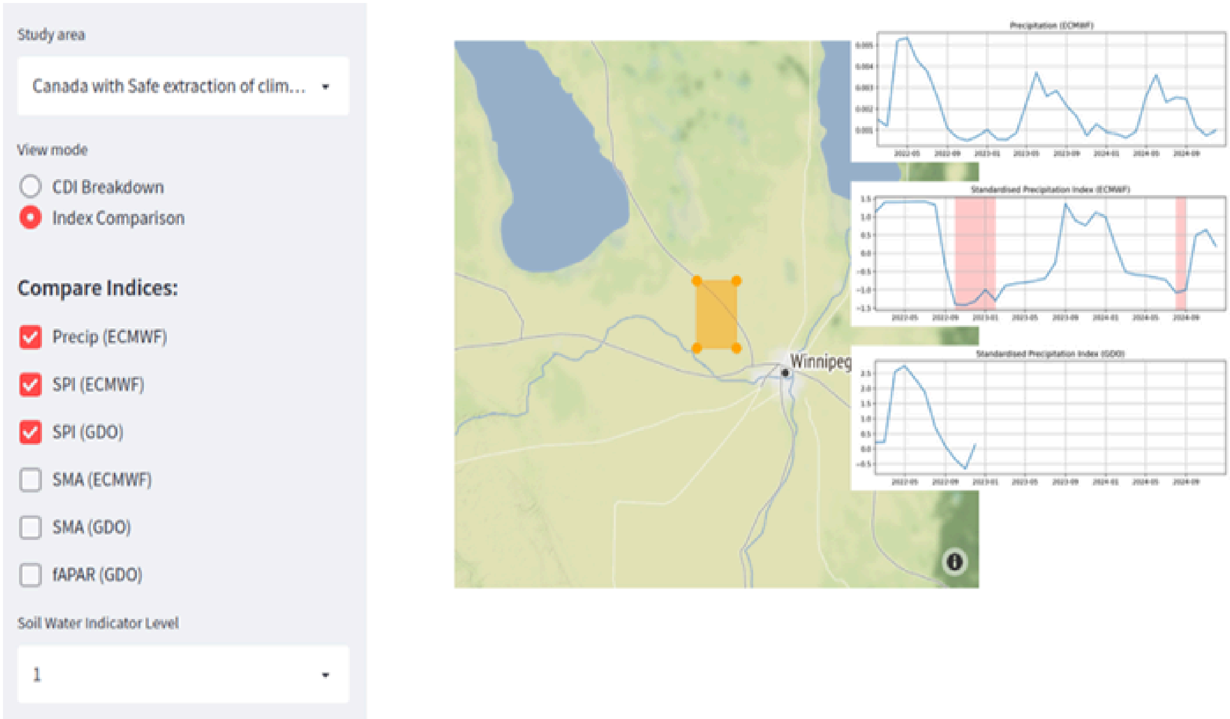

Figure B.11 — Pixalytics drought DRI component integrates future precipitation projections from Safe Software's drought indicator service with historical and present data (Samantha Lavender)

Further information on Safe Software's contributions to OGC Disaster & Climate Pilots can be found at https://community.safe.com/s/article/OGC-Disaster-and-Climate-Resilience-Pilots

The persistent demonstrators for the services used in this indicator can be found at:

- OGC API Features Service (accessible 9am — 5pm EDT, M-F)
- OGC API Records Service (accessible 9am — 5pm EDT, M-F)

B.2. Drought Crop Suitability Indicator Developed by 52 North

B.2.1. Introduction

The workflow provides crop suitability maps, highlighting the effect of local environmental conditions on crop health/yield and is implemented for the Manitoba region as a pilot test case.

B.2.2. Indicator Recipe

- **Input data**

The input data for the indicator are as follows

- The environmental data used is from the Global Ensemble Prediction System (GEPS) provided by the Meteorological Service of Canada (MSC). Specifically:
  - precipitation rate: APCP_SFC_0;
  - temperature: TMP_TGL_2m;
  - 14 days forecast — optional; and
  - 32 days forecast provided every Thursday.
- The plant requirements input data for crops are provided by the FAO ECOCROP database.
  - **Processing & Transformation** — The implementation starts from a simple land classification model based on temperature and precipitation data following the approach of Peter et al. The workflow can be described as follows.
- Since the implementation of this workflow is meant as a proof of concept, test data from the MSC are loaded directly into the docker container. Automatic download of the data could easily be realized by a kubernetes CronJob.
- The ensemble mean for precipitation and temperature data is retrieved from the MSC using grib2-data provided by the GEPS-model.
- Environmental data are combined with crop information databases by the FAO on crop needs and based on the level of agreement between datasets and land categories, with five land categories – regions with pessimal, unsuitable, marginal, suitable, optimal environmental conditions — defined.
  - **Output Data** — The final maps and data are available via an API Processes using pygeoapi. If the modeling is requested for a certain bounding box, the output is provided as a GeoJSON file with the different land categories represented by polygons. In addition, the modeling results are available as a netCDF file with separate variables for every individual land category. In case the modeling is requested for a particular coordinate pair, the GeoJSON file that is returned contains point geometry with an assigned suitability category.
  - **Technical standards or infrastructure requirements**

The infrastructure runs in a Docker container deployed in the cloud, with the API using the API Processes scheme.

+

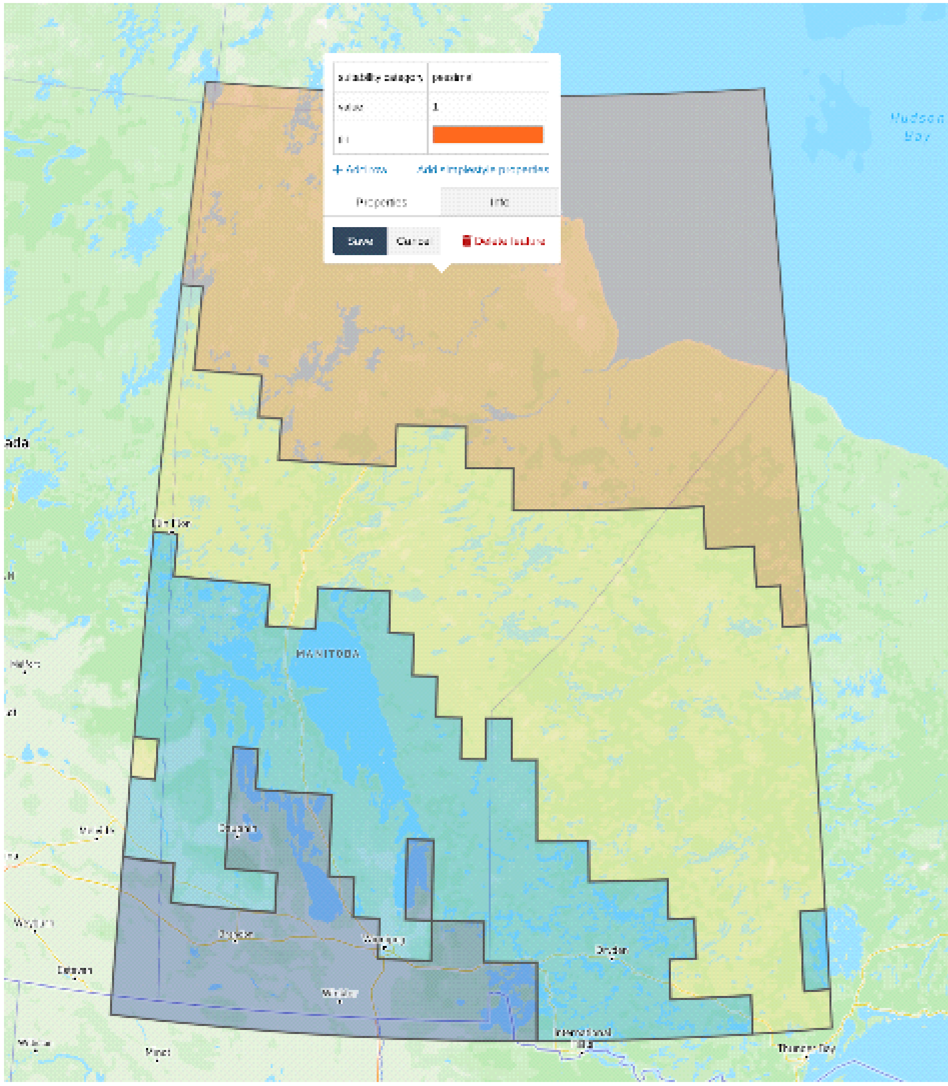

Figure B.12 — Example of a crop suitability map for the test case of Manitoba. The suitability of the environmental conditions is decreasing from suitable (blue) to pessimal (red). The visualization was done using geojson.io

B.2.3. Benefits

- Users can adapt to upcoming drought conditions and establish counter measures like the adjustment of irrigation schedules or the choice of crop species that are more suited to challenging environmental conditions.
- The main user base of this indicator are farmers. The indicator could also be used to describe economic implications of climate change in terms of yield loss.

B.2.4. Collaborations

This indicator was developed as a separate component for DP23. For the future, collaborations in the context of the Wildland Fire Fuel Indicator and Drought Severity Indicators are possible. In case of Wildland Fire Fuel, the Crop Suitability Indicator can be used as a metric of dry biomass, while for drought severity the resilience/vulnerability of crops can be shown.

B.3. Water Supply Indicator developed by RSS Hydro

B.3.1. Introduction

Satellite passive microwave sensors provide global coverage of the Earth's land surface on a daily basis and, at certain wavelengths, without major interference from cloud cover. These microwave sensors — for example, Advanced Microwave Scanning Radiometer for EOS (AMSR-E), Advanced Microwave Scanning Radiometer 2 (AMSR-2), Tropical Rainfall Measuring Mission (TRMM), and Global Precipitation Measurement Mission (GPM) — can monitor river discharge changes by measuring radiation.

As rivers rise, discharge increases and the water area within a satellite's 'gauging reach' increases. This gauging reach is typically a single 10 km x 10 km pixel. Such a gauging reach includes both water (low emission) and land (much higher emission) areas. As the proportion of water area rises, the bulk emitted radiation declines. The microwave signal is thus responsive to flow area and discharge changes. So freshwater availability can be monitored daily from 1998 onwards. As such, droughts, and also flooding, can be detected, while evolving

B.3.2. Indicator Recipe

This workflow produces a global product offering an indicator for the drought impact on freshwater availability as follows.

- ***Input Data:***

The input data for this indicator are:

- NASA/Japanese Space Agency Advanced Scanning Microwave Radiometer (AMSR-E) band at 36.5 GHz;
- NASA/Japanese Space Agency TRMM 37 GHz channel; and
- 37 GHz information from the new AMSR-2 and GPM sensors.

- ***Processing & Transformations:***

The processing undertaken for this indicator is:

- (1) obtain flood-detection-product from JRC (gridded pre-processed integrated product);
- (2) develop rating curves with reference to a nearby gauging station or hydrological model (develop equation to transfer radiation into discharge);
- (3) process time series into discharge signal;
- (4) publish time series; and
- (5) update discharge time record on a daily basis, and include that within the time series record.

- ***Output Data:***

The output is considered to be ARD, and the data are provided through a web portal in HTML format. Each gauging reach has its own web page, containing location and discharge time series. An example can be seen at: https://floodobservatory.colorado.edu/SiteDisplays/100088.htm.

B.3.3. Benefits

This workflow benefits disaster relief agencies and local authorities, by showing the magnitude of a drought disaster, to help determine a response. The workflow also offers benefits to planners as how often floods or droughts occur in an area over the last 30 years approximately can be shown.

As a global product, anyone who is interested in flood warnings, flood and flood risk evaluation, hydropower siting studies, water quality studies, and hydrologic trend analysis, would find benefit. In addition, organizations can use longer discharge time series to other sensors with shorter periods of record. In addition, disaster relief agencies and local authorities, other organizations that could benefit from this workflow, include development banks, Red Cross, World Food Programmes, etc.

B.3.4. Collaborations

Working with Joint Research Centre in Italy, World Food Programme, Red Cross, and several development banks.

B.4. Energy Climate Indicator Developed by GECOsistema.

B.4.1. Introduction

The power sector is exposed to weather and climate variability at all timescales, with impacts on both demand and supply. It is well established that global and regional temperatures are increasing, and will continue to increase with human-induced climate change, resulting in increasing electricity demand for residential cooling. Recent studies investigating the impact of climate change on demand concur that annual heating-induced demand is likely to reduce, whereas cooling-induced demand is likely to increase.

The purpose of the Energy Climate Indicator is to produce a minimum viable climate service designed to enable the energy industry and the policy makers to assess the impacts of climate variability and climate change on the energy sector in Manitoba (Canada).

The Indicator provides a time series forecast of electricity energy demand and supply from hydropower with short-term or long-term monthly, seasonal, and climate change outlooks. An improved characterization and prediction of such variability benefits production and transmission planning, leading to economic and environmental benefits. The energy indicators and associated time series forecasts can be provided both as data files, or as images. There are various ways the data can be shared between individuals and organizations following appropriate standards.

B.4.2. Indicator Recipe: Long Short-Term Memory (LSTM) Time Series Forecasting: Predicting Country-Level Energy Demand Using Multiple Features

This section illustrates how to generate a climate-based indicator using Long Short-Term Memory (LSTM) and SaShiMI networks which are advanced recurrent Neural Network (NNet) models ideal for sequence prediction, to forecast energy demand considering various climate related features: installed power generation, temperature, precipitation, wind speed, and solar irradiance.

The energy NNet SaShiMI model indicator is based on the hindcast-forecasting model, described in Google's paper Flood forecasting with machine learning models in an operational framework with the following main adaptations.

- The embedding layers have been simplified. Historical data is fed into a dense embedding layer, and then into the hindcasting model.
- The hindcasting model, instead of using an LSTM, has been made with a SaShiMi model.
- Instead of asymmetric laplacian functions, the model head is a GMM.

B.4.2.1. Data Collection

- Energy Consumption (MWh): Gather historical data regarding the country's energy consumption.
- Hydropower Energy River generation (MWh): Gather historical data regarding the country's energy river hydro production.
- Weather Data: Temperature, precipitation, wind speed, and solar irradiance data, which can influence energy consumption.

Sources might include national energy departments, meteorological organizations, or international databases.

The data used in DP23 were provided by the Copernicus CDS, with the Climate and energy indicators for Europe from 1979 to present derived from reanalysis data.

The Climate variables come from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis. Reanalyses are gridded datasets covering the globe, as in the case of ERA5, or a regional domain and are reconstructions of past climates produced through the assimilation of observations in physical numerical models which were developed explicitly for climate monitoring and research.

No bias adjustment was applied. Averages for country areas were computed for each of the climate variables.

The Electricity demand (Load) and Hydropower production are retrieved from the ENTSO-E Power Statistics database.

The data can be retrieved using CDS API as follows:

```
import cdsapi
c = cdsapi.Client()
c.retrieve(
    'sis-energy-derived-reanalysis',
    {
        'variable': 'electricity_demand',
        'spatial_aggregation': 'country_level',
        'energy_product_type': 'energy',
        'temporal_aggregation': 'daily',
        'format': 'zip',
    },
    'download.zip')
```

Figure B.13 — Script for the CDS API

The NNet model was developed and validated for Italy, but can be easily replicable to any country or region in the globe. The data set consists of daily data from 01/01/1973 to 23/08/2023 with 16 314 time-series points.

Figure B.14 reports the time series values of IT (Energy Demand in MWh), ITtemp (air temperature in K), ITprecip (Total Daily Precipitation in mm), ITwind (Average Daily Wind Speed in m/sec)

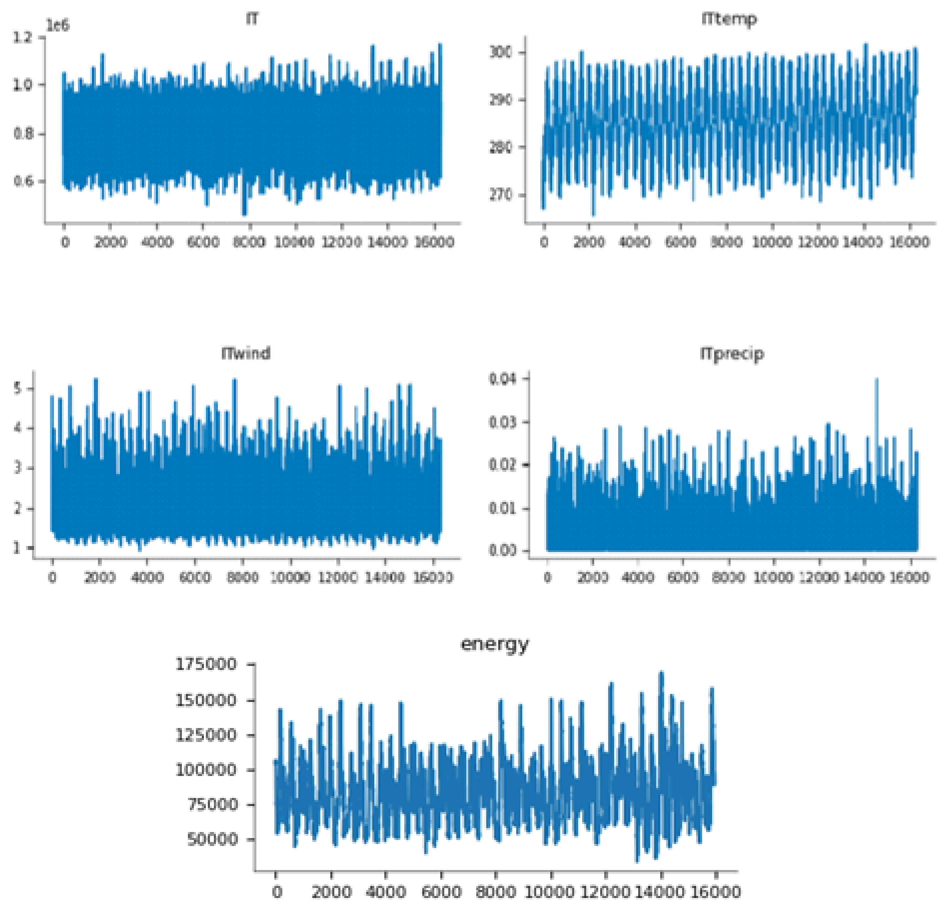

Figure B.14 — Time series values of energy demand (IT, MWh), air temperature (ITtemp, K) total daily averaged daily wind speed (ITwind, m/sec), precipitation (ITprecip, mm), and Hydro Energy Production (energy, MWh).

B.4.2.2. Data Preprocessing

- **Cleaning Data:**

Ensure there are no gaps in the data. Impute missing values using techniques suited for time series, like forward-fill or backward-fill. Remove any outliers or incorrect readings.

- **Feature Engineering:**

Create new features, if necessary. For example, calculate moving averages or rolling standard deviations that might provide additional insights.

- **Normalization/Standardization:**

Since LSTMs are sensitive to scale, each feature should be scaled. Min-max scaling (normalization) or z-score normalization (standardization) are commonly used methods.

- **Sequence Creation:**

Transform the time series data into a supervised learning format. Decide on a window size (e.g., use the past seven days' data to predict the next day's demand). This window slides through the dataset, creating input-output pairs.

```
def create_lagged_features(df, lag_days, target_col='IT'):
    df_lagged = df.copy()  # Start with a copy of the original DataFrame to keep non-lagged values
    for col in df.columns:
        if col != target_col:  # Avoid lagging the target column multiple times
            for day in lag_days:
                df_lagged[col + "_lag" + str(day)] = df[col].shift(day)
    df_lagged = df_lagged.dropna()
    return df_lagged

lag_days = [1, 2, 3, 4, 5, 6, 7]
df_lagged = create_lagged_features(merged_df[['IT', 'ITtemp', 'ITprecip', 'ITwind', 'ITirrad','Month','Day','Day_of_Week', 'Is_Holiday']], lag_days)
```

```
#normalise
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0, 1))
df_scaled = scaler.fit_transform(df_lagged)
correct_order = df_lagged.columns.tolist()

X = df_scaled[:, 1:]  # Features
y = df_scaled[:, 0]   # Target: 'IT'
```

Figure B.15 — Script for the data preprocessing

B.4.2.3. Model Building

- **Architecture Design:**

Design the LSTM model's architecture. A typical design is as follows.

- **Input layer:** Shape based on the number of steps (days) in the input and number of features.
- **LSTM layers:** Start with one layer and consider adding more based on complexity.
- **Dense (or fully connected) layer:** For producing the final output.
- **Hyperparameter Tuning:** Several hyperparameters require careful consideration:
- **Number of Neurons:** Start with a modest number (like 50) and adjust based on results.
- **Number of Layers:** More layers can capture more complexity but risk overfitting.
- **Dropout Rate:** Helps the network avoid overfitting.
- **Learning Rate:** Influences the speed and stability of learning

```python
from keras.models import Sequential
from keras.layers import LSTM, Dense

# Reshape input to be 3D [samples, timesteps, features]
X = X.reshape(X.shape[0], 1, X.shape[1])

model = Sequential()
model.add(LSTM(50, input_shape=(X.shape[1], X.shape[2])))
model.add(Dense(1))
model.compile(loss='mae', optimizer='adam', metrics=['mean_squared_error'])
```

Figure B.16 — Script for building the LSTM neural network model

```python
class Config:
    input_size: int = 288
    horizon_size: int = 30
    dataset_files: Tuple[List[Path], str] = [
        (Path("data/energy.csv"), "energy"),
        (Path("data/power.csv"), "power"),
        (Path("data/temp.csv"), "temp"),
        (Path("data/precip.csv"), "precip"),
        (Path("data/wind.csv"), "wind"),
        (Path("data/irradiance.csv"), "irradiance"),
    ]
    dataset_path: Path = Path("dataset.csv")
    target: str = "energy"
    known_covariates: List[str] = ["Month", "Day_of_Week", "Day", "precip", "wind", "temp", "irradiance"]
    n_features: int = 9
    data_overlap: int = -1
    batch_size: int = 128
    epochs: int = 50
    learning_rate: float = 1e-3
    lr_warmup: float = 0.1
    iterative: bool = True
    # Model settings
    known_covariates_embedding_size: int = 8
    hindcast_hidden_size: int = 32
    handoff_hidden_size: int = 48
    # ==== DO NOT EDIT BELOW THIS LINE ====
    # Runtime configs
    data_mean: float = 1
    data_std: float = 1
    data_target_column: int = 0
```

Figure B.17 — Script for building the SaShiMi neural network model

B.4.2.4. Training

The training involved feeding the model historical data and adjusting data weights based on prediction errors. The data were in a training set (used to adjust weights) and a validation set (used to gauge model performance during training).

```python
history = model.fit(X, y, epochs=50, batch_size=72, validation_split=0.2, verbose=2, shuffle=False)
```

Figure B.18 — Script for training the LSTM neural network model

B.4.2.5. Evaluation

Measure the model's accuracy using metrics like Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and Root Mean Squared Error (RMSE).

Compare the LSTM and SaShiMI models' predictions to actual energy demand values on a validation dataset.

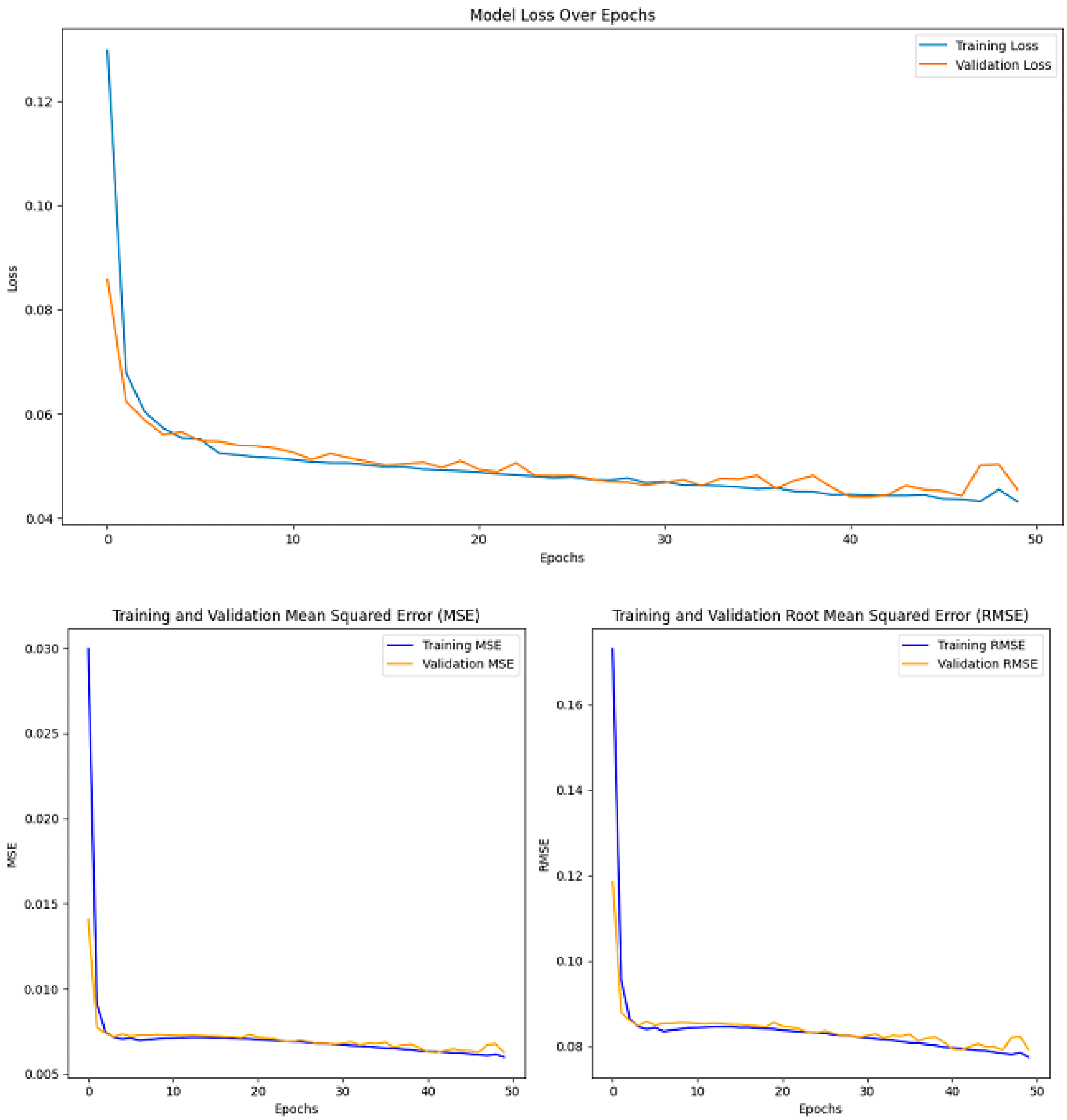

Figure B.19 — Outputs LSTM neural network model's training progress

After training, the model was used to predict values in the validation set, and these predictions were compared to the actual values.

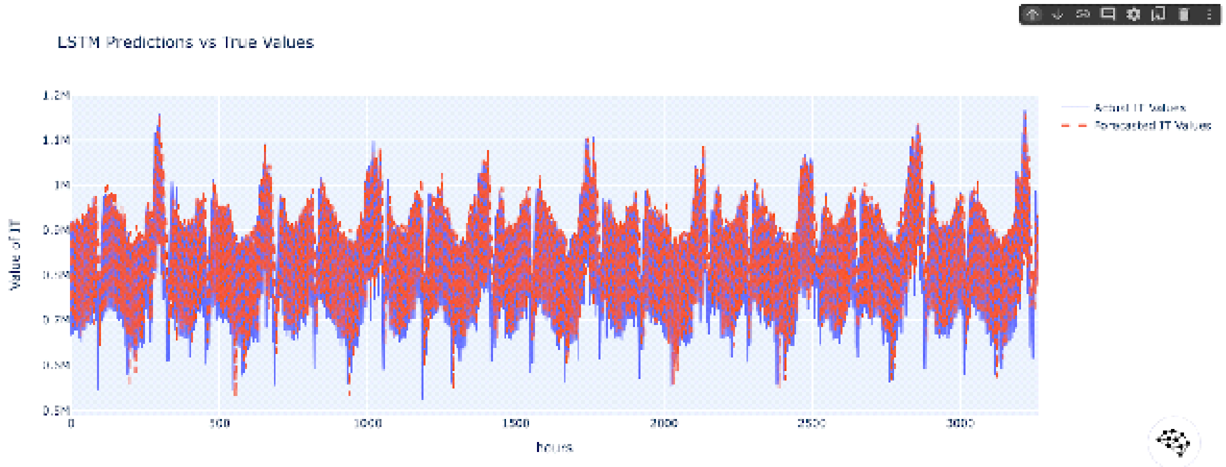

Figure B.20 — Model's actual versus predicted values

The Error Metrics for validation data associated with Italy were:

- LSTM model – Energy Demand
  - RMSE: 53 915.27 MWh
  - MAE: 30 682.07 MWh
  - MAPE: 3.96%

- SaShiMI model Energy Demand
  - RMSE: 36297 MWh
  - MAE: 17403 MWh

- SaShiMI model Hydro Power Production
  - RMSE: 50289 MWh
  - MAE: 38081 MWh

B.4.3. Deployment

After model validation, the model was then prepared for production.

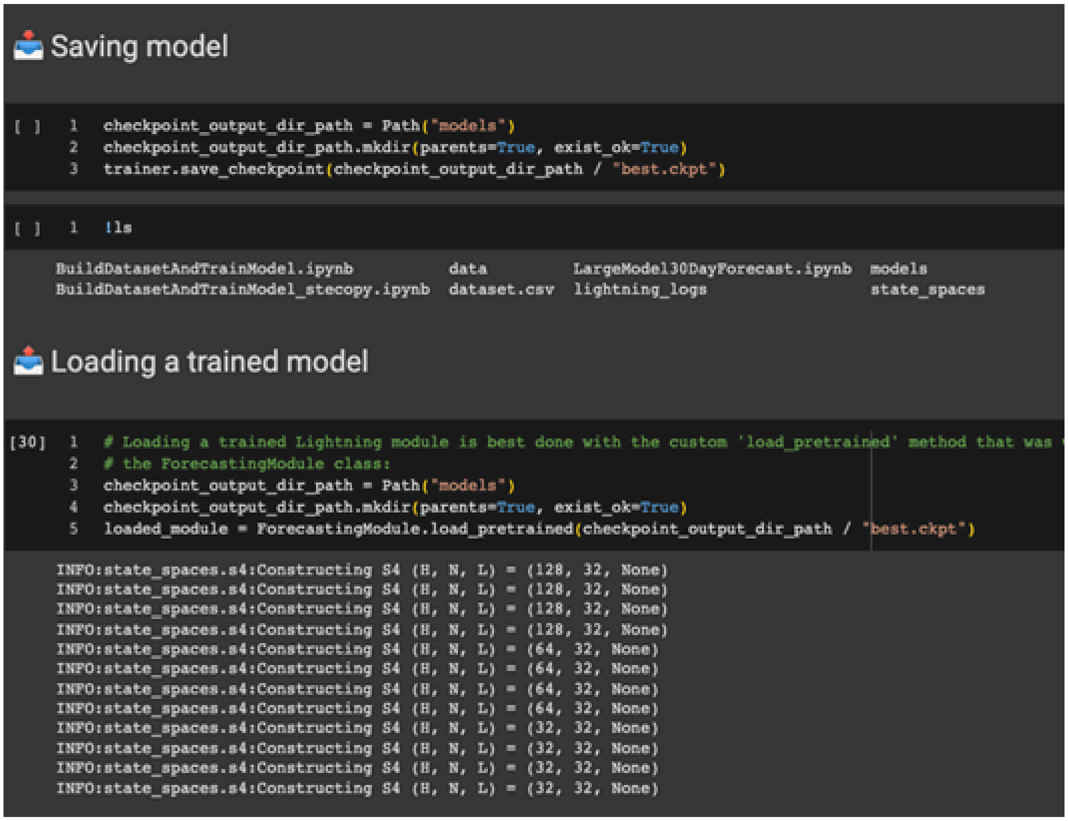

Figure B.21 — Script for running the LSTM neural network model in batch forecasting mode

B.4.3.1. Batch Long Term Forecasting:

If predictions are needed for planning, the model can be run in batches (e.g., once a month for the entire next month).

The figures B.22 and B.23 show the reported Energy Demand Forecast and Hydropower energy production for the upcoming 30 days in the validation period.

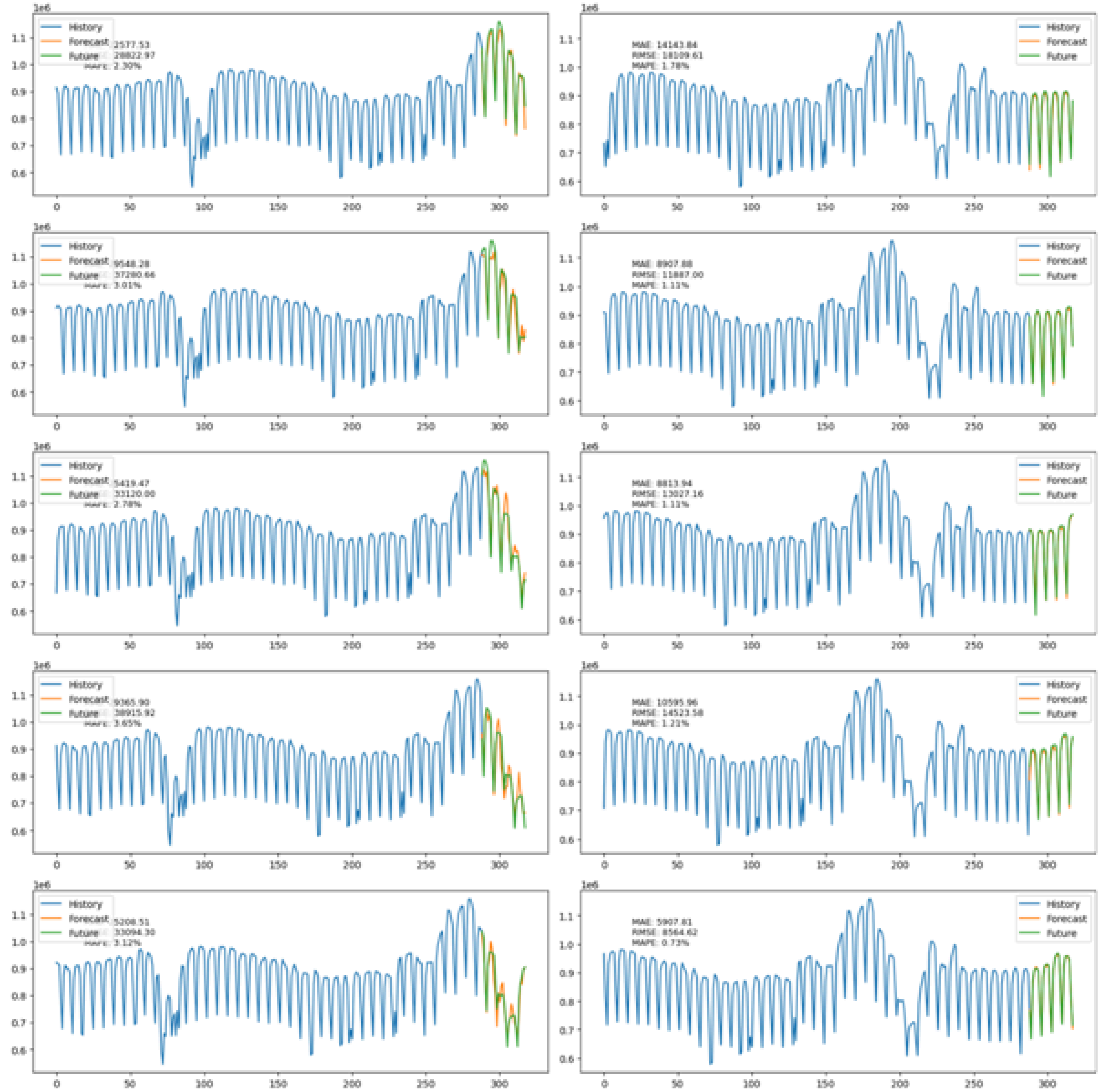

Figure B.22 — Energy Demand Batch Forecasting Mode for next 30 days computed in the validation dataset – SaShiMi model

Figure B.23 — Hydro Power River Batch Forecasting Mode for next 30 days computed in the validation dataset – SaShiMi model

The figure below presents an Energy Demand Forecast for the upcoming 30 days, dated 2023-08-31. This forecast leverages the following datasets:

- energy demand historical data for Italy spanning the previous 288 days;
- climate covariate (temp, precip, wind, irradiance) data derived from ERA5 re-analysis for the same 288-day period; and
- climate covariate Projections from the Copernicus Climate Scenario RCP2.5, specifically generated for the next 30 days.

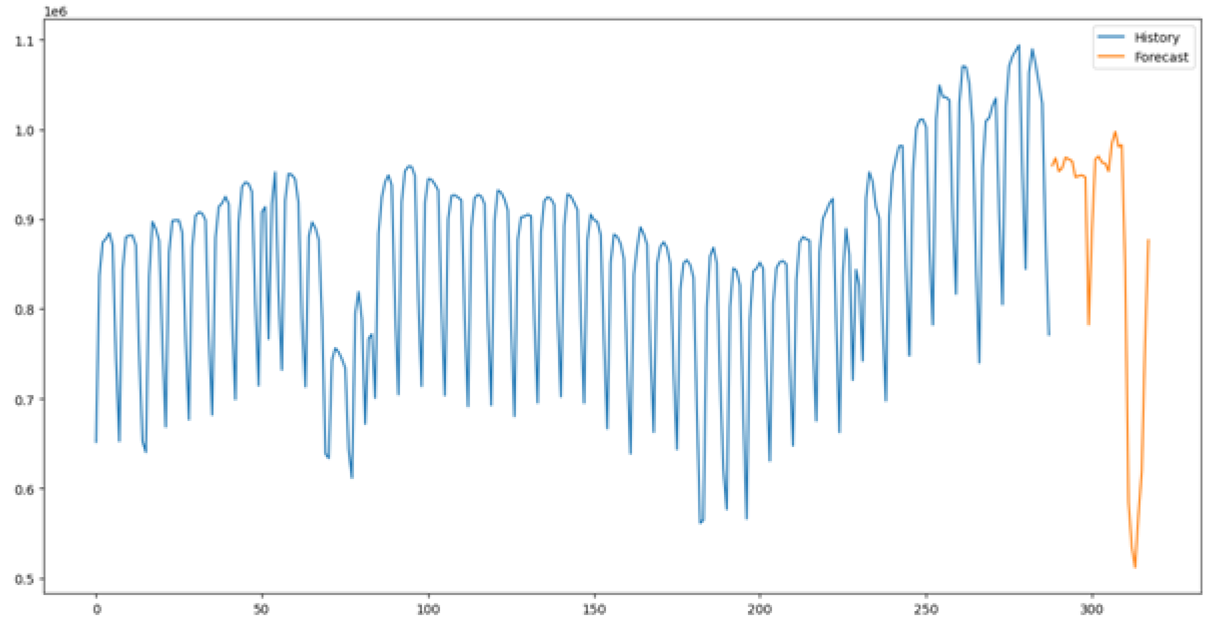

Figure B.24 — Energy Demand Batch Forecasting Mode
for next 30 days from 2023-08-31 – SaShiMi model

B.4.3.2. Real-time Short-term Forecasting:

For immediate decisions, set up the model to provide predictions in real-time, processing the most recent data on-demand. This prediction is purely based on recursive values of the target variable (energy demand).

```
n_forecast = 50 # e.g., forecast the next week
input_seq = X[-1:] # take the last sequence in your dataset as a
starting point
import numpy as np
forecasts = []

for i in range(n_forecast):
prediction = model.predict(input_seq)
forecasts.append(prediction[0][0])

# Prepare the next sequence
next_seq = input_seq[0][0][1:] # drop the first value in the sequence
next_seq = np.append(next_seq, prediction) # append the predicted value
input_seq = next_seq.reshape(1, 1, len(next_seq))
```

Figure B.25 — Script for running the LSTM neural network model in real time forecasting mode

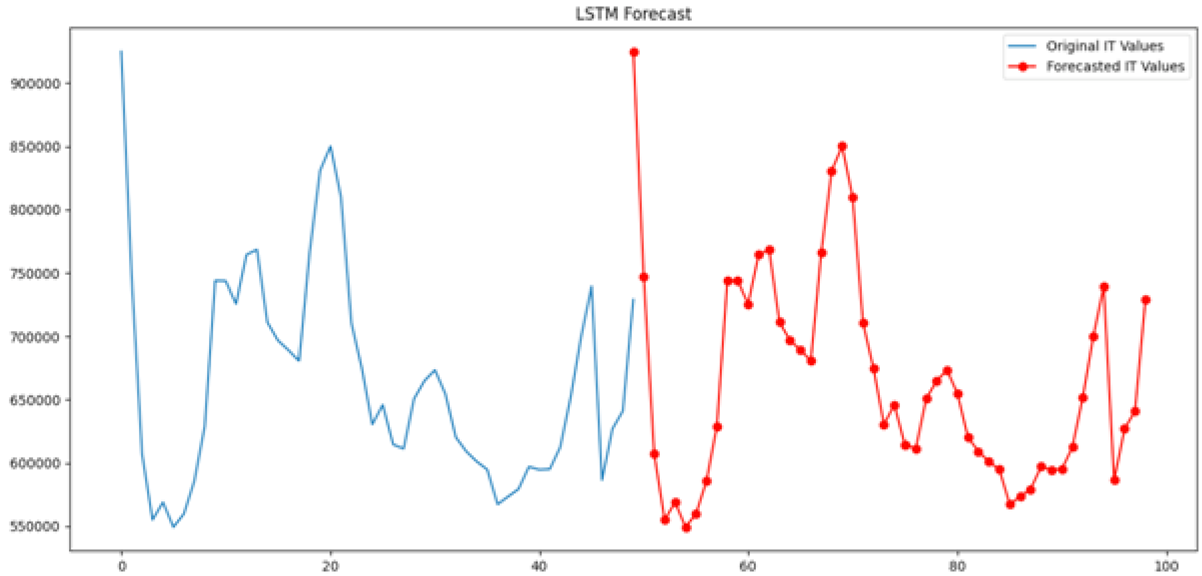

Figure B.26 — LSTM Neural Network model running in real time forecasting mode

Once satisfactory model performance was achieved, the approach can be set up for real-time forecasting. This can involve hosting on a cloud server, developing an API, or integrating it within an existing system.

Usage

For real-time predictions:

- provide the model with recent data for all features; and
- the model returns a forecast for energy demand for the future time frame.

```
n_days = 50 # or any other value
predicted_IT_values = forecast_next_n_days(future_data, n_days, model,
scaler)
```

Figure B.27 — Script to return a forecast for energy demand for the future time frame

Maintenance and Updates

- Retraining: Energy consumption patterns evolve. Periodically update the model with new data.
- Monitoring: Regularly track model performance. If accuracy drops, consider retraining or adjustments.

B.4.3.3. Dockerization of the Model

After training and validating LSTM/SaShiMi models, it is often essential to deploy the model to make predictions in real-time or batch mode in a production environment. One way to ensure consistent runtime environments from development to production is to use Docker. Docker creates a containerized version of the application, ensuring the application runs the same, regardless of where the Docker container is run.

B.4.3.4. Summary

Incorporating multiple climate features into the LSTM/SaShiMi models enhances the ability to forecast energy demand accurately. Combining energy consumption history with influential factors like weather and power generation offers a holistic view, leading to better predictive performance.

LSTM Neural Network models, with the capability to process sequences and consider multiple features, are potent tools for forecasting tasks like country-level energy demand. A systematic approach to data handling and model evaluation is vital for obtaining reliable forecasts.

This section reflects the incorporation of multiple features into the LSTM/SaShiMi models for forecasting energy demand. Depending on the granularity of the data and deployment complexities, further refinements might be needed.

B.4.4. Benefits

The benefits of, and decisions supported by, the Energy Climate Indicators are as follows.

- **Proactive Resource Allocation**:

Predictive insights on energy production allow emergency planners to understand potential shortfalls or blackouts during disaster events, enabling the allocation of resources like generators to critical areas in advance.

- **Critical Infrastructure Planning**:

Knowing potential energy constraints helps in designing and strengthening critical infrastructure, like hospitals or evacuation centers, to withstand energy shortages during emergencies.

- **Integration with Other Emergency Systems**:

Energy forecasts can be integrated into broader emergency response systems to provide comprehensive situational awareness, making it easier to coordinate responses.

- **Assisting Recovery Efforts**:

After a disaster event, restoring power is one of the primary recovery efforts. Having accurate forecasts can guide these efforts, prioritizing areas based on their future energy production and needs.

- **Data-Driven Decision Makin**g:

Real-time and forecasted energy data equip decision-makers with actionable insights, enabling informed decision making that can save lives and resources during emergencies.

B.5. Drought Health Risk Indicator Developed by HSR Health

B.5.1. Introduction

Drought affects thousands of people every year in the United States and Canada and is a longer-term natural disaster compared to wildland fires, hurricanes, or tornadoes. As a result of its long-term nature, there is a broad and multi-faceted impact on the populations suffering from drought. It is important to understand where vulnerable populations are in drought areas to provide ongoing information to governments, local communities, and response personnel that can aid in relief and response efforts.

HSR.health produced a health risk index that identified the vulnerable populations by combining population characteristics with health conditions and overlaying vulnerable populations with drought severity indicators.

The Drought Health Risk Index was being produced for the province of Manitoba, Canada.

B.5.2. Indicator Recipe

The components of the Drought Health Risk Index are as follows.

- **Input data**

The primary input datasets for the Drought Health Risk Index are demographic data, health condition data and data on drought severity. The data sources for this are: **demographic data and population characteristics from the Canadian Census Bureau;** underlying Health Conditions from the Canadian Chronic Disease Surveillance System; and ** drought Severity from the North American Drought Monitor.

- The aim was also to include input data from other DP23 participants as this became available, in particular:
  - Drought Severity Indicators from UN University, Pixalytics and Safe Software; and

- Mobile Crowdsourced data from GISMO-Basil Labs collected via the ELLA tool.

  - **Processing & Transformation**

    The current Drought Health Risk Index identifies the direct risk to the population from the drought itself for the at-risk populations across drought affected areas. Figure B.28 shows the overall workflow used to create and distribute the Drought Health Risk Index:

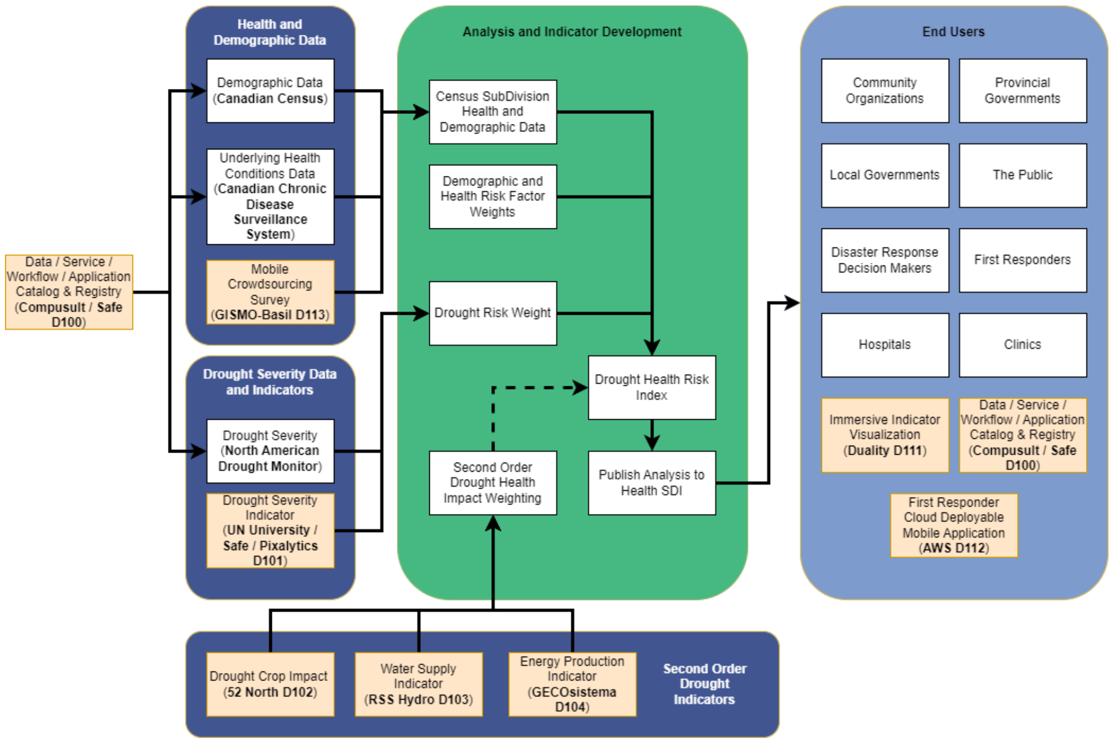

Figure B.28 — Drought health risk index collaborations & workflow

The highlighted cells show components where collaboration with other DP23 participants have, or were planned, to take place.

The primary data inputs for the Drought Health Risk Index are demographic data, health condition data, and data on drought severity and risk. The demographic data come from the Canadian Census Bureau, the health condition data come from the Canadian Chronic Disease Surveillance System, and the initial drought severity data come from the North American Drought Monitor. The target granularity for the Risk Index is the census subdivision administrative level for the province of Manitoba, Canada.

The Drought Health Risk Index calculation is a combination of two primary components: the health vulnerability of the underlying population and the drought severity. The population vulnerability risk is a combination of health and demographic factors through a combined risk weighting analysis that provides a-priori information on where vulnerable and at-risk populations are. Some of the factors informing the vulnerability risk include: Age, Disability Status, Transportation Access, Fluency, Low Income, Housing Cost Burden, Single Parent Households, Pregnant/Breast Feeding Women, COPD, Cancer, Chronic Kidney

Disease, Asthma, and more. The weightings for each factor were determined through input from the public health team, published research, and analysis. The population vulnerability risk is combined with the drought risk weight which is based on drought severity.

- **Output Data** — The Health Risk Index and associated data are published to HSR.health's GeoMD Platform as well as other spatial data infrastructures and data catalogs as made available through DP23, and made available through OGC API, WMS, and WFS to be shared with stakeholders and participants.

  Additionally, HRS.health demonstrated and explored continuing interoperability between multiple catalog systems and, to ensure it was possible to ingest and share data and analytical outputs across multiple entities, both pilot participants and stakeholders.

- **Technical standards or infrastructure requirements**

Interoperability was at the core of this development, and HSR.health ensured the work in DP23 focused on exploring and demonstrating interoperability for inputs, outputs, and analytics.

+ It is also hoped this work will continue to expand the development of the Health Spatial Data Infrastructure (SDI) including the addition of an OGC API endpoint for access to the data available through the health (SDI) to move towards a Health Data Retrieval API.

B.5.3. Benefits

- **Who does this help?**

The aim is to inform governmental organizations, disaster response personnel and decision makers, Community and Aid Organizations, medical personal, local residents, and the public of the health and social conditions on the ground to aid in response and relief efforts in drought affected areas.

+ Health-impacts of drought can include and are not limited to Food Insecurity, Water Insecurity, Decrease in Air Quality, Heat Stress, Increase in Infectious Disease Risk, and Reduced Access to Electricity from Hydro-Power Sources.

- *What decisions are supported by this indicator/tool?
- End Users and stakeholders can utilize the data and analysis presented to understand where vulnerable populations are, and how to create policies and relief plans to alleviate the impact of the drought on these populations.
- **Details of job roles that would use this data?**

The job roles that might use this information include a DRI Analyst and a DRI Decision Maker.

B.5.4. Collaborations

HSR.health collaborated with UN University, Pixalytics, Safe, and GISMO-Basil Labs regarding data inputs for the workflow. HSR.health also collaborated with AWS and Duality who ingest the output from the risk index. Finally, collaboration with Compusult and Safe to explore and demonstrate interoperability between the DP23 data catalogs and the Health SDI.

The Index can be expanded to incorporate second and third order health impacts from ongoing drought conditions through the inclusion of indicators produced in this pilot by fellow pilot participants including the following.

- Drought Crop Impact by 52 North
- Water Supply Indicator by RSS Hydro
- Energy Production Indicator by GECOsistema

Details of Persistent demonstrators

HSR.health's goal of participation in DP23 was to provide visibility into persistent demonstrators of health information in the disaster response ecosystem. The persistent demonstrators are available at: https://opengeomd.hsrhealthanalytics.org/#/

B.6. Direct and Indirect Health Impact Indicators of Drought Developed by IIT Bombay.

B.6.1. Introduction

Drought was documented to be a major disaster around the world, and especially in India. While the longer-term aspects of drought naturally overlap with other factors of human society including economic development and institutional support, it has major direct impacts that manifest through SDG indicators as well as multiple public health and governance related indicators.

B.6.2. Indicator Recipe

The components of the direct and indirect health impact indicators of drought are as follows.

- **Input data**

The primary input datasets for the Drought Health Risk Index are demographic data, health condition data, and data on drought severity. The data sources for this are:

- demographic data and population characteristics from several census datasets (as time series);
- National Health Survey datasets (publicly sourced); and
- secondary datasets sourced from summaries of reported Public Health Centers (PHCs).
  - **Processing & Transformation**

The Drought Health Risk Index identifies the direct risk to the population from the drought itself for the at-risk populations across drought affected areas. The data sources and transformations are listed in Figure B.29.

↓Transformations\Data →	Census	NHS Data	PHC Data	NSSO	Secondary Data
Spatial aggregation	✓	✓	✓	✓	✓
Spatial interpolation	✓	✓	✓	✓	✓
Temporal aggregation	✓	✓	×	×	×
Temporal interpolation	✓	×	×	×	✓
Change modeling	✓	×	×	✓	×

Figure B.29 — Data sources & transformations for the indicator

Furthermore, Figure B.30 shows the overall workflow for creation of the indicators at aggregated and individual levels and it is perceived that indicator data for health impact, especially for indirect effects, will need aggregation at spatial and temporal levels to understand the slow development of drought conditions as well as the longer time scale of the disaster. The availability of spatio-temporal aggregation as a part of the processing chain is also shown in the figure.

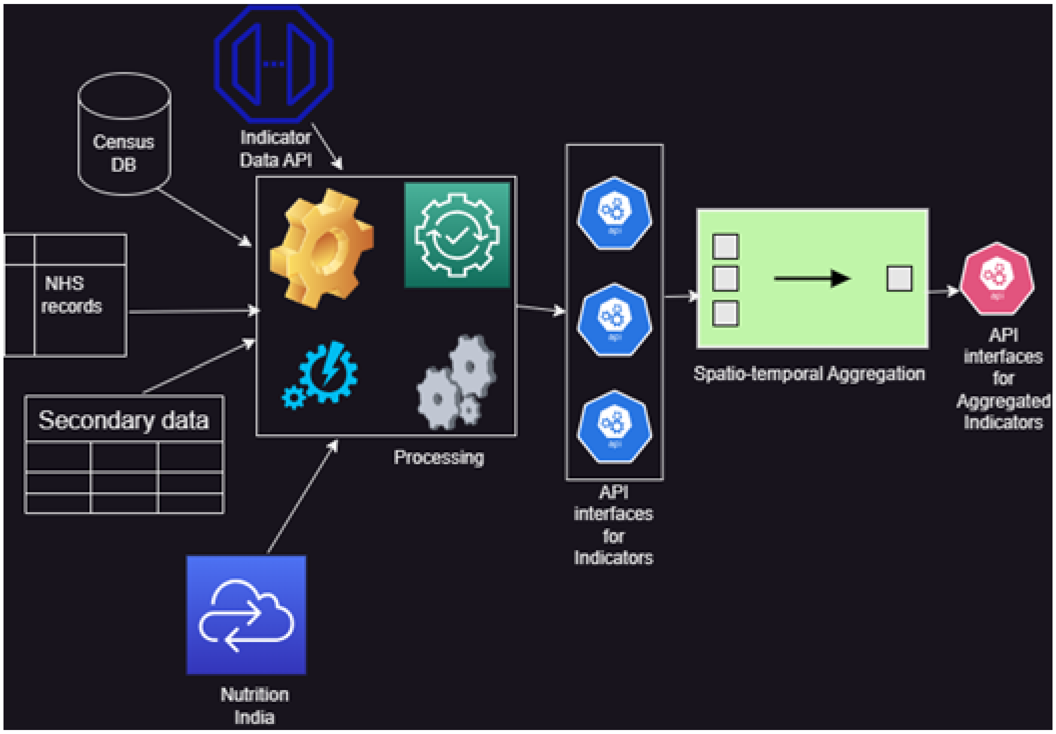

Figure B.30 — Dataflow and API interfaces for health impact indicators and spatio-temporal aggregation

- **Output data**

An example of the type of dashboard that can be produced, is similar to the one currently used for the health and nutrition data for all districts of India in collaboration with the Ministry of health and family welfare, Government of India.

B.6.3. Benefits

These indicators are important at all levels for public health practitioners and also help aid agencies aiming to build resilience in communities in different scenarios especially in regions that rely exclusively on local resources of food, water, and economic gains. Furthermore, this helps medical practitioners, hospitals, and healthcare centers working with communities that face increased vulnerability to droughts in understanding and providing long-term health remedies.

The main objective of these indicators is in the context of understanding evolving health impact scenarios of drought affected communities and supporting decision making on the provisioning of resources for resilience efforts.

Local, state, and national agencies engaged in creating climate resilient infrastructures, especially in the context of climate induced disasters, will be the main users and thus public health managers and administrators will be the job roles that would use this data.

B.6.4. Collaborations

Drought health impacts are usually linked to climatic indicators of drought such as Standardized Palmer Drought Index (SPDI), Standardized Precipitation Evapotranspiration Index (SPEI), Palmer Drought Severity Index (PDSI), and so on, in a complicated chain of lag variables that explain the temporal connection of “meteorological drought” to “socio-economic drought.”

IITB aimed to leverage the possibility of data sharing through open standards to develop spatio-temporal prediction algorithms, especially through global drought indicators. In particular the aim was to leverage the following two DP23 activities.

- Drought Crop Impact by 52 North
- Water Supply Indicator by RSS Hydro

C

ANNEX C (NORMATIVE) WILDLAND FIRE WORKFLOWS/CAPABILITIES DEVELOPED

ANNEX C (NORMATIVE) WILDLAND FIRE WORKFLOWS/CAPABILITIES DEVELOPED

Wildland fires are fast-moving disaster situations, and 2023 saw significant wildfires across various states in the USA, Canada, and Europe: the 2023 Canadian Wildfire season was the worst on record, and a wildfire in Greece in the summer was the largest ever recorded in the European Union.

Forest fires are becoming more widespread with climate change causing hotter and drier conditions, meaning the area burnt and the intensity are both increasing. The United Nations Environment Report indicates that extreme wildfires could increase by 50% by the end of this century. These fires need fuel, which is often increased through drought where vegetation is bone dry. When the fires start, rapid evacuations are often necessary.

The workflows developed by the Disaster Pilot 23 (DP23) participants to provide specific information regarding the impact of, and potential impact of, wildland fires are as follows.

- Annex C.1 Wildland Fire Fuel Indicator developed by Ecere
- Annex C.2 Wildland Fire Ignition Risk Indicator developed by Compusult
- Annex C.3 Wildland Fire Evacuation Indicator developed by Skymantics
- Annex C.4 Wildland Fire Health Impact Indicator developed by HSR.health
- Annex C.5 Wildland Fire Immersive Indicator Visualizations developed by Duality

The detailed technical information about each of these workflows can be seen below:

C.1. Wildland Fire Fuel Indicator Developed by Ecere

C.1.1. Introduction

As changes in climate can exacerbate the risk of wildfire ignition, understanding the factors that form a catalyst can empower emergency responders and policymakers with knowledge of how to better manage these factors. Vegetation fuel type is one such predictive factor on the basis that certain types of vegetation may spread fire more intensely than others. Using imagery and prediction modeling, it is possible to create classified images that illustrate risk, and allows policy makers to prepare for wildfires.

C.1.2. Description

Ecere developed a Wildland Fire Fuel Indicator workflow that generates vegetation fuel type classification using Machine Learning training and prediction, which signifies the type of vegetation organized such that each type contributes to the spread and intensity of fire in particular ways.

This indicator workflow is available at:

https://maps.gnosis.earth/ogcapi/collections/wildfire:S2VegetationFuelTypes

C.1.3. Indicator Recipe

C.1.3.1. Input data

The indicator takes as an input ESA Sentinel-2 Level 2A data (including atmospheric correction), see Figure C.1.

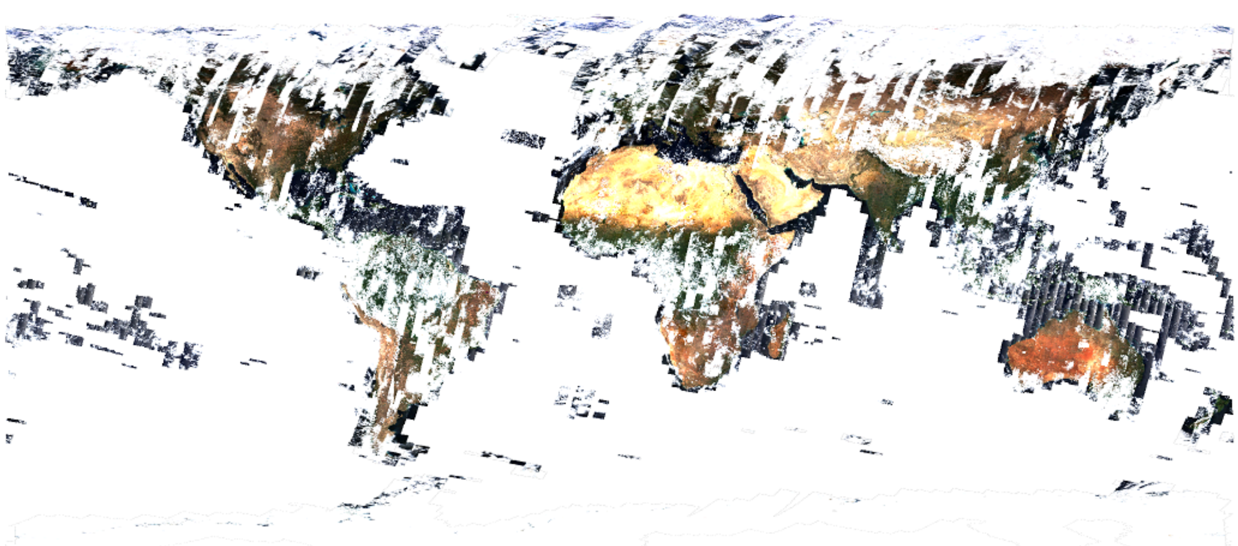

Figure C.1 — ESA sentinel-2 data from AWS open dataset managed by Element 84

For the purpose of training the Machine Learning (ML) classification model, the https://www.landfire.gov/version_download.php [US Fuel Vegetation Types of 2022] produced by the U.S. Department of Agriculture Forest Service and U.S. Department of the Interior on the www.landfire.gov website, were used. See Figure C.2.

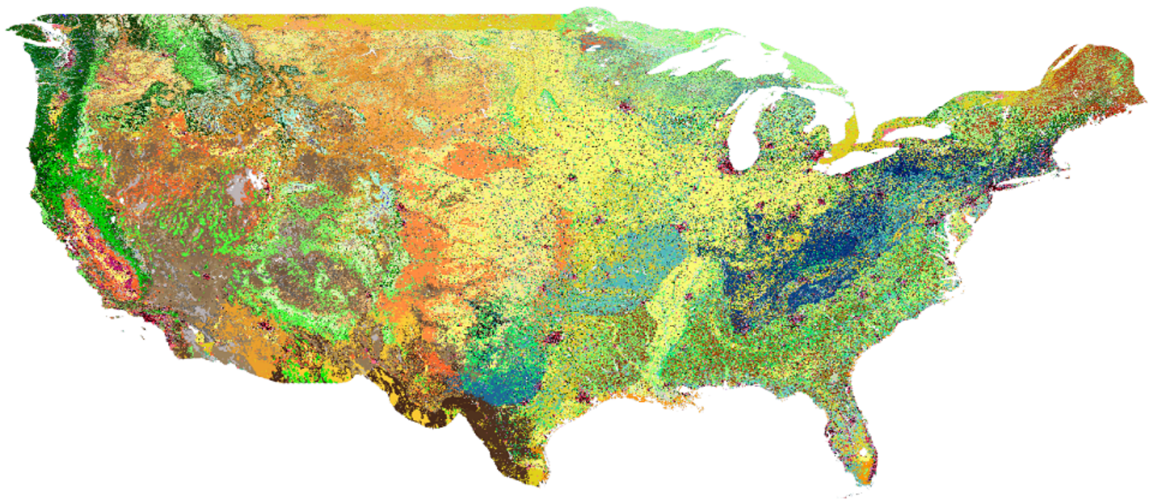

Figure C.2 — Fuel Vegetation Types for continental United States (from landfire.gov)

C.1.3.2. Processing and transformation

The wildland fire fuel indicator workflow classifies Sentinel-2 Level 2A source imagery into high level types of vegetation, which can then optionally be mapped to a fuel density through an additional step.

This prediction is performed with a RandomForest classifier using the Scikit-learn Python library. The RandomForest model is trained using the US Vegetation Fuel Types. For example, see Figure C.3 and Figure C.4.

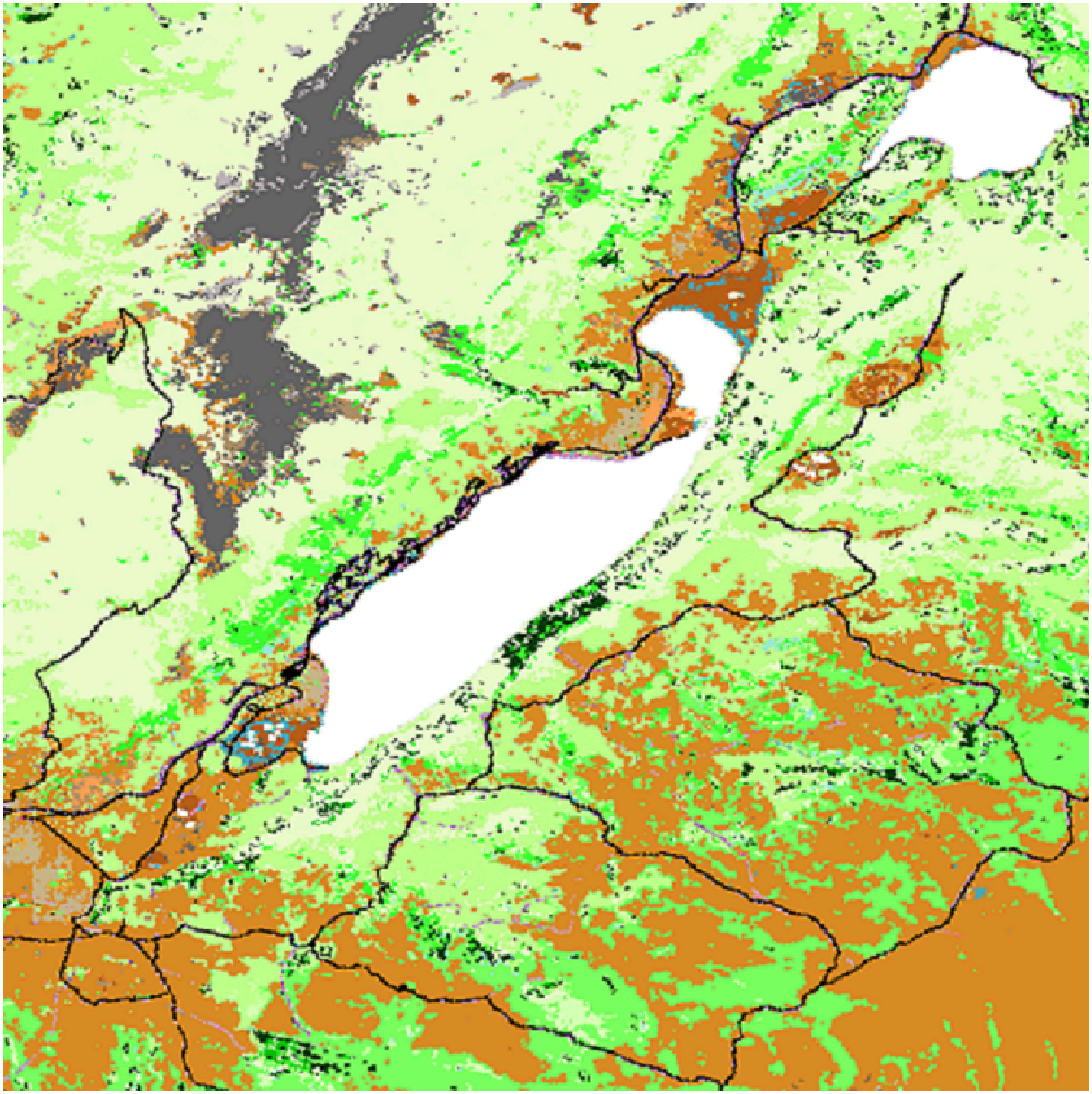

Figure C.3 — Fuel Vegetation Types (from landfire.gov) for Fish Lake area

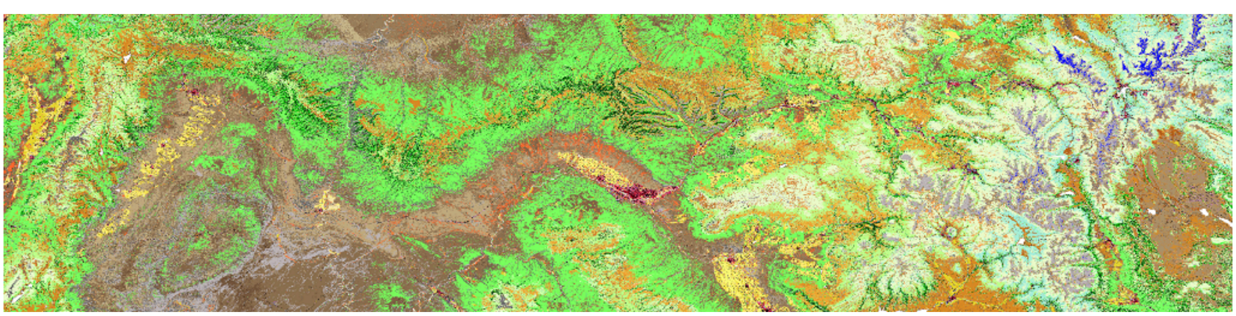

Figure C.4 — Fuel Vegetation Types (from landfire.gov) of full training area for Fish Lake (2022)

Since this dataset has a very large number of vegetation types that would be difficult to map to a fuel density and would also either require very large and complex classification trees or yield poor results, these numerous types are first mapped to ten high level vegetation types.

These high level vegetation types are shown in Table C.1, together with the fuel density percentage to which the vegetation types were mapped (for the sake of demonstration, and not intended to be sound or valid for any practical purpose). The hexadecimal string for the color with which both the types and density were represented in rendered styled maps is also included in this table.

The remapping of the US Fuel Vegetation Types from landfire.gov to high level vegetation types was accomplished using the *PassThrough* process also available on the GNOSIS Map Server end-point, providing an opportunity to use the "input fields modifiers" requirements class of *OGC API — Processes — Part 3*, using US Fuel Vegetation Types as the source collection. Example of the output are shown in Figure C.5, Figure C.6 and Figure C.7.

Table C.1 — High level vegetation types and density mapping

CLASS ID	COLOR	HIGH LEVEL FUEL VEGETATION TYPE	FUEL DENSITY	DENSITY COLOR
11	#0000FF	Open Water	0%	(transparent)
12	#9FA1F0	Snow/Ice	0%	(transparent)
20	#343434	Urban	70%	#FFB200
31	#BFBFBF	Barren	5%	#F0E68C
80	#FFD277	Agriculture	60%	#FFD700
2001	#646464	Sparsely Vegetated Systems	30%	#6b8E23
2008	#CBFFAB	Trees	100%	#FF0000
2064	#CCB687	Shrubs	80%	#FF8C00
2122	#FFCC33	Grassland	40%	#808000
2908	#403DA8	Developed area	60%	#FFD700

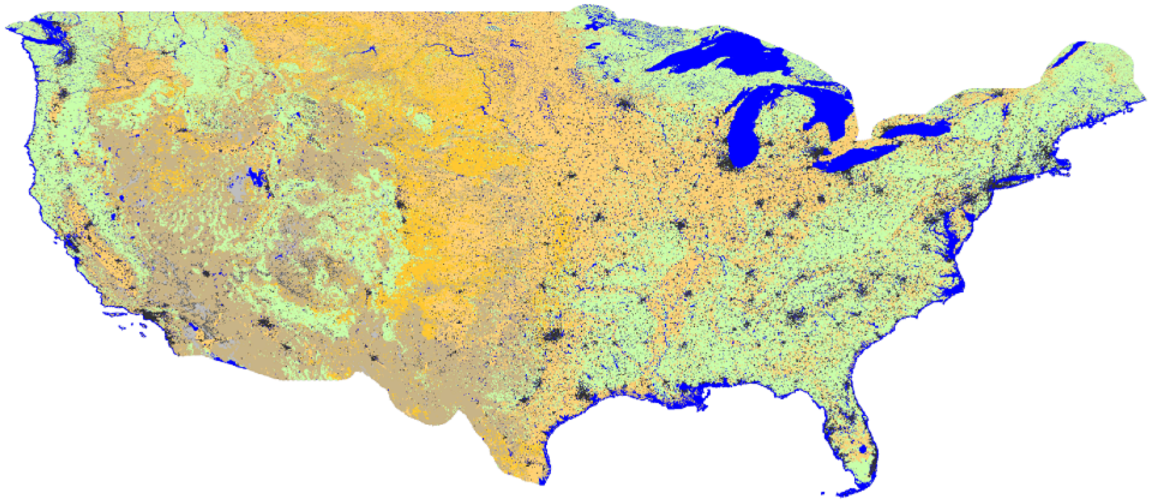

Figure C.5 — Remapped High Level Fuel Vegetation Types for continental United States

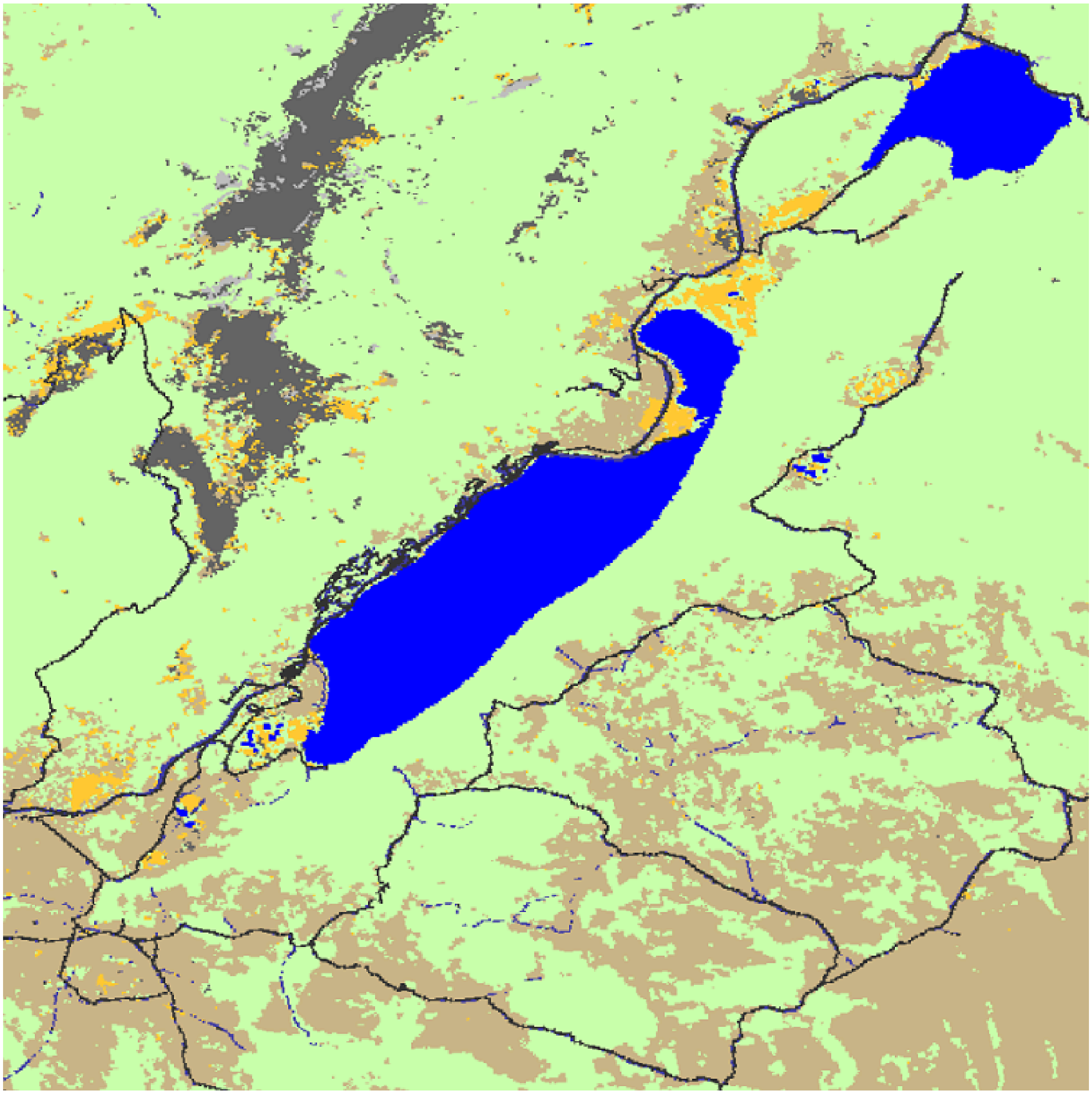

Figure C.6 — Remapped High Level Fuel Vegetation Types for Fish Lake area (2022)

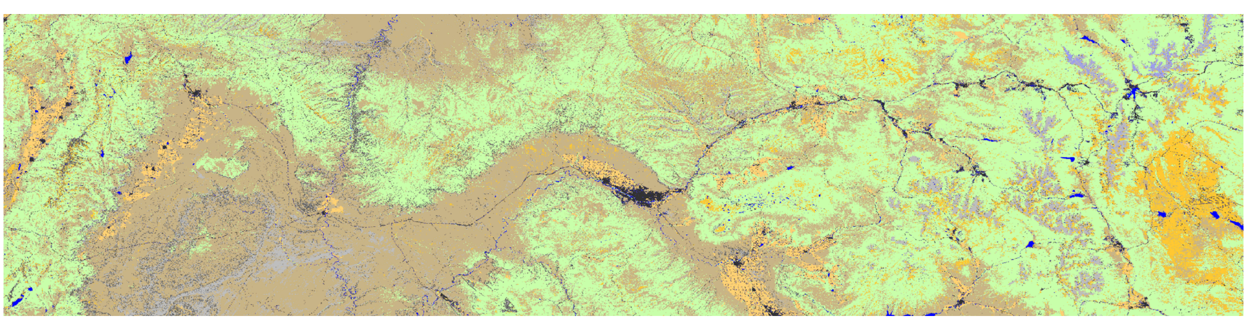

Figure C.7 — Remapped High Level Fuel Vegetation
Types of full training area for Fish Lake (2022)

The training was undertaken using all bands available from the AWS open-data Sentinel-2 dataset, for three separate seasons in 2022: spring (May 15-25), summer (July 15-25), and autumn (September 15-25). Examples are shown in Figure C.8 and Figure C.9.

Figure C.8 — Sentinel-2 Imagery of Fish Lake (September 15-25, 2022)

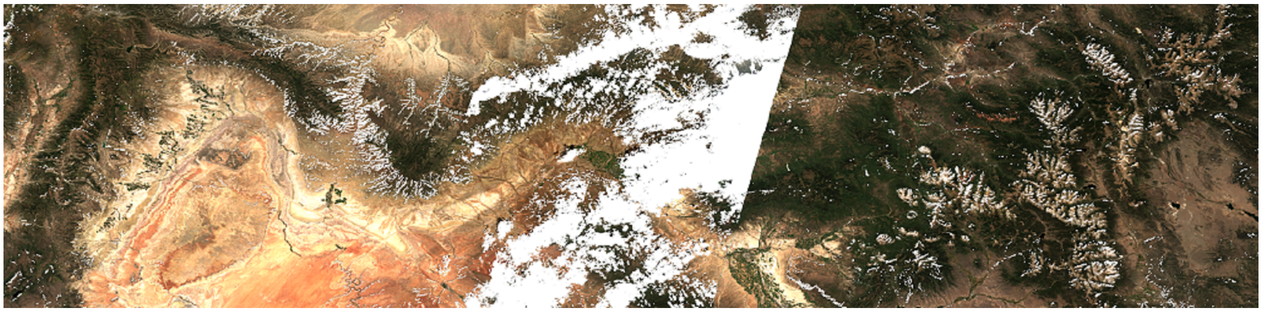

Figure C.9 — Sentinel-2 Imagery of training area for Fish Lake (September 15-25, 2022)

A filter was first applied to the Sentinel-2 Scene Classification Layer (SCL) band to eliminate clouds (medium and high probability, cirrus, cloud shadows), as well as no data, saturated/ defective, and dark area, using the OGC Common Query Language (CQL2) filtering expression:

```
(SCL >=4 and SCL <= 7) or SCL=11
```

Listing C.1

This SCL band, shown in Figure C.10 and Figure C.11, is also used as an input to the training and prediction.

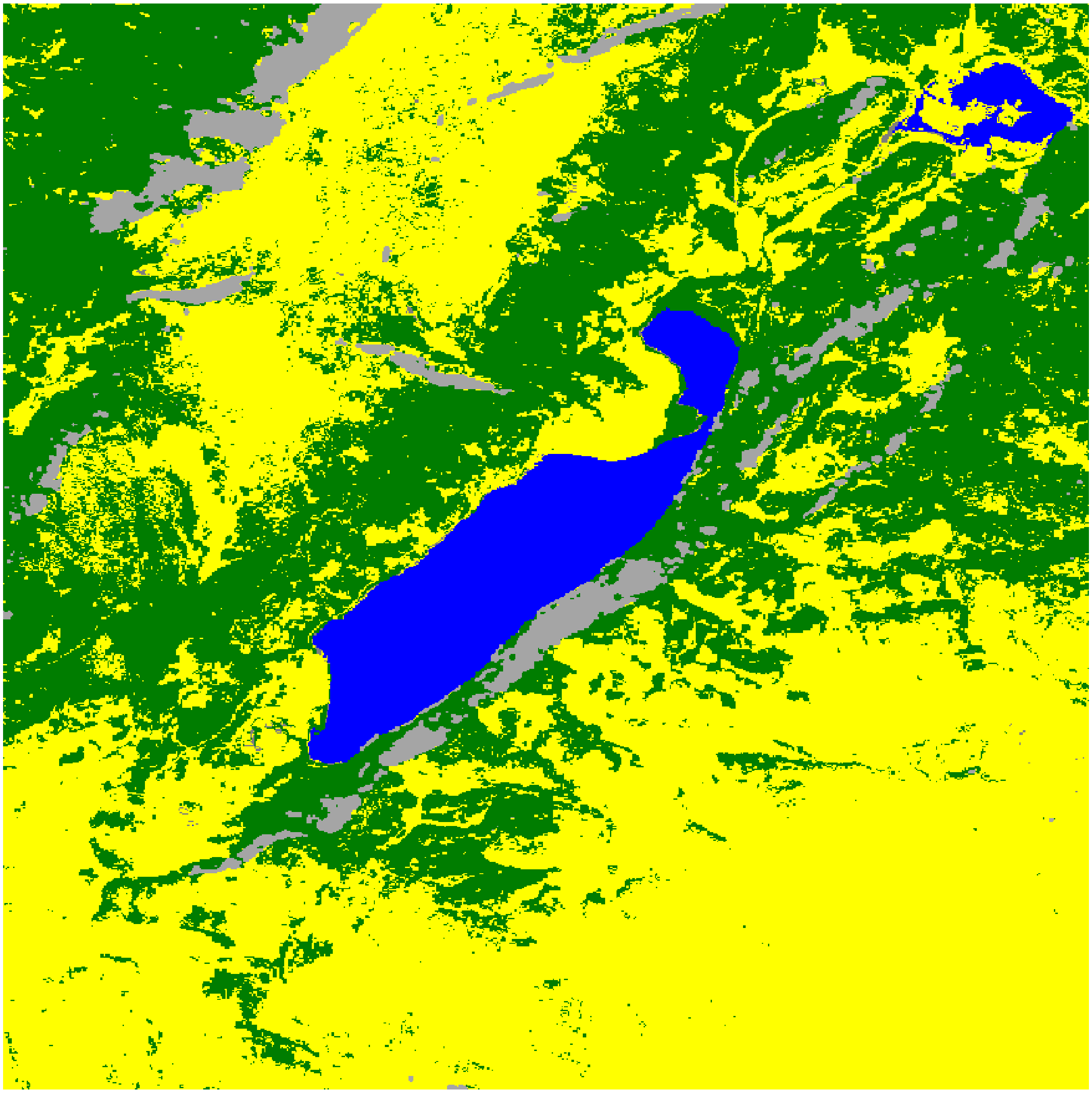

Figure C.10 — Sentinel-2 Scene Classification Layer (SCL) of Fish Lake (September 15-25, 2022)

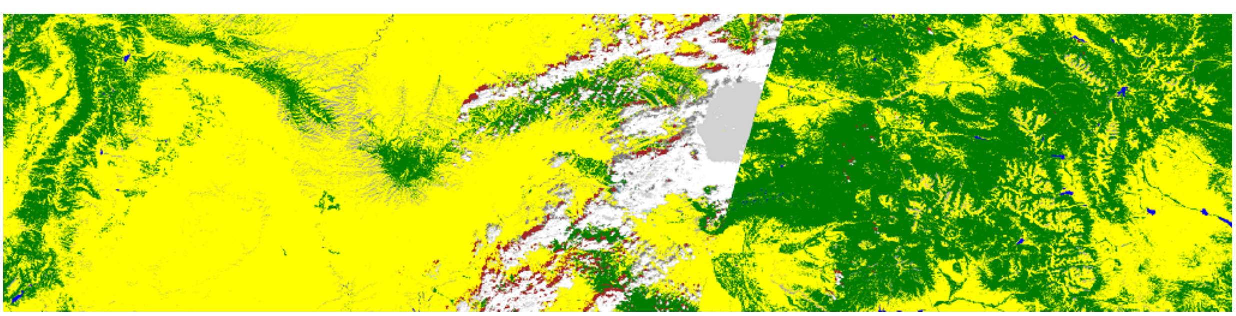

Figure C.11 — Sentinel-2 SCL of training area for Fish Lake (September 15-25, 2022)

In addition, an intermediate Enhanced Vegetation Index (EVI) raster is pre-computed as an additional input sample for both training and classification, using the formula:

```
2.5 * (B08 - B04) / (1 + (B08 + 6 * B04 - 7.5 * B02))
```

Listing C.2

making use of the Near-Infrared (B08), Red (B04), and Blue (B02) bands. An example is shown in Figure C.12.

Figure C.12 — Sentinel-2 Enhanced Vegetation Index (EVI) of Fish Lake (September 15-25, 2022)

The model was trained for three areas:

- A small area surrounding Fish Lake in Utah (`subset=Lat(38.475:38.625),Lon(-111.780:-111.630)`, shown in Figure C.12);
- A larger region extending North-East from Fish Lake to a snowy area (`subset=Lat(38.475:40),Lon(-111.780:-105.5)`, shown in Figure C.13); and
- Mount Adams in Washington State (`subset=Lat(46.0546875:46.23046875),Lon(-121.640625:-121.2890625)`, seen in Figure C.16 in Annex C.1.3.3 below).

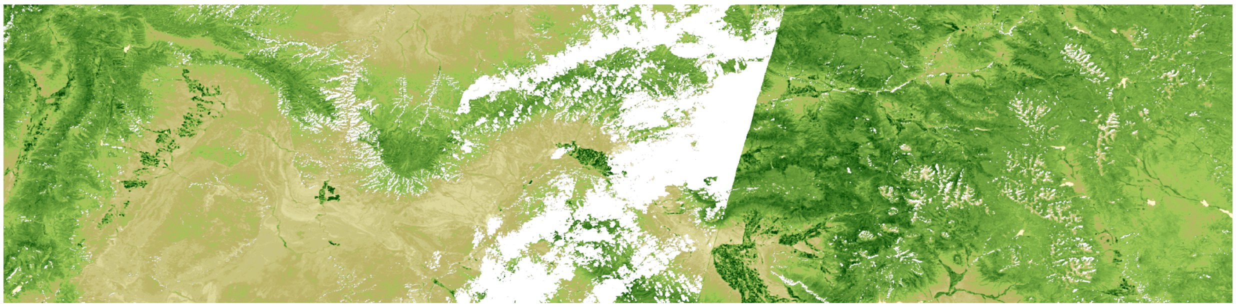

Figure C.13 — Sentinel-2 EVI of training area for Fish Lake (September 15-25, 2022)

The same seasonal Sentinel-2 data are used during the prediction resulting from triggering the indicator workflow, for the year of the specified time of interest (the month and day of the request are ignored).

C.1.3.3. Output Data

Using the trained Machine Learning model, the indicator produces an output that is a gridded high level classification vegetation type coverage.

A persistent virtual collection of the Wildland Fire Fuel indicator workflow, with predicted high level vegetation fuel types, for the three is shown in Figure C.14, Figure C.15 and Figure C.16. It can be accessed on the GNOSIS Map Server demonstration end-point at: https://maps.gnosis.earth/ogcapi/collections/wildfire:S2VegetationFuelTypes.

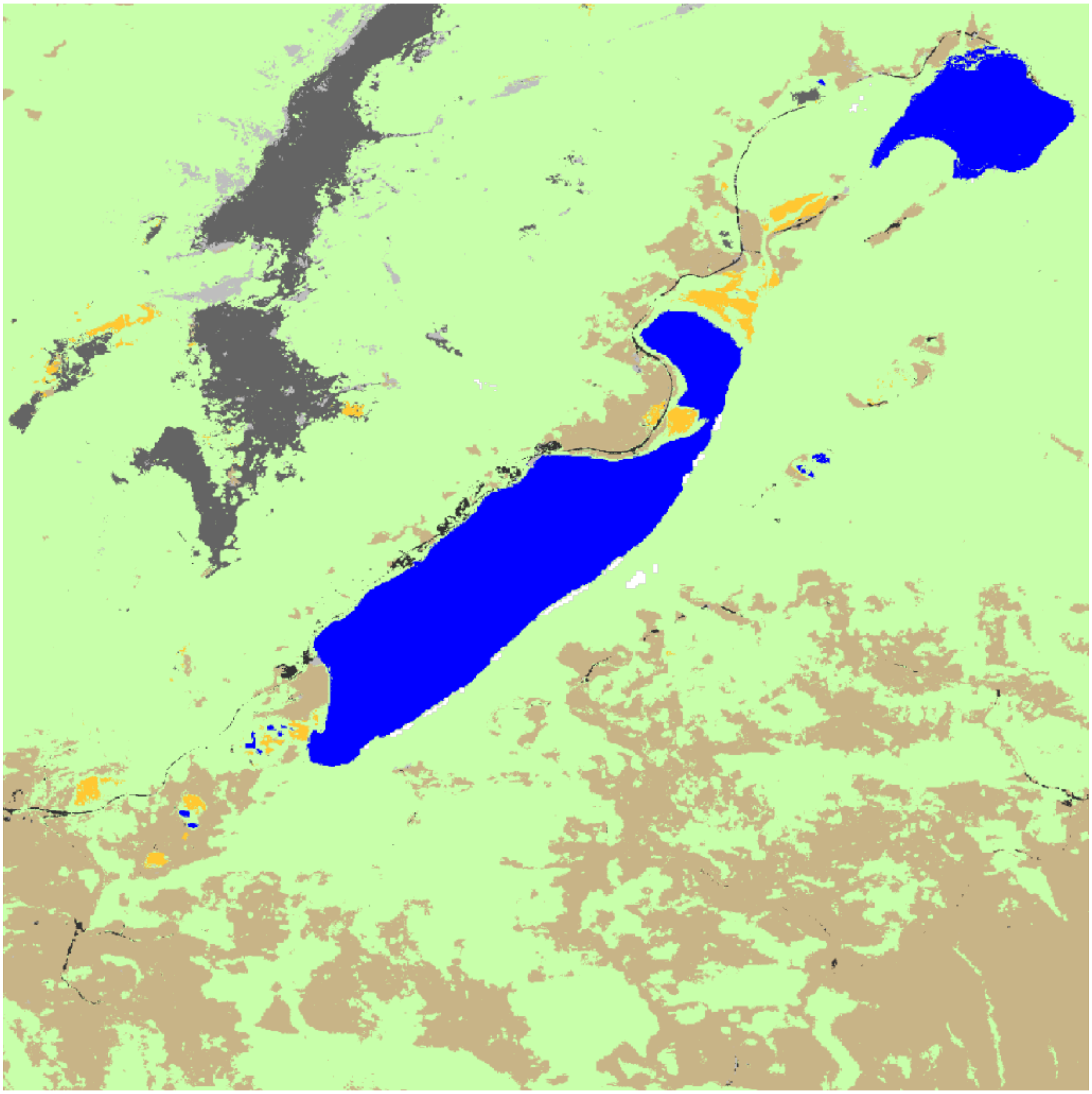

Figure C.14 — Wildland Fire Fuel Indicator Workflow - Predicted high level fuel vegetation types (Fish Lake, 2022)

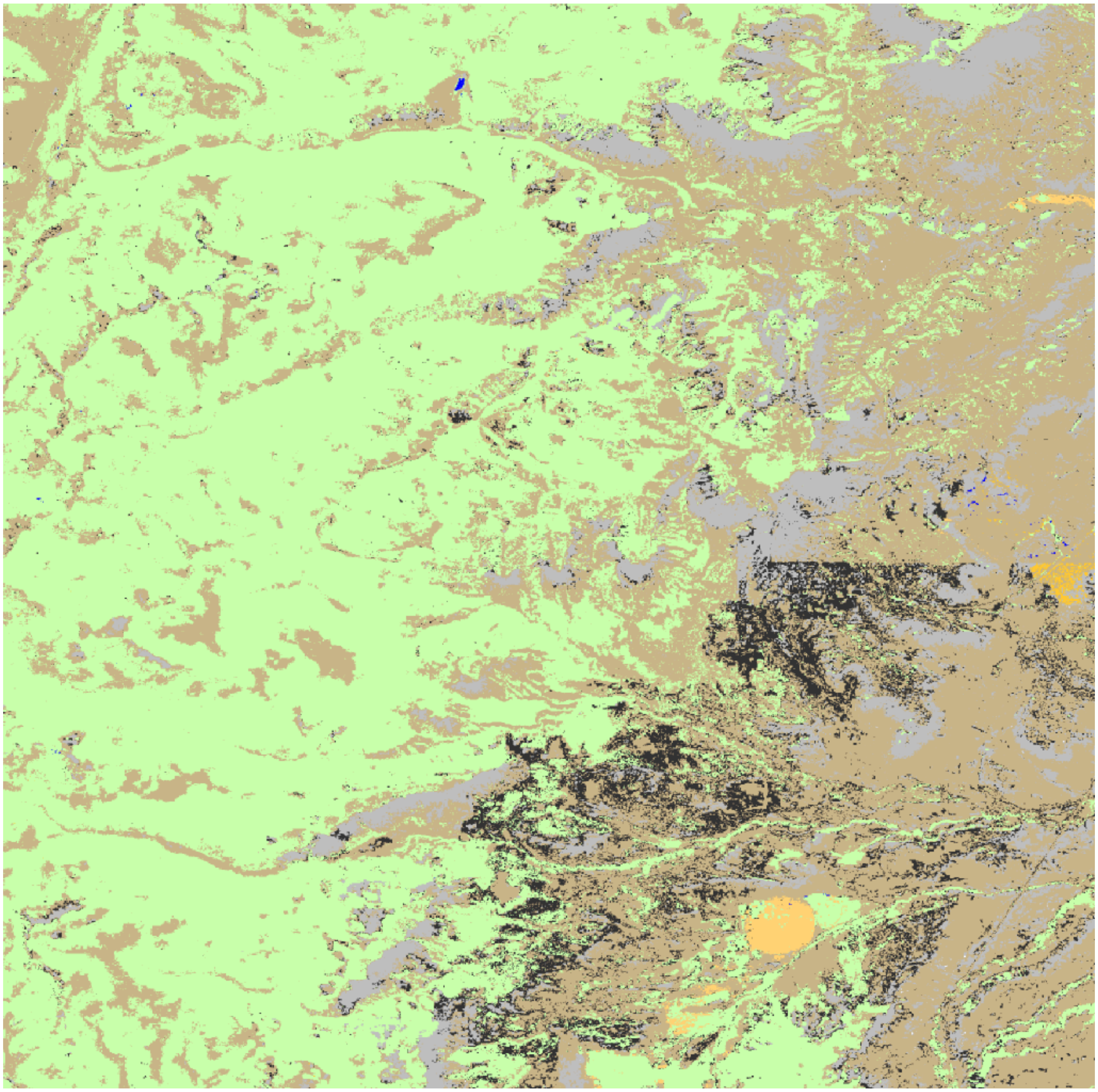

Figure C.15 — Wildland Fire Fuel Indicator Workflow - Predicted high level fuel vegetation types (North-East of Fish Lake, 2022)

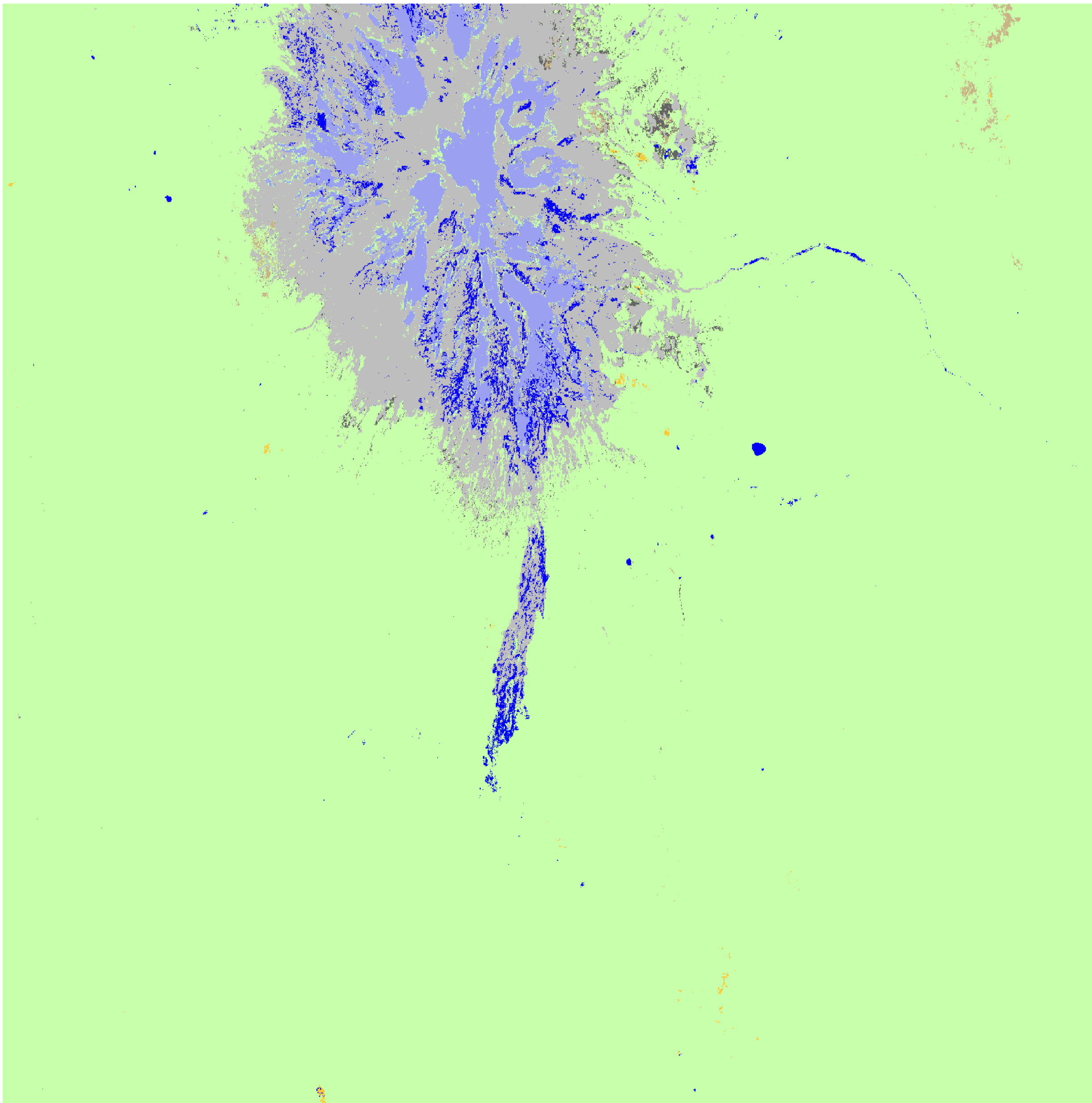

Figure C.16 — Wildland Fire Fuel Indicator Workflow - Predicted high level fuel vegetation types (Mount Adams, Washington State, 2022)

A virtual collection mapping these vegetation fuel types to a density of fuel on a scale of 0% (no fuel, such as for open water) to 100% (very high amount of fuel, such as for trees), using a rudimentary mapping (for the sake of demonstration, and not intended to be sound or valid for any practical purpose), is shown in Figure C.17 and available from:

https://maps.gnosis.earth/ogcapi/collections/wildfire:S2VegetationFuelDensity.

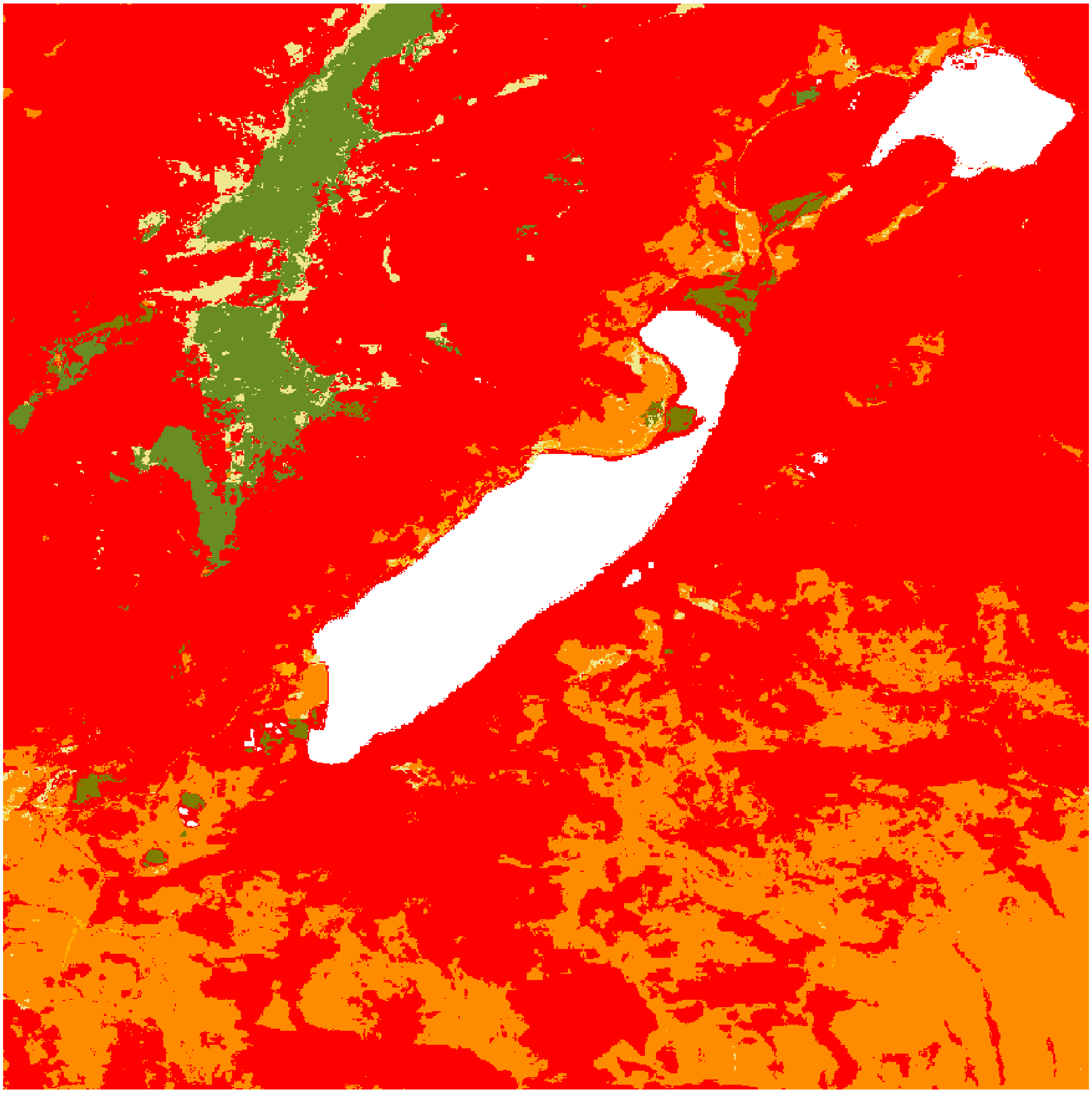

Figure C.17 — Wildland Fire Fuel Indicator Workflow
- Mapping predicted vegetation types to fuel density

In addition to this indicator, the same GNOSIS Map Server end-point also offers, through OGC API standards, several datasets retrieved from the Copernicus Climate Data Store climate-related datasets relevant to wildfire spread, including climate data such as temperature and precipitation, as well as derived fire danger indices.

C.1.4. Technical standards

The indicator is accessible through an API conforming to OGC API standards including *OGC API — Processes* and its draft *Part 3* extension for workflows, *OGC API — Tiles*, *OGC API — Coverages*, *OGC API — Maps* and *OGC API — Discrete Global Grid Systems*.

The indicator is set up by default to use a Sentinel-2 datacube offered on the GNOSIS Map Server demonstration end-point, which covers the entire global land mass. The spatial region covered by the indicator is therefore global, although the results will likely be more accurate in the area used for training around Fish Lake, Utah and Mount Adams, Washington. If using the indicator through the deployed virtual collection or using the *Collection Output* requirements class of *OGC API — Processes — Part 3: Workflows and Chaining*, processing will be performed on demand based on data access requests for a specific year and region of interest.

This process will trigger classification modeling using existing training data from vegetation fuel types to generate a classified image.

C.1.5. Benefits

The use of this wildfire indicator could help stakeholders and responders plan and make informed decisions to better prepare for a wildfire disaster.

C.1.6. Collaborations

Ecere collaborated with several other DP23 participants by providing this indicator as a potential input for other workflows, as well as the Sentinel-2 and climate datacubes.

C.2. Wildland Fire Ignition Risk Indicator Developed by Compusult

C.2.1. Introduction

Compusult enhanced its Web Enterprise Suite to provide access to Geo Data Cubes, and built an OGC API — GeoDataCubes to support its Wild Fire Risk Indicator.

Compusult also has the ability to ingest data from various sources, store it locally in Geo Data Cubes, Postgres databases, NetCDF, and other formats and make these data available as OGC API Features, EDR, Coverages, Map, or Processes.

C.2.2. Indicator Recipe

- **Input Data**
  - SeasFire cube (2022): a global dataset for seasonal fire modeling in the earth system containing:
    - 21 years of data (2001-2021) in an 8-days' time resolution and 0.25 degrees grid resolution;
    - a diverse range of seasonal fire drivers;
    - atmospheric and climatological variables;
    - vegetation and socioeconomic variables; and
    - other target variables, such as burned areas, fire radiative power and wildfire-related CO2 emissions.
  - The SeasFire data cube is a combination of many datasets, primarily provided by Copernicus and NASA MODIS, and is used as the basis for the dataset, extending it with updated data for variables used to calculate fire risk.
    - Alonso, Lazaro, Gans, Fabian, Karasante, Ilektra, Ahuja, Akanksha, Prapas, Ioannis, Kondylatos, Spyros, Papoutsis, Ioannis, Panagiotou, Eleannna, Mihail, Dimitrios, Cremer, Felix, Weber, Ulrich, Carvalhais, and Nuno. (2022). SeasFire Cube: A Global Dataset for Seasonal Fire Modeling in the Earth System (0.2) [Data set] available via Zenodo.
- **Processing & Transformation** — The Fire Potential Index (FPI) is a model of fire ignition risk based on relative greenness, temperature, relative humidity, and land cover classes, created by members of the United States Geological Survey in 2000. This modified version removed the fuel model. FPI uses Normalized Difference Vegetation Index (NDVI) to calculate the maximum live vegetation ratio.

  The average NDVI during a timeframe was used to calculate the relative greenness of the area. Using temperature, relative humidity, and equilibrium moisture constant, it calculated the 10-hour time lag fuel moisture. Areas with non-flammable land cover classifications were removed from the dataset. Finally, the 10-hour time lag fuel moisture, relative greenness, and maximum live vegetation ratio were used to calculate the FPI.

  Analysis was based on many variables, including:
  - atmospheric and climatological variables;
  - vegetation variables; and
  - socioeconomic and the target variables related to wildfires, such as:

- burned areas;
- fire radiative power; and
- wildfire-related CO2 emissions.

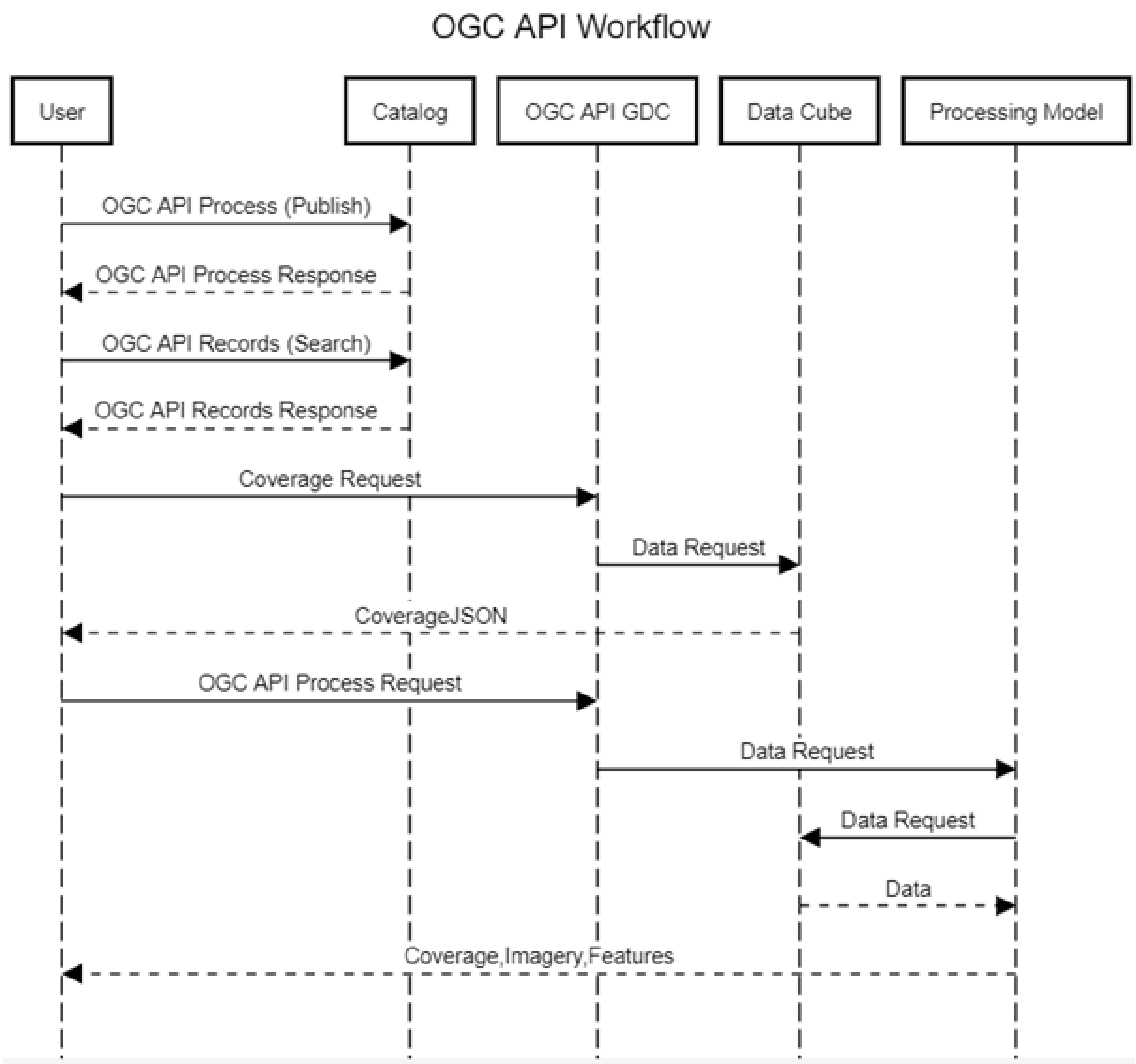

Figure C.18 — OGC API workflow for wildland fire risk indicator

- **Output Data** — Output formats of the process can either be Zarr files containing integration-ready data of the FPI values for the desired geographical locations and time frame, or PNG images of the integration-ready data values, color coded from red to blue to signify high risk to low risk of fire ignition.
- **Technical standards or infrastructure requirements** — Each of the OGC API Processing services use OGC API Coverages, Features, and Maps to provide output to the user. In addition, the following standards are used:

    - OGC API Common
    - OGC API Process
    - OGC API Coverage
    - OGC API Styles

C.2.3. Benefits

The benefits this indicator could offer include the following.

- These OGC API Process services could be used to help plan, edit, and administer responses to an ongoing climate emergency, such as a fire.
- Emphasizing the importance of fuel-related variables, which should be used in combination with meteorological drivers to assess the likelihood of large fire events. The process uses the following drivers to determine the fire risk:
    - NDVI
    - Forested Areas
    - Relative Humidity
    - Air temperature two meters above the land surface
    - Agricultural Area
- The Compusult deliverables enhance the situational awareness and common operating picture used by disaster response and resilience teams.
- The Compusult video shows how users can find the data and services and create a Digital Twin of a fire risk area.
- SWG and DWG communities can use the deliverables to help enhance and test the interoperability between OGC standards, including:
    - OGC API Records
    - OGC API Processes
    - OGC API Coverages.

C.2.4. Collaborations

Compusult was looking at the Western US states for the demonstration. Figure C.19 shows details on the demonstration.

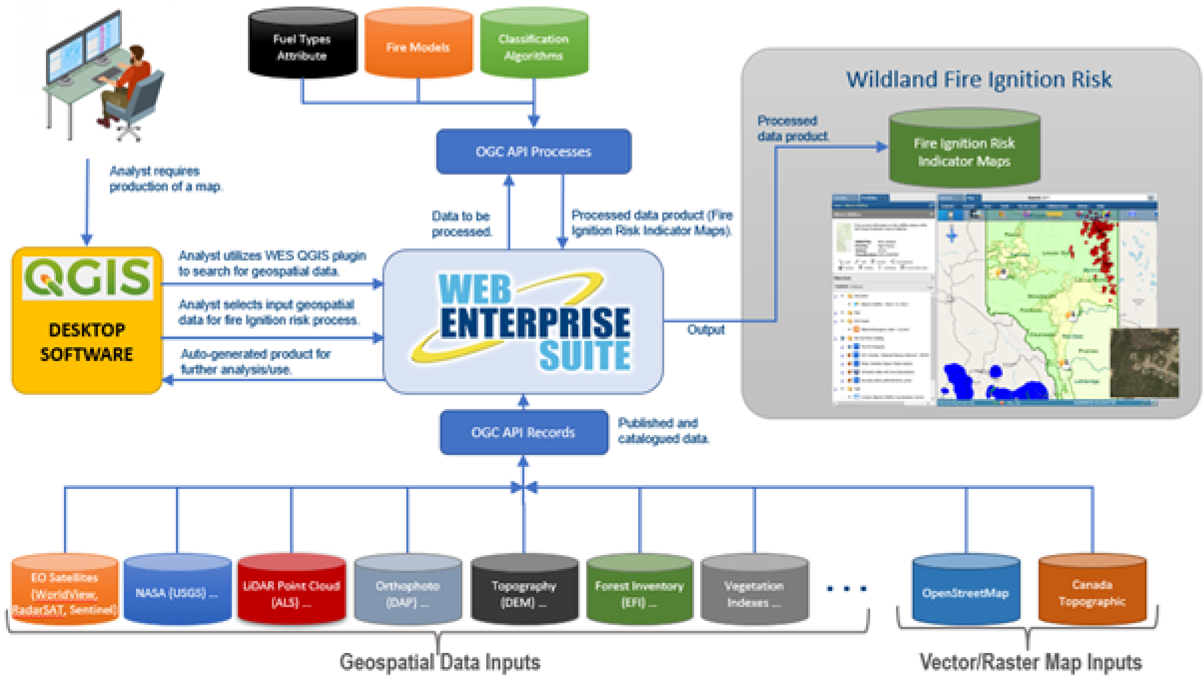

Figure C.19 — Demonstration sites for the wildland fire risk indicator

C.3. Wildland Fire Evacuation Indicator Developed by Skymantics Europe

C.3.1. Introduction

Skymantics developed a data workflow to allow an emergency manager to organize evacuation plans for populations affected by wildfires in the vicinity. including the relative priority of neighborhoods to be evacuated and specific navigation or evacuation instructions.

The need for an evacuation indicator arises from the fact that populated areas affected by a wildfire are not all equal in terms of vulnerability or time to evacuate to safety. Evacuation agencies require some information about the demographics and geographical distribution of the population area to quantify the impact of a wildfire, assess evacuation challenges, and organize an ordered evacuation that optimizes the use of available roads.

C.3.2. Indicator Recipe

- **Input Data** - This workflow uses mostly static or quasi-static input datasets (updated weekly to multi-yearly):

- Population demographics. A synthetic population dataset was generated based on Census micro data and health condition statistics (U.S. Census and Canada Census). Note: this information includes Wildland Fire Health Risk Index computed per neighborhood.
- Road network. Open Street Maps was used to ingest the road geometries and their capacity characteristics.
- Fire danger index and fire spread index from Copernicus Emergency Management Service using data from 14 June 2023. Note that a real-time index could be ingested instead, if available, to support tactical fire evacuation and response with real-time updated data after a wildfire is declared.

- **Processing and Transformation** — The workflow recipe functions as follows:

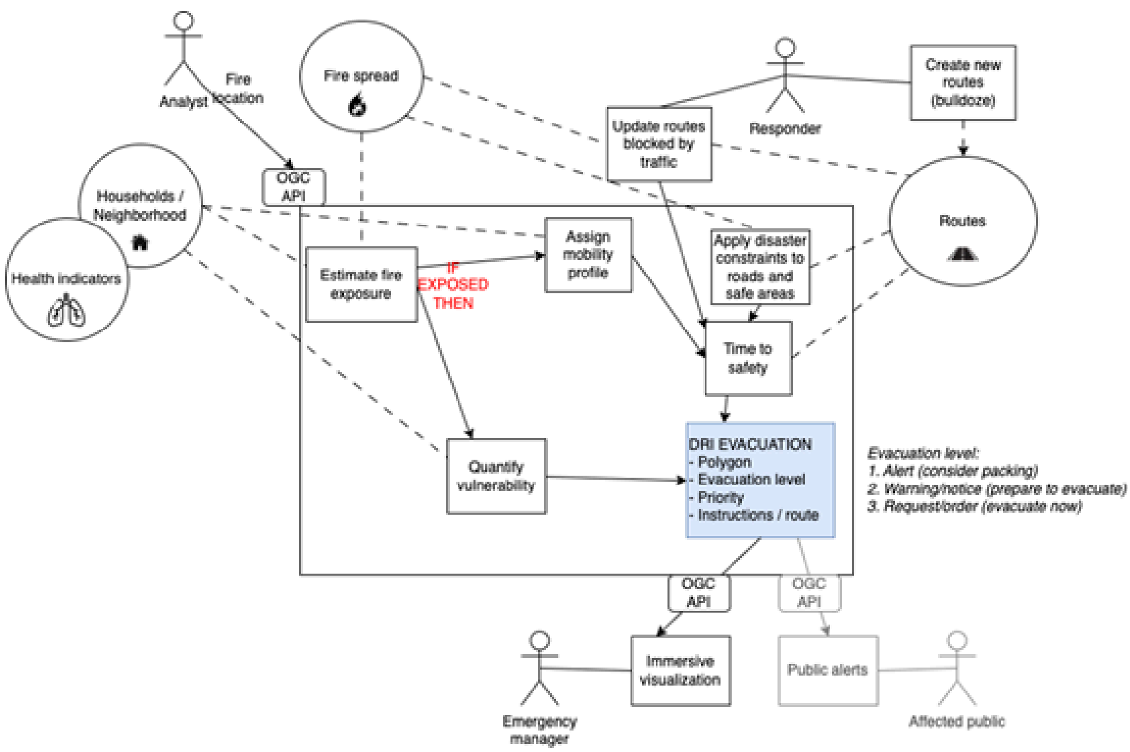

Figure C.20 — Wildland fire evacuation indicator workflow

1. Analysis Ready Datasets (ARD) are available describing the projected spread of the leading edge of wildfire. For DP23, this indicator is a combination of Fire Danger Index and Fire Spread Index from Copernicus data (updated weekly). However, in a tactical scenario, the indicator could be real-time information. Based on knowledge of fire ignition likelihood, or observations of an actual fire, the user declares a fire by defining the location of its edge, and projection is limited to severity and expected spread speed. This information can be used for tactical execution of evacuation plans.

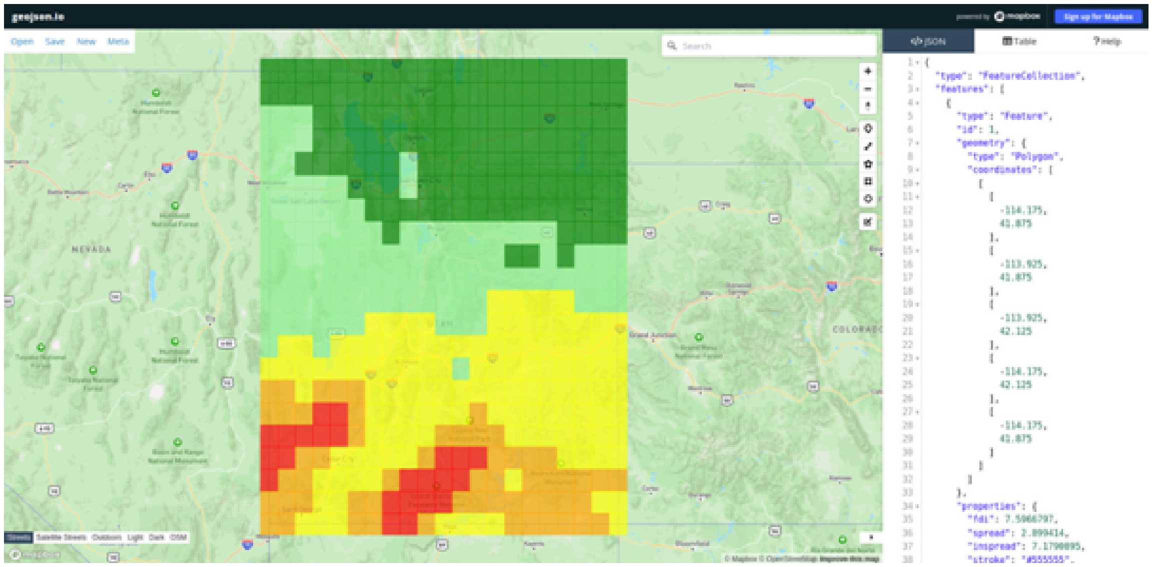

Figure C.21 — Initial fire spread index for the state of Utah (August 14th 2023)

2. There is a description of the population living in the vicinity, aggregated per neighborhood (Block group – Census defined area with 600 – 3,000 inhabitants). Neighborhoods are geolocated as points indicating their respective centers of gravity (i.e., center of population density). Description includes distribution of age, socioeconomic status, and health conditions. In addition, health impact risk indicators are pre-calculated for each household. Population was pre-generated as synthetic data based on Census surveys and thus cannot be traced to actual individuals living in households.

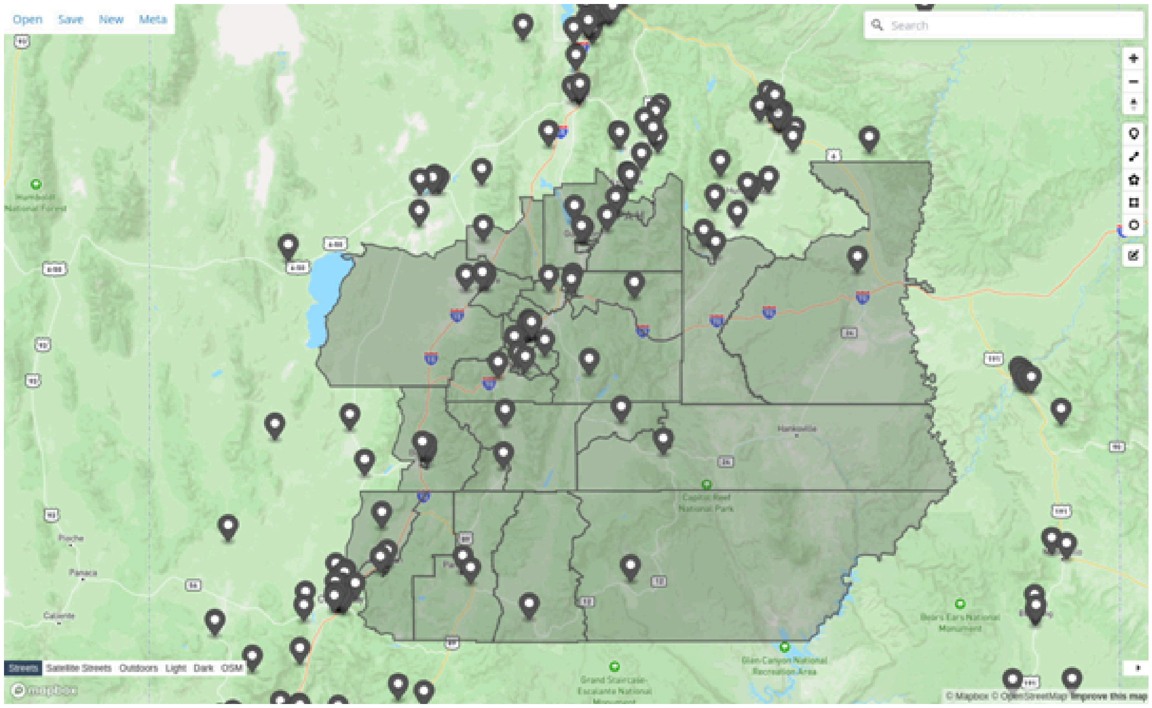

Figure C.22 — Demographic block groups for Utah scenario and respective centers of gravity

3. There is a graph model of routes in the area (segments and edges), including route hierarchy and capacity limits per segment (vehicles / minute). First responders on the field can manage traffic (e.g., assign all lanes in one direction), observe congestion, and update route conditions based on these observations. First responders could even create new evacuation routes not originally in the route network. These inputs are user-generated.

Figure C.23 — OSM road layer for Utah scenario

4. Upon request of an emergency manager, an analyst runs the model. This model calculates the following.

    - Which population areas (polygons) are exposed to fire in the foreseeable time horizon (i.e., when each neighborhood will be impacted by fire).
    - What is the vulnerability of exposed populations depending on factors like age, health conditions, and expected fire spread (including smoke spread).
    - What are the mobility profiles of the exposed population (do they have a vehicle? any mobility constraints? how large is the household to be evacuated?).
    - What constraints should be applied to the route network depending on the expected fire spread (including smoke spread) and distance of route segments to the fire. Also assign safe areas (either predefined, or calculated as areas “far enough” from fire).
    - What is the time for each of the vulnerable population areas to reach a safe area from their origin household?

- **Output Data** — The model generates the following Decision Ready Information and indicators (DRI), which can be used directly by the operational user, or integrated into a visualization tools such as those in Annex A (in which case they are treated as Integration Ready Data).
    - Polygons representing the boundaries of the affected neighborhood.
    - Evacuation level (alert, warning, or evacuation order) based on the time to exposure and required evacuation time.
    - Evacuation priority. The areas under evacuation order are assigned an ordered priority based on the required evacuation time and the relative vulnerability.
    - Evacuation route(s) to be followed by the population in the neighborhood.
    - Special instructions for specific demographics or vulnerable populations in the neighborhood. In DP23, instructions may include additional transportation needed, number of households requiring translators, number of households with elderly people, and estimated number of people with critical health conditions (Chronic Kidney Disease, Chronic Obstructive Pulmonary Disease, Asthma).

C.3.3. Technical Infrastructure

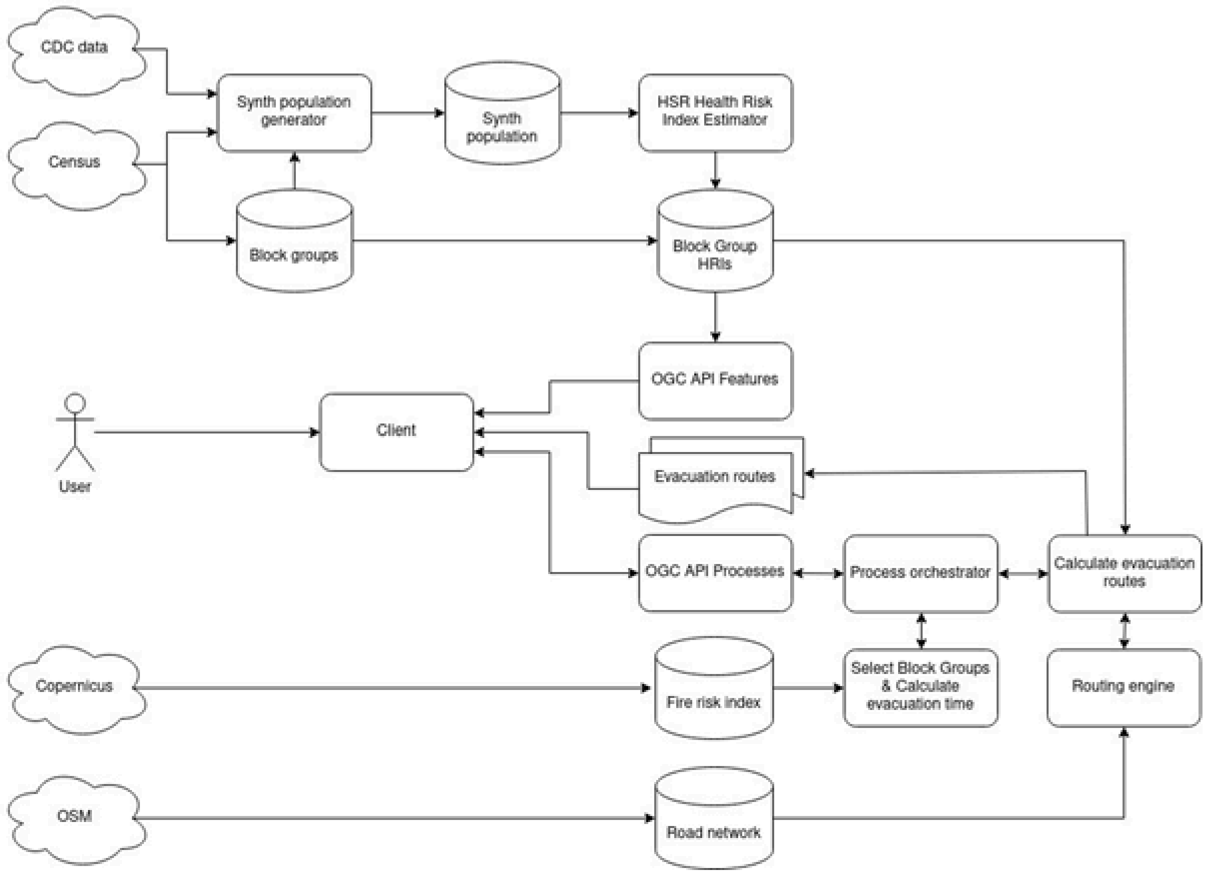

Figure C.24 — Wildland fire evacuation indicator technical implementation schema

All components were hosted in the Skymantics cloud environment. The data sources were processed offline and stored in the processed ARD components (block group HRIs, fire risk index, and road network). The block group collection, with the geographical, social, and economic information of the neighborhood, is accessed directly via an OGC API — Features [API Features] instance.

The user runs the workflow via an OGC API — Processes, providing the information of the location of a firebreak. The API then calls a process orchestrator in the backend. Based on the fire risk and spread indexes downloaded from Copernicus, the orchestrator selects exposed block groups, calculates evacuation routes and DRIs by calling the Skymantics routing engine, and returns the results via the OGC API — Processes [API Processes] instance. Evacuation routes are stored in JSON files linked from the OGC API — Processes results, and can be downloaded by the client. Routes are encoded following the OGC Route Exchange Model standard [REM].

Finally, the user accesses the results using the user's client, or using the Skymantics client developed for DP23 as shown in Figure C.25. This client simulates a web interface accessible to a field agent and has additional interactive features where the user can block or add road segments before running the workflow again.

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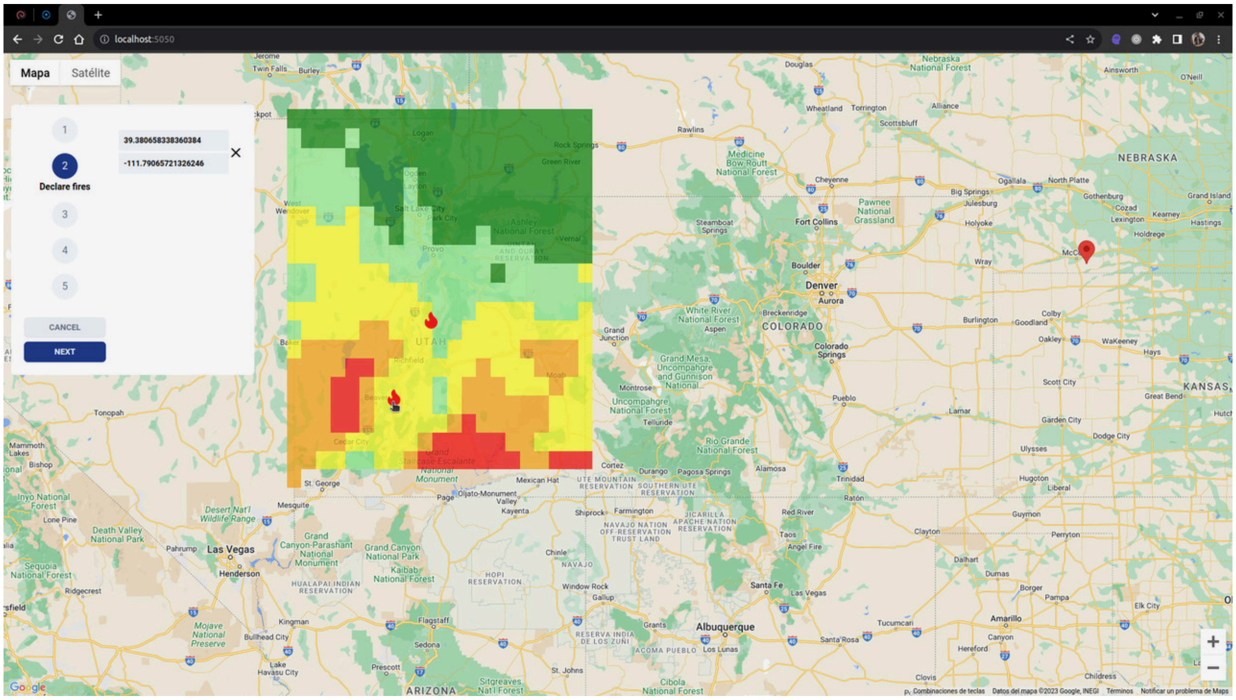

Figure C.25 — Web client showing fire exposure and vulnerability areas

C.3.4. Benefits

This workflow can benefit the disaster and emergency response community in the following three aspects.

- Have a customized level of granularity in the picture of the population to be evacuated from a wildfire. Thanks to synthetic data generation, population areas can be described demographically realistically without the use of personal sensitive information. The scale and level of granularity can be adapted and still maintain statistical accuracy. This allows for emergency agencies to describe demographically affected neighborhoods in the area, as long as demographic survey and statistics data are available. In turn, this localized granularity allows emergency agencies to take into account differences in population characteristics and vulnerability to wildfires to prioritize and organize an ordered evacuation plan.

- Organize strategic evacuation plans before wildfires are declared, taking into account probabilities of fire ignition and spread. Then, the same model allows organization of tactical evacuations once a wildfire is declared in a specific location. This duality allows emergency agents to test how strategic planning works in specific scenarios of actual wildfires.

- Trying different evacuation scenarios with varying assumptions. The underlying models to calculate fire exposure, population vulnerability, and evacuation routes allow data exchangeability. For instance, a different dataset defining fire spread rate or demographics can be replaced, which can be used to recalculate the evacuation plan. This allows for searching optimal solutions such as improving evacuation routes, clearing out vegetation, or relocating populations, to minimize vulnerability to wildfires.

The job roles of the people who would use this indicator are as follows.

- Emergency managers require access to intermediate data indicators to understand how the data indicators combine to produce optimal evacuation plans under varying situations. The three actionable observations (fire exposure, time to safety, and vulnerability) inform the emergency manager about aspects to improve in the environment and also allows the emergency manager to perform what-if scenario analysis by configuring variations of the environment which have a sensitivity impact on these indicators.

- Responder visualizes the evacuation plan to be executed – be it a firefighter squad to assist on a neighborhood evacuation, or an EMT team to send additional resources to a vulnerable area, or a traffic agent to ensure a change in road traffic directions to maximize capacity. Responders need information of the population areas to be evacuated, the population's level of urgency and priority, and special instructions including evacuation routes to be followed. In addition, responder actions affect the environment (i.e., a change in traffic capacity, or an observed blocked road), and thus responders can input these changes into the workflow.

- The affected public is informed about the same DRIs as the responder via public dissemination tools. For the public, it is important to know when to prepare and leave, and which evacuation routes to follow to safety.

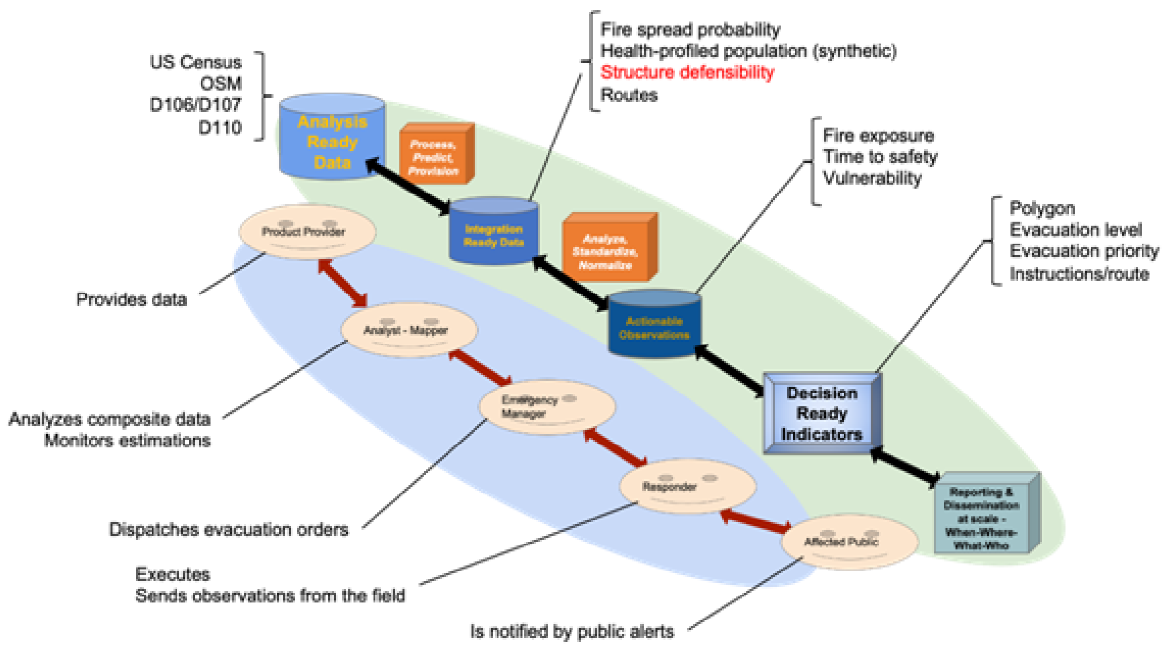

Figure C.26 — Wildland fire evacuation indicator data & user chain

C.3.5. Collaborations

In developing this indicator Skymantics collaborated with several DP23 participants, namely the following.

- Wildland Fire Health Impact Indicator Workflow developed by HSR.health uses the demographic information at neighborhood/block group level to compute the health risk indicators for each area. These indicators then become attributes of the synthetic population representing each of the affected areas.

- Wildland Fire and Drought Immersive Indicator Visualization developed by USGS-GeoPathways can use the DRIs as inputs to visualize.

  It is hoped that future collaboration can include working with Wildland Fire Ignition Risk Indicator Workflows to develop an indicator that shows the fire ignition risk, but also the severity and spread of the fire edge, in real time. Consuming this in real time would support tactical evacuation scenarios.

  In addition, in the future the Mobile Crowdsourcing Survey/Reporting Applications being developed could evolve into a mobile app that allows first responders in the field to report observations such as blocked roads or new evacuation routes cleared. Consuming this in real time would support tactical evacuation scenarios.

  The persistent demonstrator exposed by OGC API can be retrieved at Wildland Fire Indicator Demonstrator

C.4. Wildland Fire Health Risk Indicator Developed by HSR Health

C.4.1. Introduction

Wildland fires affect thousands of people every year in the United States. It is important to understand where vulnerable populations are in fire prone areas and in areas in the direct path of a current wildland fire. HSR.health produced a Wildland Fire Health Risk Index that identifies the vulnerable populations by combining population characteristics with health conditions.

By having this information available a-priori to future wildland fires, the index can help speed the response and evacuation efforts by providing emergency response managers and first responders additional information to help inform their response effort.

The Wildland Fire Health Risk Index was produced for the western United States in line with the target areas identified from the sponsors including Colorado, Utah, Arizona, and California.

C.4.2. Indicator Recipe

The components of the Wildfire Health Risk Index are as follows.

- **Input data**

The primary input datasets for the Wildland Fire Health Risk are demographic data, health condition data, and data on wildland fire extents and risks. The data sources are:

- demographic data and population characteristics from US Census Bureau;
- underlying Health Conditions from the US Centers for Disease Control and Prevention; and
- historical Wildland Fire Extents from the USGS.

  The aim was also to include input data from other DP23 participants as this became available, in particular:

- Ignition Risk Indicators from Compusult; and
- Fire Fuel Indicator from Ecere.
  - **Processing & Transformation**

    Figure C.27 shows the overall workflow used to create and distribute the Wildland Fire Health Risk Index, which identifies where at-risk populations exist across the wildland fire affected areas.

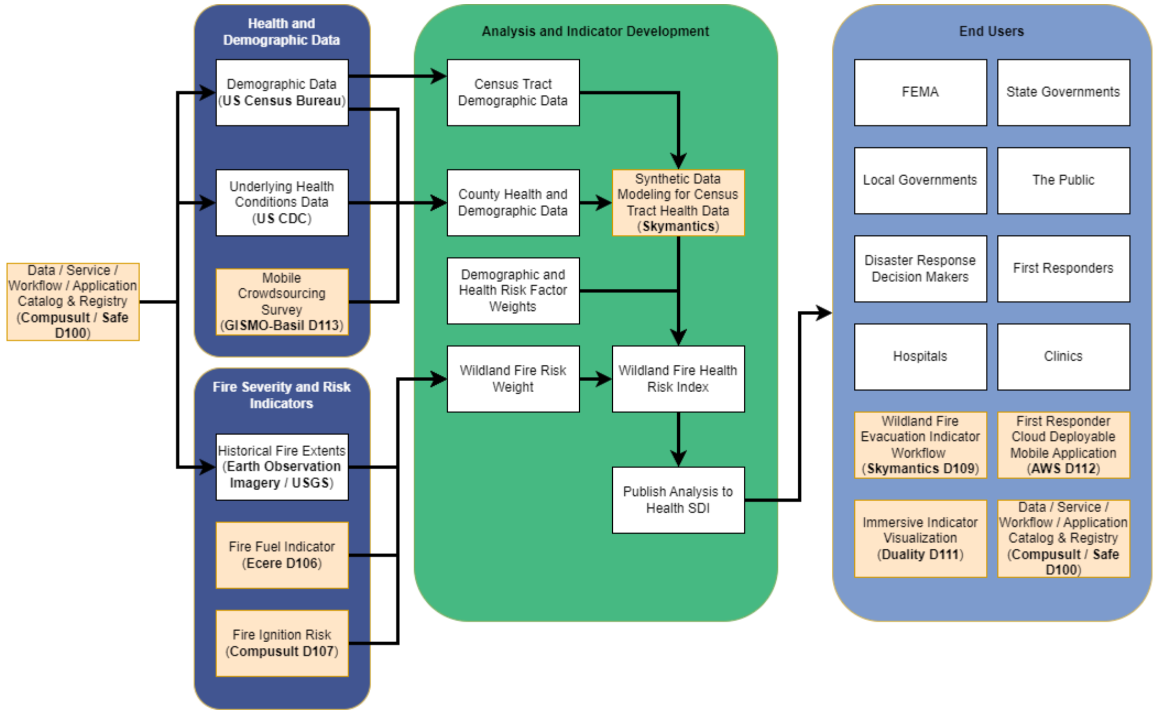

Figure C.27 — Wildfire health risk indicator collaborations & workflow

The highlighted cells show components where collaboration with other DP23 participants have, or were planned, to take place.

The primary data inputs for the Wildland Fire Health Risk Index were demographic data, health condition data, and data on wildland fire severity and risk. The demographic data come from the US Census Bureau, the health condition data come from the US Centers for Disease Control and Prevention, and the initial wildland fire severity and risk data come from the USGS. The target granularity for the Risk Index was the Census tract administrative level for the United States. The demographic data were available at the Census tract level, however the health conditions data were not, so HSR.health worked with Skymantics to develop a synthetic data model to estimate the Census tract level prevalence for the underlying health conditions data.

The Wildland Fire Health Risk Index calculation was a combination of two primary components: the vulnerability of the underlying population, and the wildland fire risk. The population vulnerability risk was a combination of health and demographic factors through a combined risk weighting analysis that provides a-priori information on where vulnerable and at-risk populations are. Some of the factors included in the vulnerability risk include: Age, Disability Status, Transportation Access, Fluency, Low Income, Dialysis Dependent Populations, COPD, Asthma, and more. The weightings for each factor were determined through input from the public health team, published research, and internal analysis. The wildland fire risk weighting component of the index was determined through a combination of historic fire extents. The risk index weight can be augmented with the indicators for Fire Fuel and Fire Ignition Risk from Ecere and Compusult, respectively.

- **Output Data**

The risk index and associated data were published to HSR.health's GeoMD Platform as well as other spatial data infrastructures and data catalogs as made available through DP23 and through OGC API, WMS, and WFS to be shared with stakeholders and participants.

Additionally, HSR.health demonstrated and explored continuing interoperability between multiple catalog systems to ensure that ingesting and sharing data and analytical outputs across multiple entities, both with DP23 participants and stakeholders, is possible.

- **Technical standards or infrastructure requirements**

  Interoperability was at the core of this development, and HSR.health ensured the work in DP23 focused on exploring and demonstrating interoperability for inputs, outputs, and analytics.

  It is also hoped this work will continue to go forward to expand the development of the Health Spatial Data Infrastructure (SDI) including the addition of an OGC API endpoint for access to the data available through the health SDI to move towards a Health Data Retrieval API.

C.4.3. Benefits

- **Who does this help?**

The aim was to inform governmental organizations, disaster response personnel and decision makers, Community and Aid Organizations, medical personal, along with local residents and the public of the health and social conditions on the ground to aid in response and relief efforts in wildland fire affected areas.

- **What decisions are supported by this indicator/tool?**

End users and stakeholders can utilize the data and analyses presented to understand where vulnerable populations are and how to create policies and relief plans to respond to, and alleviate the impact of, wildland fire affected populations.

- **Details of job roles that would use this data?**

The job roles that might use this information include a DRI Analyst and a DRI Decision Maker.

C.4.4. Collaborations

- **Collaborations Undertaken & Potential Combination with other Workflows**

HSR.health collaborated with Ecere, Compusult, and GISMO-Basil Labs as data inputs for the workflow, and with Skymantics, AWS, and Duality which ingested the output from the risk index. Finally, collaboration occurred with Compusult and Safe to explore and demonstrate interoperability between the data catalogs that were developed for DP23 and the Health SDI.

- **Details of Persistent Demonstrators**

HSR.health's goal of participation in DP23 was to provide visibility into and persistent demonstrators of health information in the disaster response ecosystem.

+ The persistent demonstrators is available at: https://opengeomd.hsrhealthanalytics.org/#/

C.5. Wildland Fire Immersive Indicator Visualizations Developed by Duality

C.5.1. Introduction

Duality developed unique insights into the adoption of Digital Twins (DTs) for complex simulation, interaction, and visualization workflows and the ability to extract critical synthetic data and insights from diverse Digital Twin scenarios.

Central to the approach was the use of Duality's Digital Twin integration platform called Falcon and a growing library of reusable DTs. This framework allows teams to flexibly craft and simulate the scenarios important for the team's domain and to modify individual twins and add to the DT library as mission requirements change. Such flexibility supports expanding system capabilities and operational domains as well as changing test environments such as the wildland fires terrain in western United States as part of DP23.

The enterprise metaverse composed of Digital Twins holds the promise of solving real world data problems through: immersive visualization, collaboration and training; synthetic data generation; and closed loop simulations of complex systems and processes such as route planning for disaster evacuation.

The true power of this enterprise metaverse is unlocked by allowing different physical resource managers and data providers, including government agencies, companies, and research teams, to share virtual counterparts of physical assets and DRIs in a structured and synchronous way within scenarios of interest. Falcon has been architected with exactly these kinds of multi-DT and multi-participant workflows in mind.

While scenario makeup, their functional needs, and data objectives can vary widely, a shared Digital Twin catalog and the Falcon workflow bring together all of these modular and reusable pieces together in diverse ways to achieve a variety of goals.

C.5.2. Description

For DP23, Duality extended Falcon's architecture for building Site Twins (described later) to incorporate DRIs. DRIs are acquired and mapped to modular, reusable DTs. These twins could then be combined with a library of other DTs that represent terrain, vegetation, energy infrastructure, transportation networks, communication networks, drones, sensors, etc., to have limitless flexibility in representing the scenarios described above as well as others not yet considered.

C.5.2.1. Digital Site Twins

In Figure C.28, the workflow on the left represents Falcon's Geographic Information System (GIS) and AI powered workflow to build digital Site Twins.

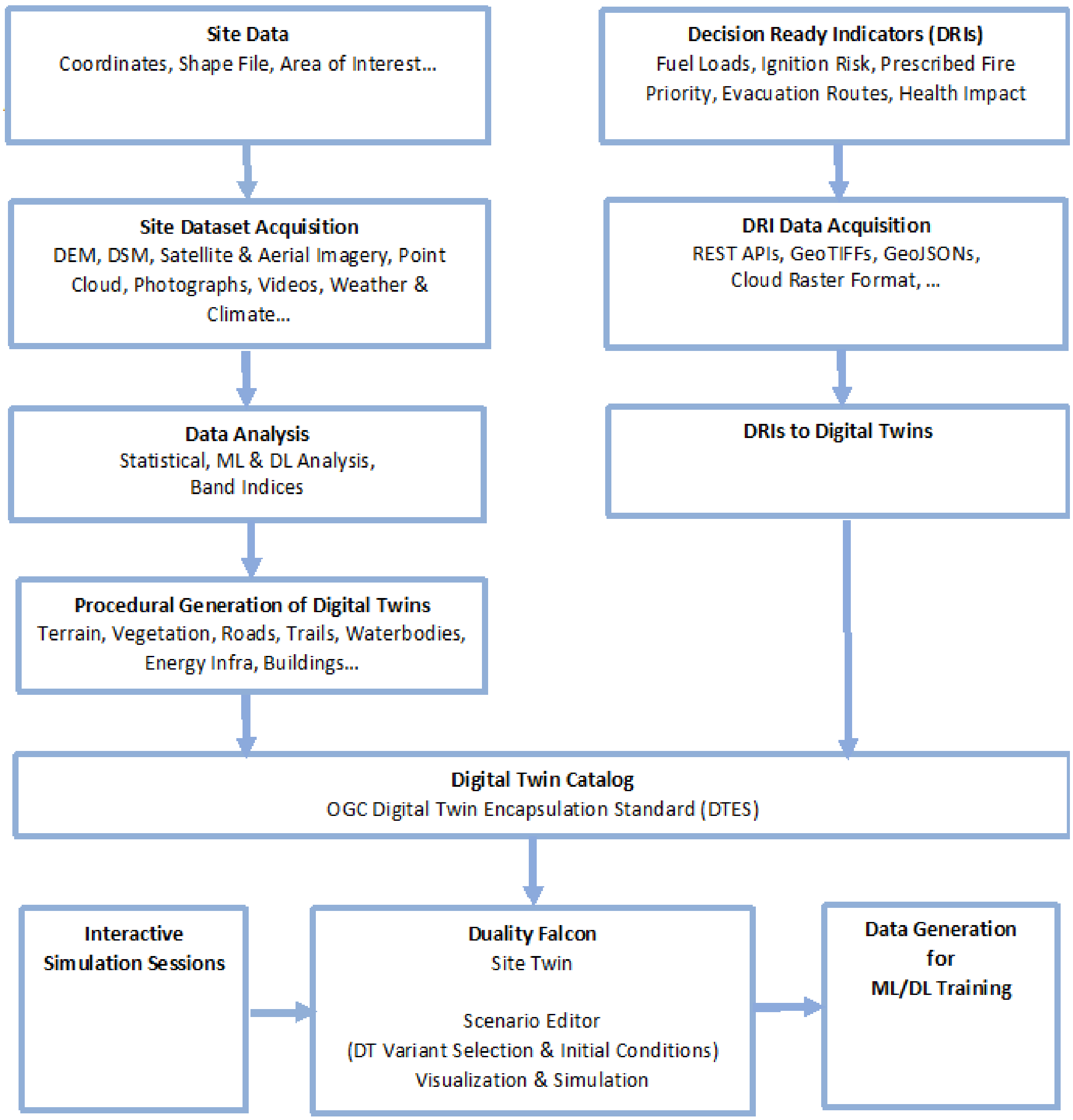

Figure C.28 — Falcon's enhanced workflow maps DRIs to DTs in an open-source Digital Twin encapsulation standard (DTES) format, which can be combined with other Digital Twins in a modular way to create a wide variety of scenarios for interactive visualization, planning, validation, and synthetic data generation.

Simulation has always been the best tool for predicting the future. These predictions, however, are only valuable if the simulation data have the required fidelity and precision to successfully translate to the real world. Put another way: when exploring any question of interest, the data generated by a simulation are only useful if the data can approximate what would happen in the real world with a high degree of accuracy.

Consider Wildland Fire, decision makers would like to simulate various scenarios to learn possible evacuation route options and potential bottlenecks, time needed for evacuation, potential health hazards, and hence, evacuation priority. For projects like DP23, generalized scenarios are not enough — real locations and real-world data are called for.

Digital Site Twins (also referred to as simply Site Twins) — are virtual environments, based on diverse sources of GIS data of real locations. When semantic information from GIS data are joined with the infinitely modifiable nature of a Digital Twin, the door is opened to any “what if” questions relevant to that environment (limited only by the availability and quality of the GIS data sources). Whether testing deployment of an emergency response plan or evaluating disaster response protocols in an urban or rural setting, the fidelity of the Digital Twin virtual environment and accurate representation of the real-world location are necessary in bridging the Sim2Real gap.

Creating Site Twins, after all, can be quite daunting. This is why Duality researched and developed an AI-powered pipeline, one that enables customers to build any desired Site Twins from already available data. The following two images describe Duality Falcon’s GIS and AI powered pipeline to create Digital Site Twins.

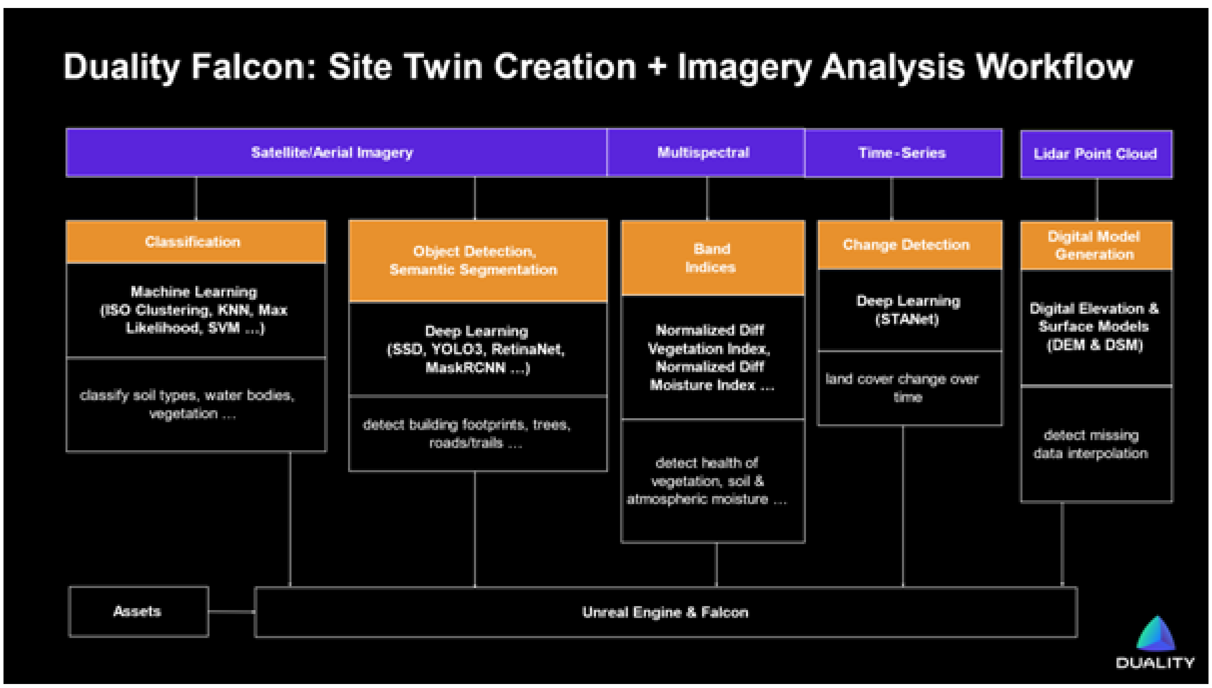

Figure C.29 — Workflow of Falcon’s GIS and AI powered pipeline to create Digital Site Twins of the existing real locations for immersive visualization and simulation.

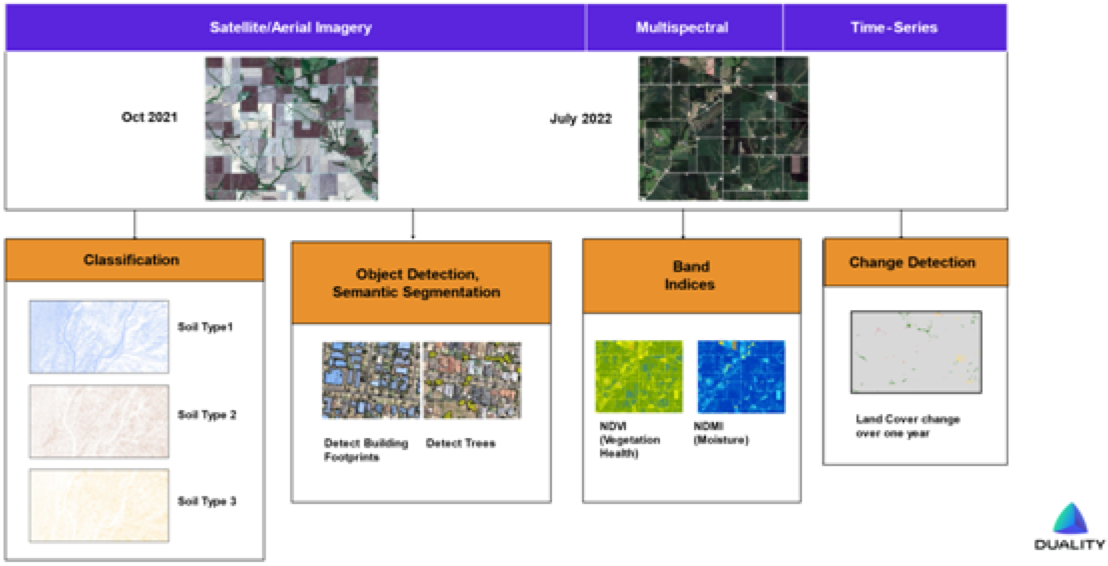

Figure C.30 — Workflow with example imagery and analysis of Falcon's GIS and AI powered pipeline to create Digital Site Twins of the existing real locations for immersive visualization and simulation.

C.5.2.1.1. Digital Elevation Model

For DP23, Duality built a Digital Site Twin of around 8400 square-km of Fish Lake National Forest, Utah.

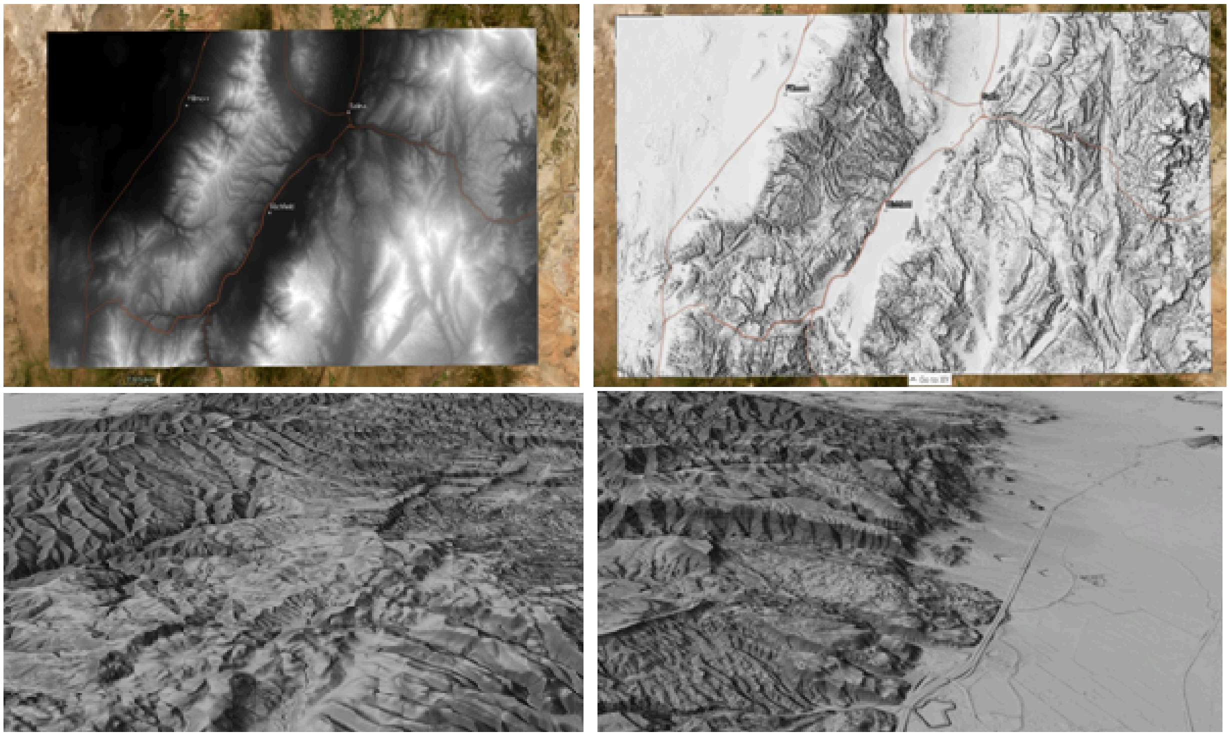

Figure C.31 — Digital Elevation Model (DEM) of Fish Lake, Utah. This DEM was created by merging and resampling around 200 DEMs from USGS mapping surveys carried out in 2016, 2018, and 2020. Th top left image is that of the DEM. The rest of the images showcase DEM's 3D Hillshade views covering various parts of the terrain.

C.5.2.1.2. Satellite Imagery

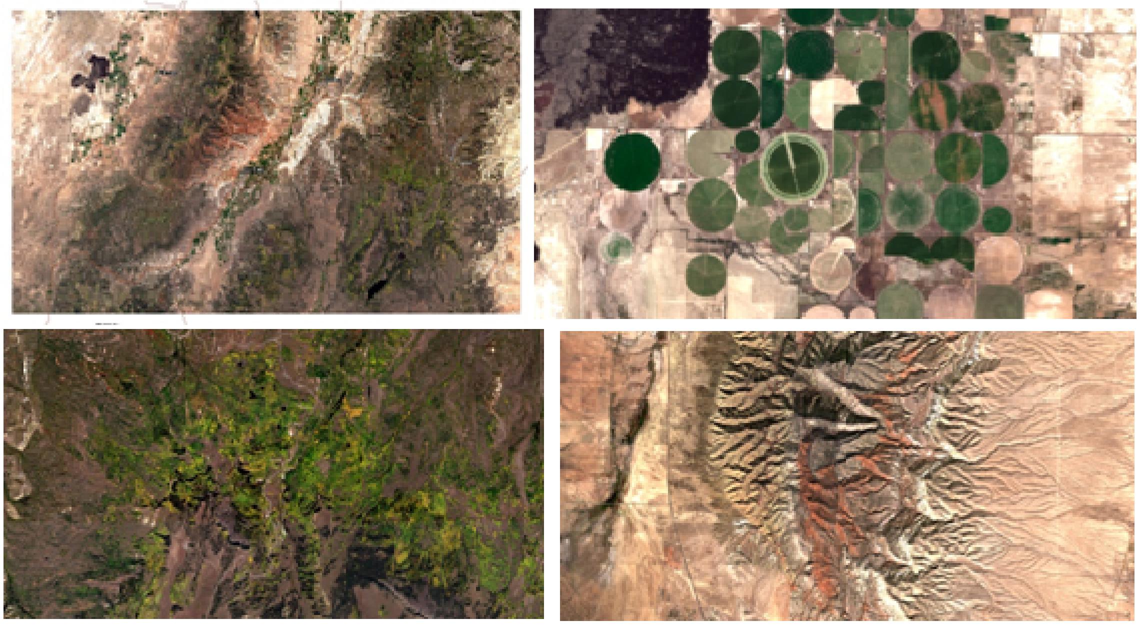

Figure C.32 — Sentinel-2 10m resolution Satellite Imagery of the area of interest. The top left image shows the 8400 square-km of the area of interest. The rest of the images showcase soil and vegetation variations.

C.5.2.1.3. AI Analysis of Satellite Imagery

The satellite imagery is classified into various soil and vegetation classes through ISO Clustering and Maximum Likelihood Machine Leaning models. Classification results are exported as the following geo-referenced masks.

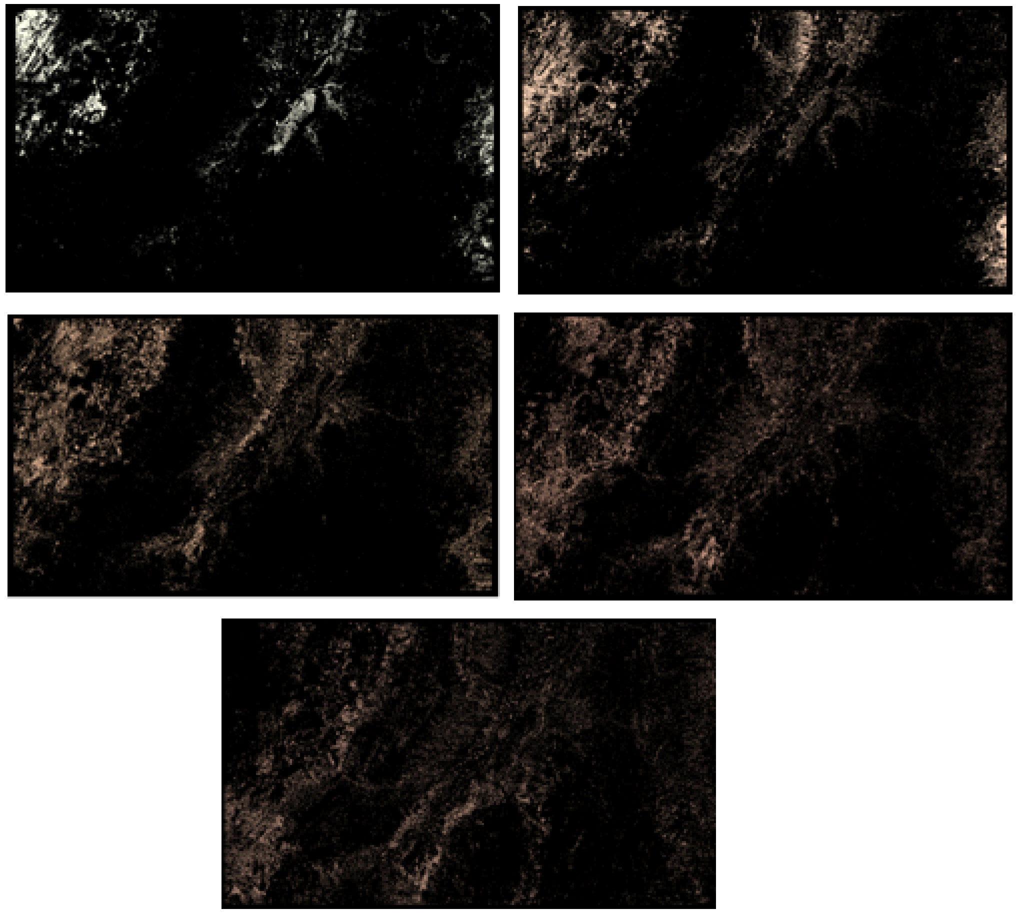

Figure C.33 — Soil classification masks from top to bottom, from left to right: (a) whitish soil, (b) golden brown soil, (c) light brown soil, (d) mid brown soil, and (e) dark brown soil.

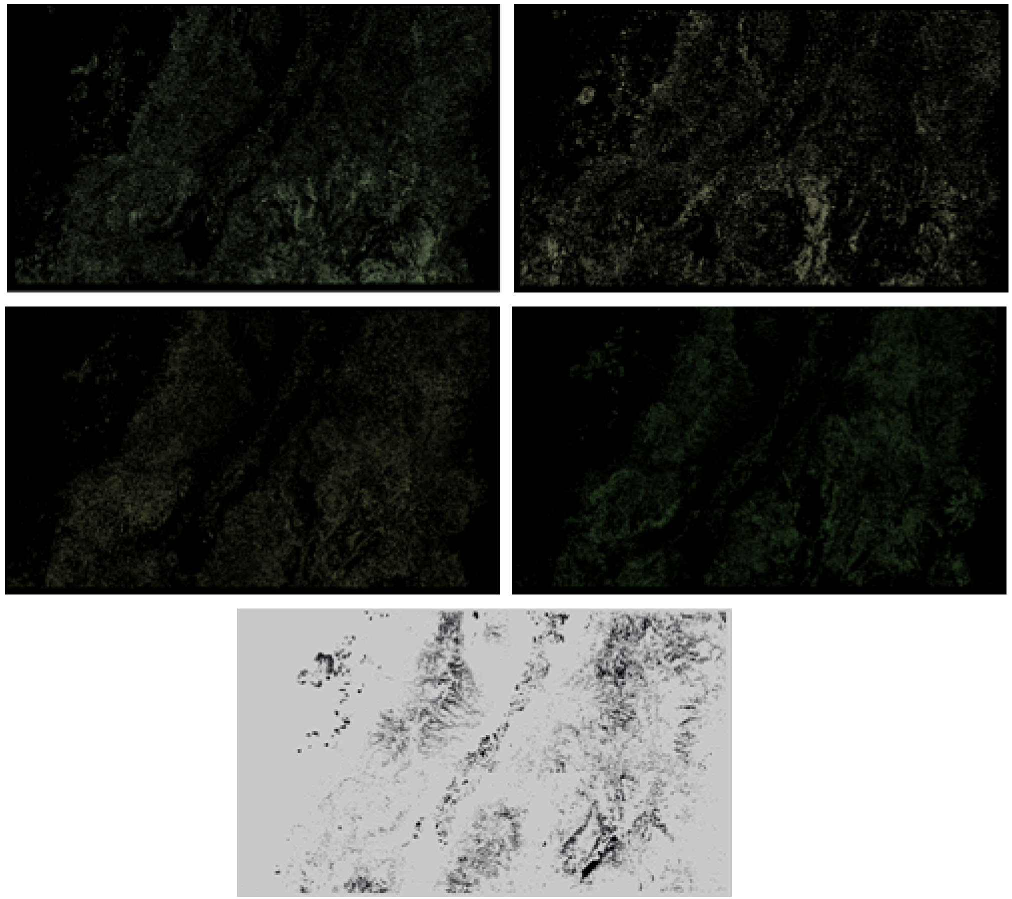

Figure C.34 — Vegetation classification masks from top to bottom, from left to right: (a) light green vegetation, (b) mid green vegetation, (c) brown green vegetation, (d) dark green vegetation, and (e) black green vegetation.

C.5.2.1.4. Road & Street Network

To build a road and street network for the area of interest, Duality relied on the AI powered Satellite/Aerial imagery Semantic Segmentation, Open Street Map, and United States Census Bureau's Road and Street dataset. For Semantic Segmentation, availability of the high-resolution imagery is a must.

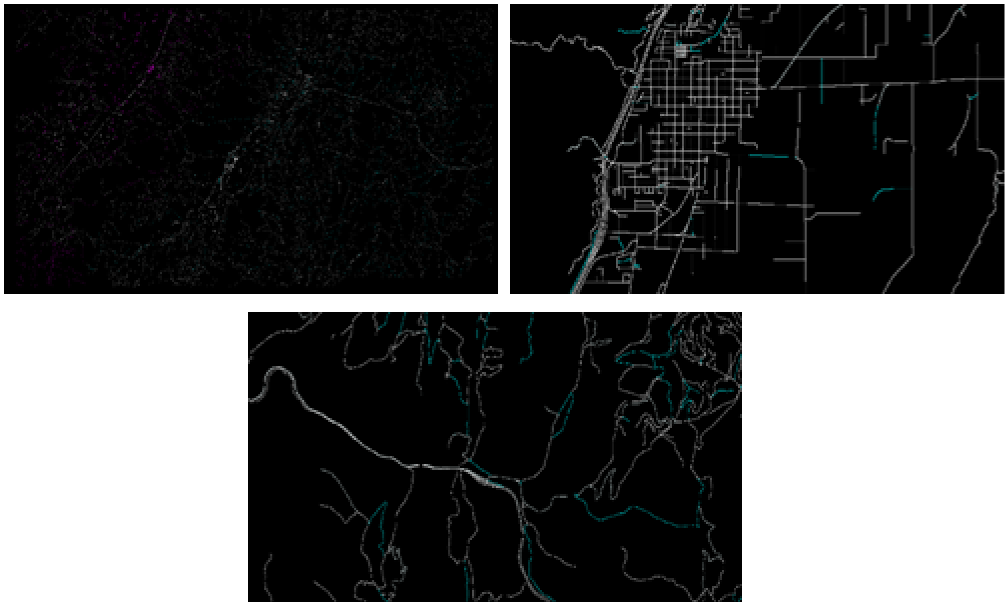

Figure C.35 — Acquiring and processing roads and streets network for the area of interest. Source: United States Census Bureau.

C.5.2.1.5. Generating Terrain Mesh

In simulation, it makes sense in some cases to pre-generate static data. To rebuild it 60 times per second in the simulation would not be ideal as it would consume resources that could be better used for increasing fidelity. DEMs are an example of this kind of static data. Duality uses Side Effects Houdini to generate terrain meshes from DEMs. The python module Rasterio loads in GeoTIFF DEM. Houdini's surface operation nodes create a mesh in which the elevation per mesh point is set from the elevation per pixel in the GeoTIFF. Surface operations also process bodies of water by replacing the Lidar-generated surface with a separate water surface mesh. In areas where the DEM has no data or the gradient is inaccurate, Houdini can interpolate the terrain elevation or approximate actual ground truth with a noise function.

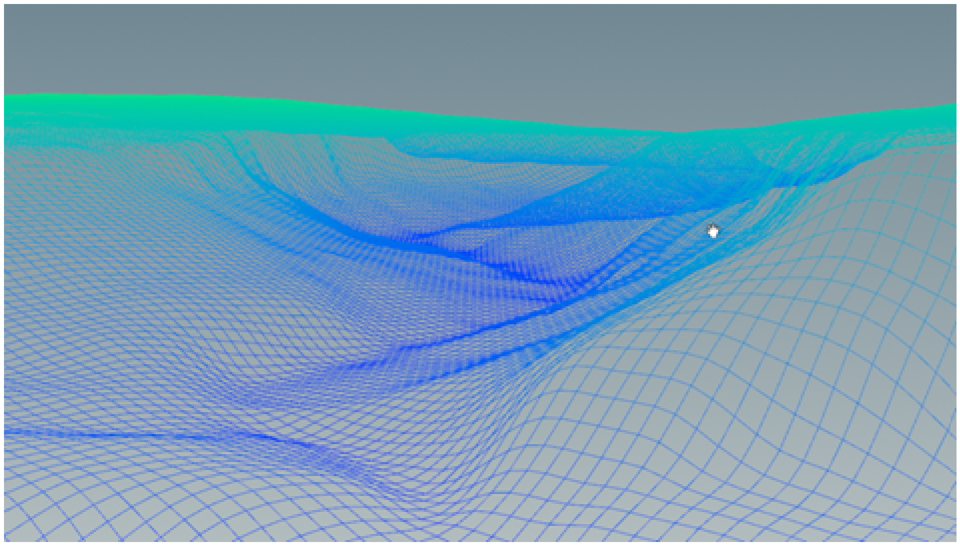

Figure C.36 — Generating terrain mesh from DEM.

C.5.2.1.6. Creating Terrain Layers

Mesh generated from the DEM, as well as soil, vegetation, and road and street network masks are used to create a layered 3D environment in Unreal Engine & Falcon. Various masks give the ability to visualize different surfaces correctly, apply physics as needed, populate foliage, forestry, and rock masses.

C.5.2.1.7. Mapping DRIs to Digital Twins

As described in Figure C.28, Falcon has been extended to fetch DRI datasets using APIs of the respective DRIs. Falcon subsequently converts these datasets into Digital Twins as specified by the OGC DTES (Digital Twin Encapsulation Standard). These DRI Digital Twins are then consumed by Falcon through Falcon's Python APIs

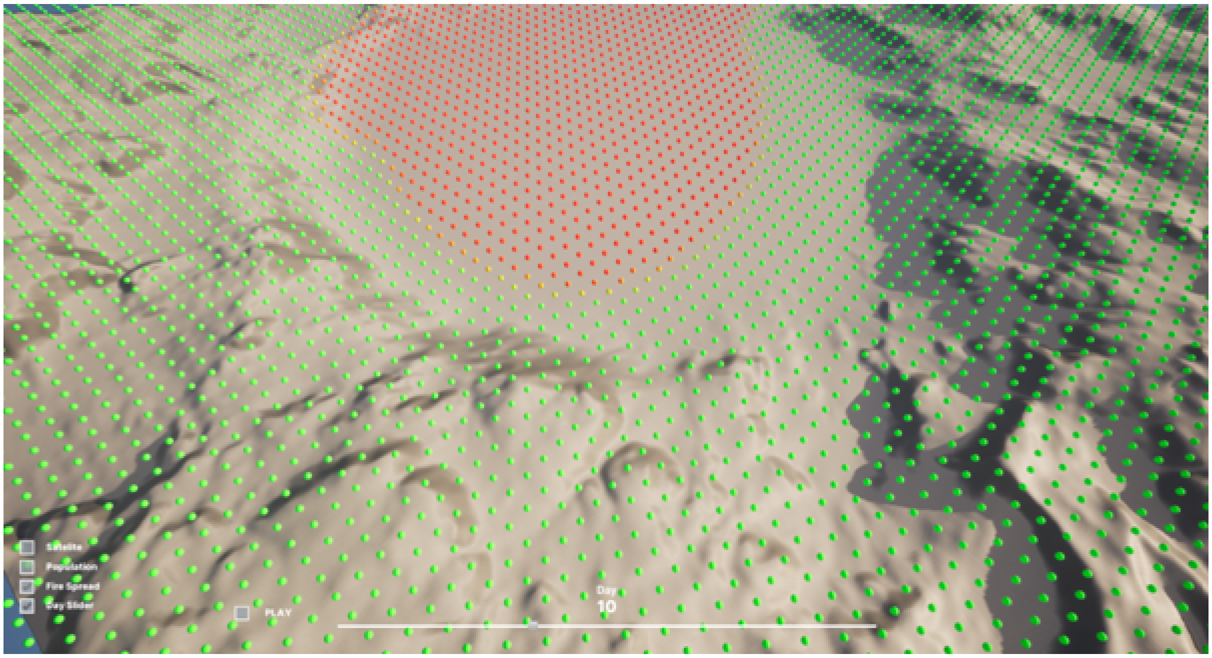

Figure C.37 — This work in progress image shows: (1) creation of various terrain layers using DEM, soil, vegetation, and road network masks, and (2) an example prototype of the Fire Fuel Indicator DRI overlayed on the 3D Site Twin.

C.5.2.1.8. Inputs

- Area of Interest
- High Resolution Time-Series Satellite Imagery
- Digital Elevation Model
- Road and Street Network
- Decision Ready Indicators (DRIs)

C.5.2.1.9. Outputs

- 3D Digital Site Twin with Navigation
- DRI Overlays

C.5.2.1.10. Supported Platforms

From a simulation and data management perspective, Falcon, built on the Unreal Engine, provides: flexible scene management; real time rigid body physics; real time rendering; and

UI layout management and widgets. Run time execution is supported on Windows and Linux computers, cloud service providers (with pixel streaming), and VR-AR displays. Falcon offers a comprehensive Python API for runtime control and integration of external simulators, data lakes, and data management pipelines. Duality will leverage the API to prototype the integration of data being sourced in real time in an IoT environment or being streamed from an external simulator.

C.5.3. Benefits

A geo-referenced Digital Site Twin of an existing location with immersive visualization, navigation, and ability to simulate various scenarios opens many opportunities for federal, state, and local government organizations, disaster response personnel, decision makers, aid organizations, and citizens. Some illustrative examples:

- immersive visualization for planners and command centers;
- what-if analysis over short and long horizons to evaluate competing strategies;
- testing end-to-end deployment of workflows and disaster response that combine autonomous, semi-autonomous, and human operated systems;
- synthetic data to train AI-ML models for satellite and aerial infrastructure monitoring;
- immersive training of first responders; and
- educating the community at large by accurately turning data sources into accessible and visceral visual media.

C.5.4. Collaborations

To overlay DRIs on the 3D Digital Site Twin for immersive visualization, Duality worked with Skymantics, HSR.health, and Compusult.

As part of DP23, the following DRIs were supported.

- Wildland Fire Evacuation Indicator Developed by Skymantics
- Wildland Fire Ignition Risk Indicator Developed by Compusult
- Wildland Fire Health Risk Indicator Developed by HSR.health

D

ANNEX D (INFORMATIVE) FLOODING WORKFLOWS/CAPABILITIES DEVELOPED UNDER DISASTER PILOT 21

D

ANNEX D (INFORMATIVE) FLOODING WORKFLOWS/CAPABILITIES DEVELOPED UNDER DISASTER PILOT 21

D.1. Flooding & landslide hazards within the Rimac and Piura river basins in Peru

The data and indicators reviewed and developed by the Disaster Pilot 21 (DP21) participants were to provide specific information regarding the impact, and potential impact, of flooding and landslides within the Rimac and Piura river basins in Peru:

- Annex D.1.1 Flood-focused ARD & DRI to support decision-makers
- Annex D.1.2 Landslide events

D.1.1. Flood-focused ARD and DRI to Support Decision-Makers

DP21 explored different Analysis Ready Datasets (ARD) and Decision Ready Information and Indicators (DRI) that could be considered by decision-makers during the whole event, starting from indicators that can serve to support the prediction of the event and an assessment of the consequences.

- **Sea Surface Temperature (SST)**: Historically, scientists have estimated the intensity of El Niño based on SST anomalies in a certain region of the equatorial Pacific. For El Niño Costero, the SST increase was produced closer to the coast, see Figure D.1. Multiple historical datasets were available to observe the trends and standard values (e.g., NOAA Extended Reconstructed Sea Surface Temperature). Being able to monitor these values, especially in El Niño Costero, would be very useful when trying to predict, anticipate, and be better prepared for such events earlier in advance.

  Satellite SST is a mature application of ocean remote sensing. Passive observations are made with InfraRed (IR) sensors onboard multiple polar-orbiting and geostationary platforms, and microwave sensors onboard polar platforms. The IR sensors have higher spatial (1-4 km) and temporal (10-15 min, onboard geostationary satellites) resolution, and superior radiometric performance. Also, satellites like Sentinel-3 with a daily revisit can be used if higher spatial resolution is needed.

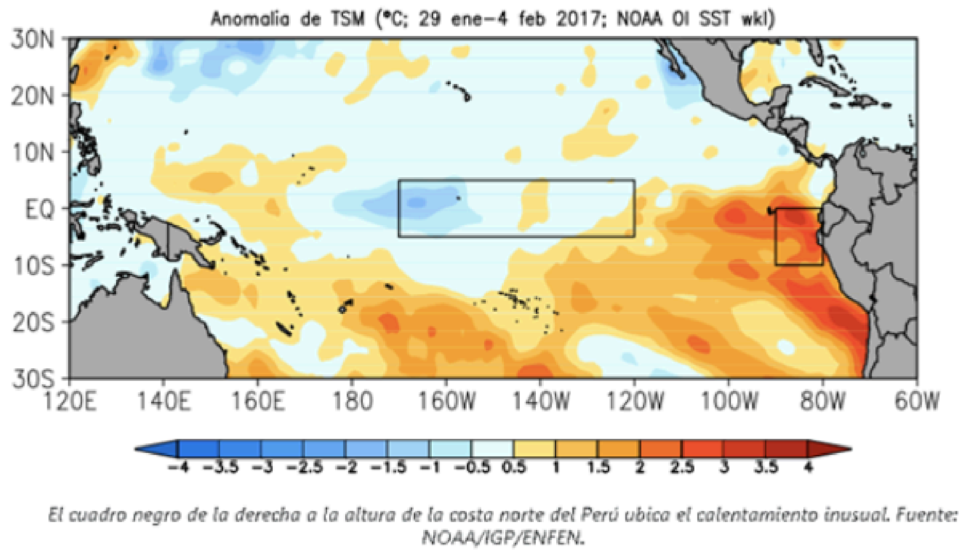

Figure D.1 — SST anomaly in El Niño Costero 2017. Unusual heating shown by the right-most black square generated by the European Union Satellite Centre (SatCen).

- **Wind**: Wind could be also considered an important parameter. In the case of El Niño Costero (2017), rain caused a decrease in the wind speed that prevented the reduction of SST, generating a virtuous cycle.

- **Precipitation**: Prediction and monitoring of precipitation are crucial since precipitation is the cause of the flooding. As an example, Figure D.2 shows the most affected departments according to the significant increase of precipitation with respect to the previous (2016) and following (2018) years. The bigger deviations were observed in the regions most greatly affected by the effects of El Niño Costero during 2017, e.g., Lambayeque and Piura.

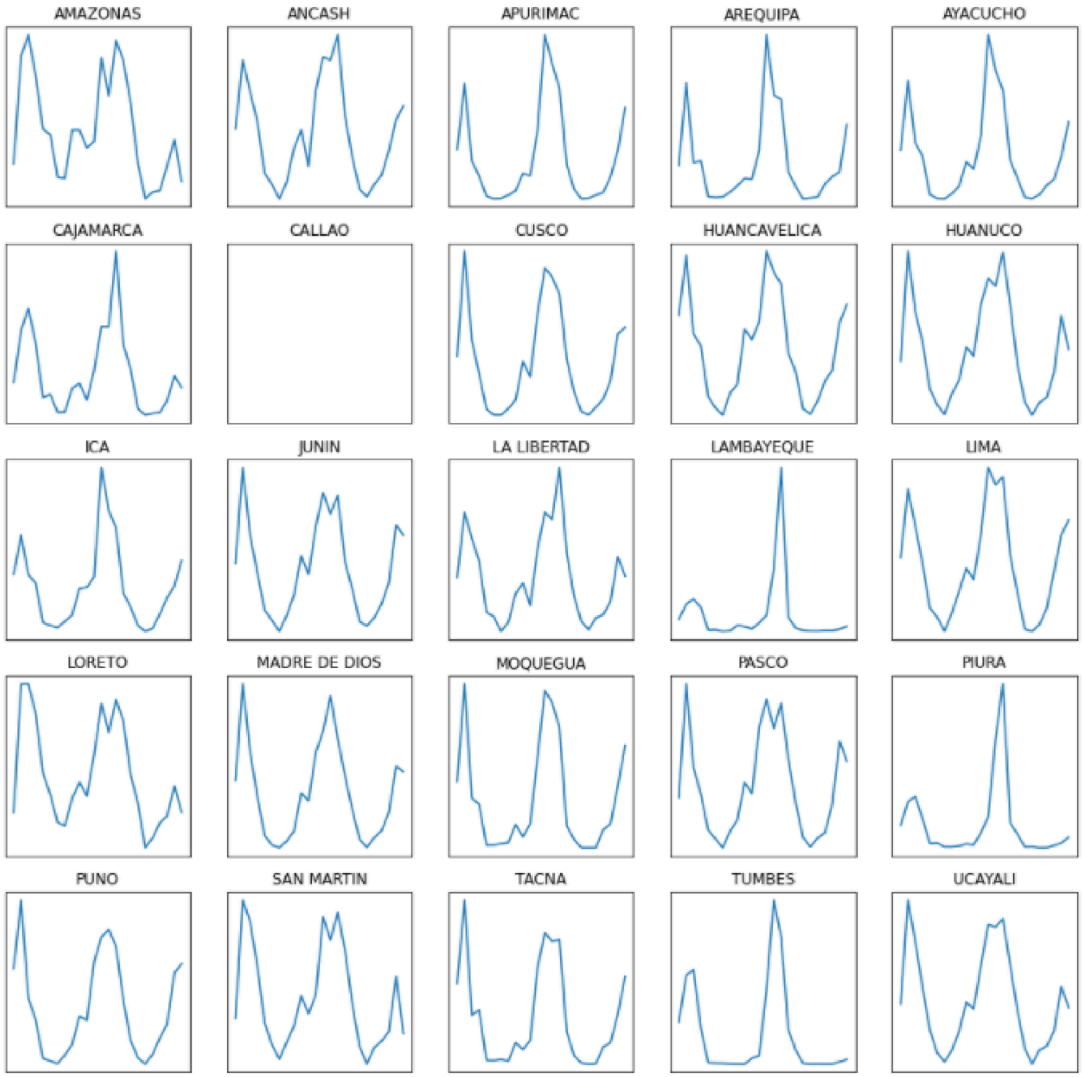

Figure D.2 — Precipitation in different Peruvian regions 2016-2018; generated by SatCen.

- **Earth Observation data**: Remote sensing data from space may be used for characterizing and monitoring large-scale phenomena such as floods, as it allows users to obtain data over large areas at a scale difficult to reach using field-based instruments and methods. In addition, the availability of open data with high temporal resolutions, such as that provided by the Copernicus Program, makes the data very well suited for the scenario under analysis. In particular, the following two main sensors were considered.
  - Synthetic Aperture Radar (SAR): SAR is very useful for mapping flood extent since SAR can acquire images in all weather conditions, see Figure D.3. However, SAR's adequacy also depends on the characteristics of the area under analysis. In this sense, different strategies have to be applied depending on the characteristics of the terrain:
    - in **open areas**, water surfaces are smooth and the specular reflection produces low backscatter (black pixels in the image);

- in **forested areas**, if the SAR penetrates the canopy, the backscatter is higher than the reference image in flooded areas due to double bounces;
- in **urban areas**, due to the strong scatterers, it is difficult to detect flooding with SAR.

Figure D.3 — Sentinel-1 (SAR) processed backscatter during the flood event 2017; generated by SatCen.

- Optical: As seen in some of the examples, see Figure D.4, optical sensors can also be used for mapping flood extent. The changes are easily detected visually with algorithms such as Change Vector Analysis that can be applied to automate the task. The main disadvantage of optical data sources is the dependency on weather conditions, since if there are clouds, no information is available.

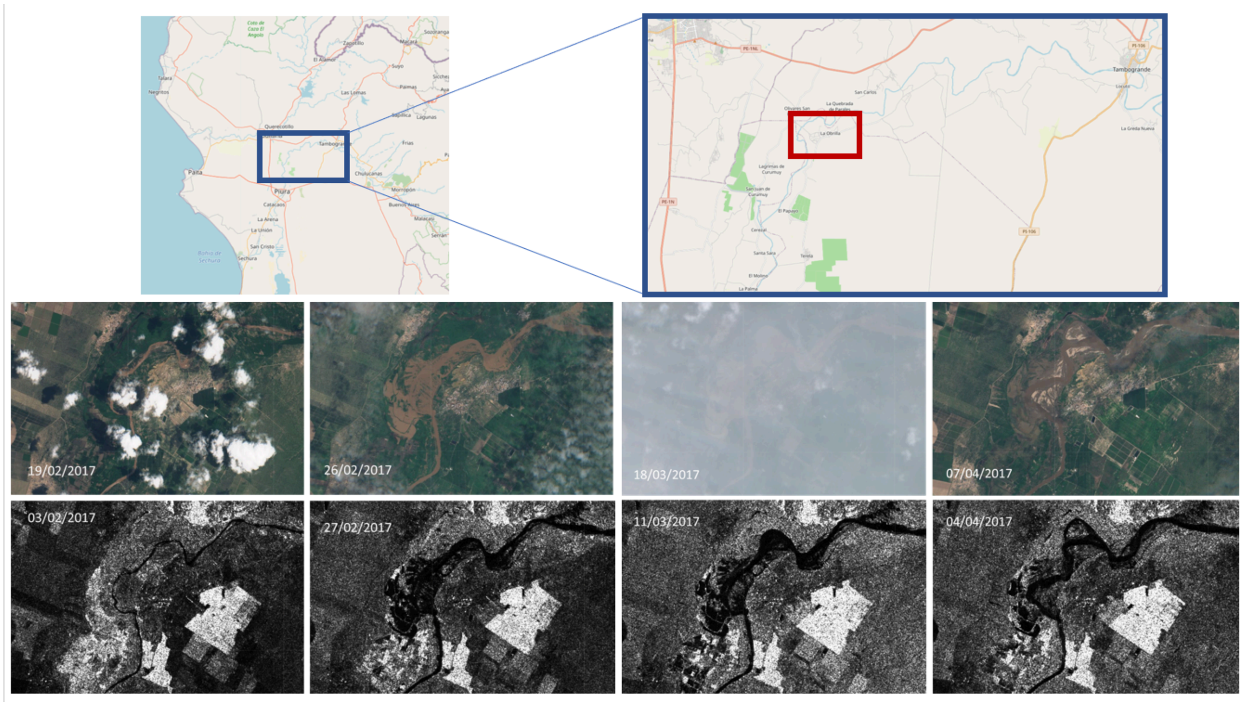

Figure D.4 — Sentinel-1 (SAR) and Sentinel-2 (optical) during the flood event 2017; generated by SatCen.

- **Change detection algorithms and products**: The automatic detection of changes in the remotely sensed imagery can be an important asset in the detection of flooded areas and serves to automate the analysis and provide information to decision-makers that can be directly used, for example, to prepare contingency plans or to understand the areas that have been more greatly impacted by flood events. Several approaches for detecting changes in SAR imagery are proposed as follows.

  - Amplitude Change Detection (ACD), see Figure D.5: An RGB composite of the backscatter of two images before and after the event, which highlights the flooded areas that are visually more straightforward to understand than raw SAR amplitude images.

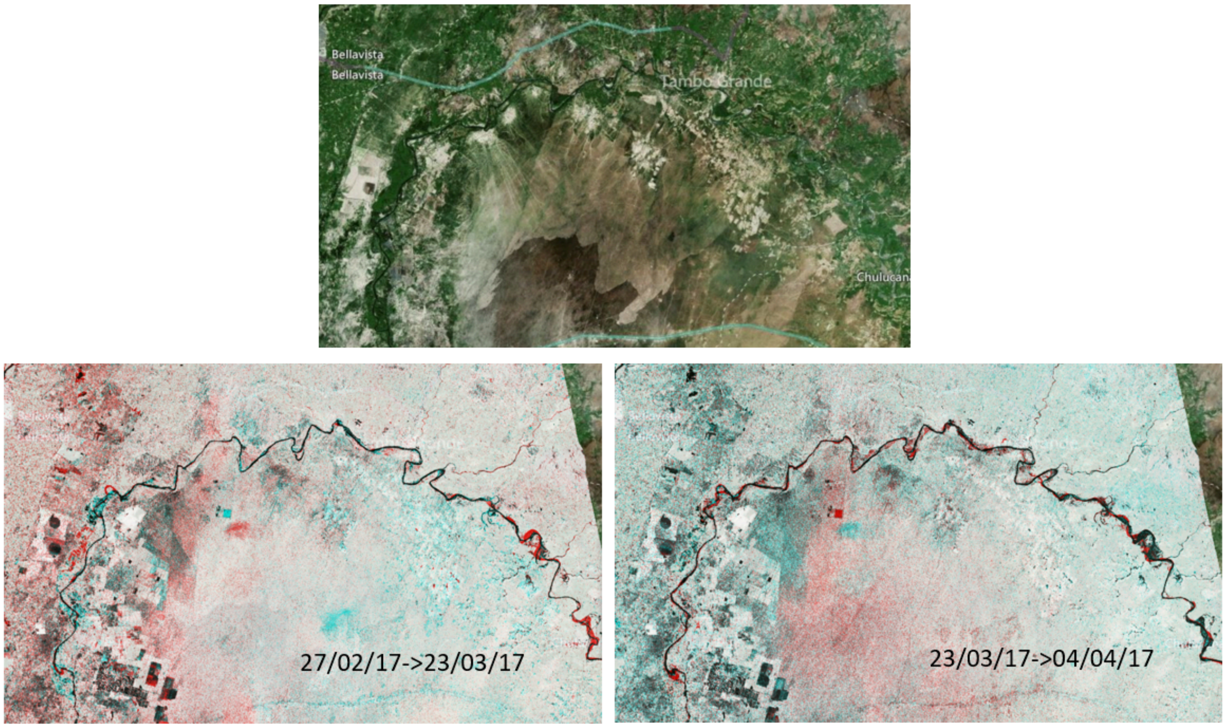

Figure D.5 — Example of ACD products generated with Sentinel-1. Red areas close to the rivers highlight the flooded area during the period; generated by SatCen.

- Multi-Temporal and Coherence (MTC), see Figure D.6: An RGB composite of the backscatter of two images before and after the event and the coherence, which represents the amplitude of the correlation between the images. As the coherence between two interferometric acquisitions is a measure of the degree of correlation between the phase of the signal in the two acquisitions, it is a very good and reliable method for detecting changes in pairs of SAR images. In the cities, the predominant color is white (high values in R and G channels because of high backscatter) and high value in B channel because of high coherence (no changes), but if there are changes, they will be highlighted in red, green, or yellow depending on origin which could be useful to detect possible infrastructures affected by flooding or landslides for example.

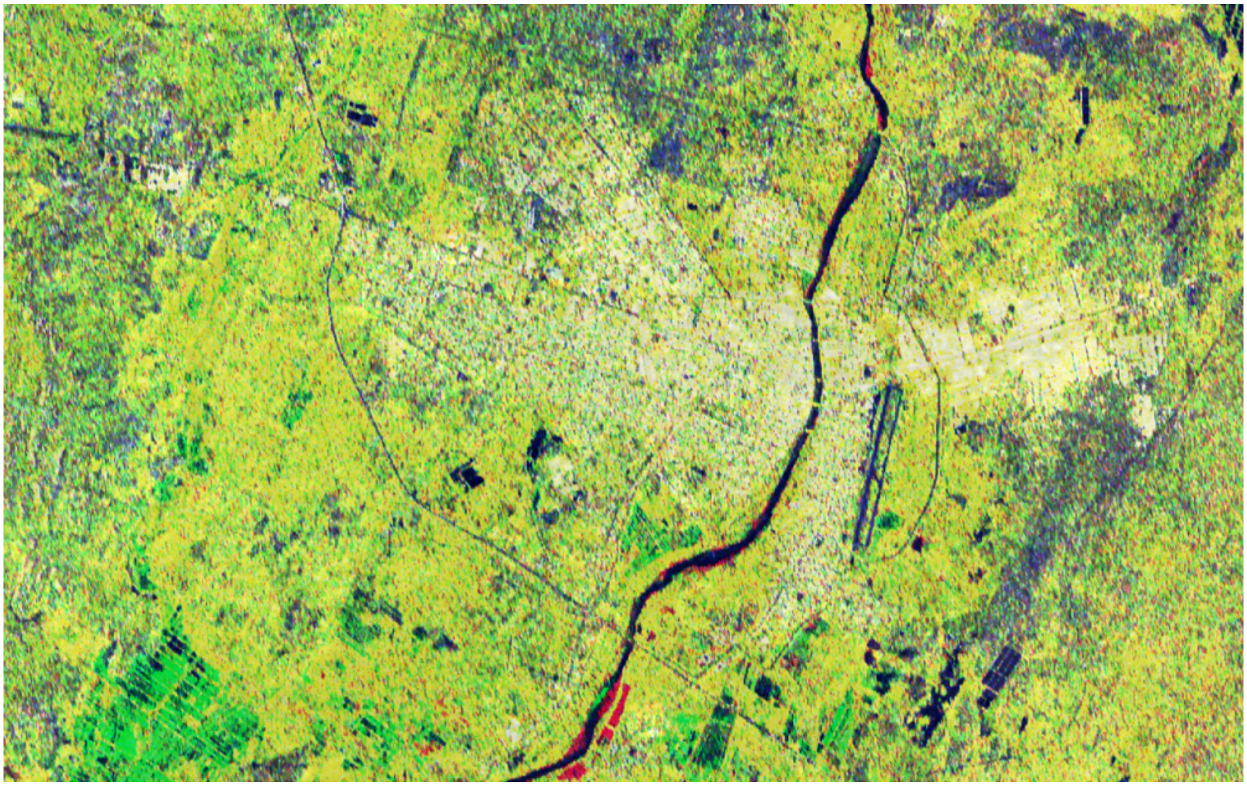

Figure D.6 — Example of MTC product generated with Sentinel-1 over Piura. Red areas close to the rivers highlight the flooded area during the period as generated by SatCen.

- **Flood monitoring**: Based on the above-mentioned Change Detection products, it was possible to extract a flood mask through, for example, image segmentation techniques such as simple thresholding, see Figure D.7. The flood mask could consequently be used to monitor the extension of the affected areas as well as to overlay the extension with reference maps (e.g., as obtainable from OpenStreetMap) to identify possible affected critical infrastructure.

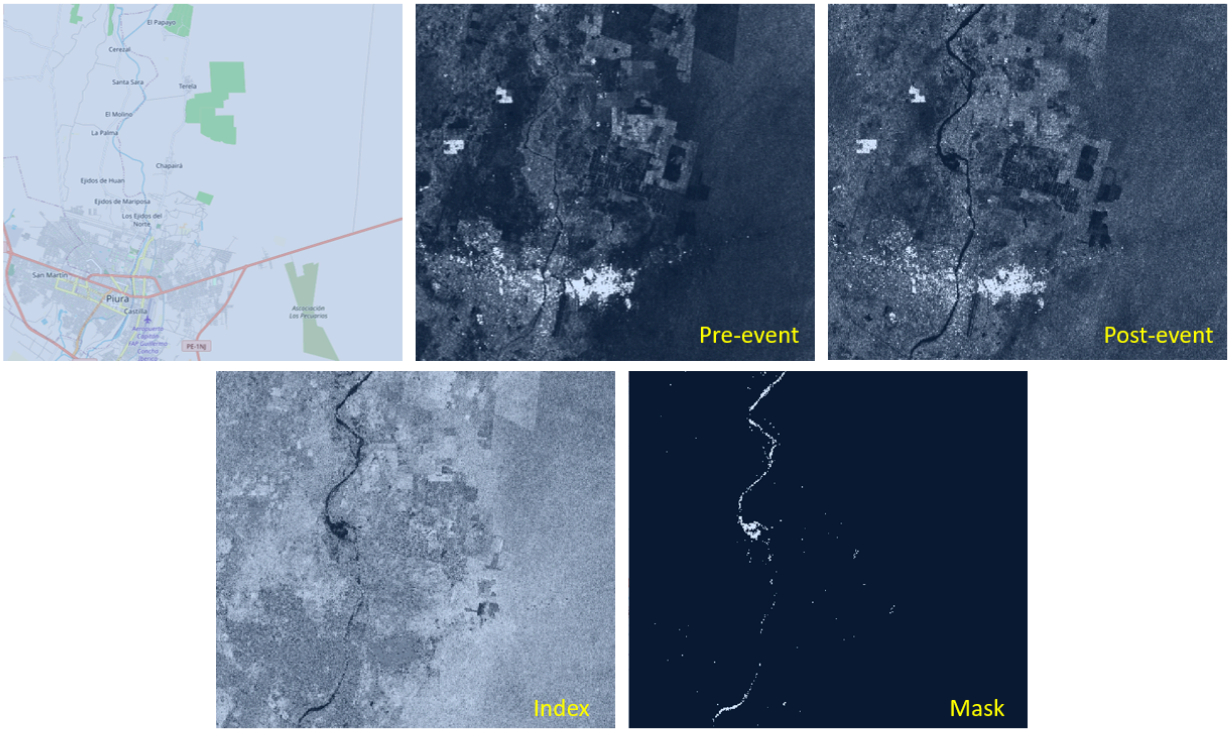

Figure D.7 — Example of flood mask computed from Sentinel-1 data; generated by SatCen.

D.1.2. Landslide events

D.1.2.1. Introduction

Landslide is a general term used to describe the downslope movement of soil, rock, and organic materials under the effects of gravity and also the landform that results from such movement. The landslides can be of different types according to the material involved and the movement (fall, topple, slide, spread. or flow).

The triggers for a landslide are diverse, including intense rainfall, rapid snowmelt, prolonged precipitation, flooding, earthquake, volcanic eruption, etc., and can be aggravated by natural (weak materials, erosion, etc.) and human (excavations, deforestation, etc.) causes.

Peru is classified as a high-susceptibility area for landslides because of the country’s rainfall patterns, terrain slope, geology, soil, and land cover. Localized landslides are then a frequent hazard phenomenon and usually linked to flooding.

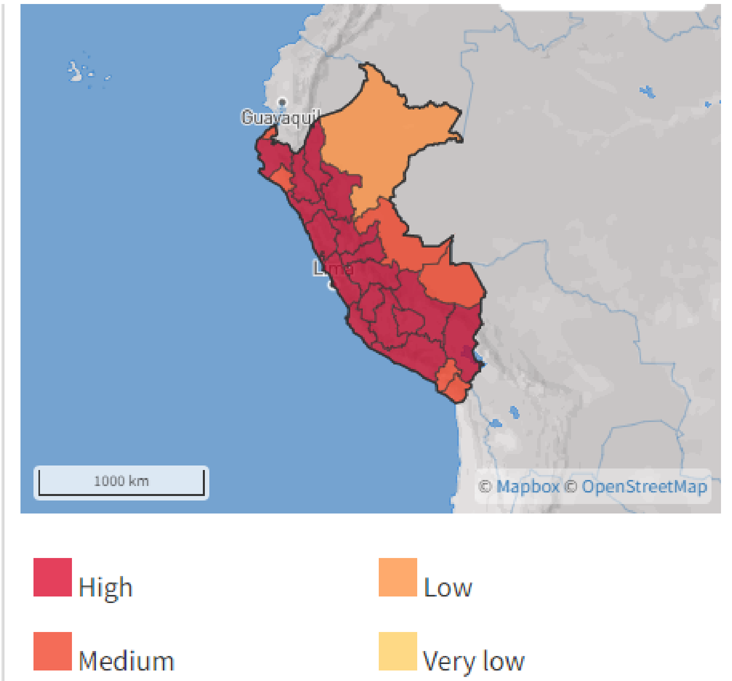

Figure D.8 — Landslide susceptibility in Peru.

D.1.2.2. Landslide-focused ARD and DRI to support decision-makers

DP21 explored different ARD and DRI that could be considered by decision-makers during the whole event, starting from indicators that can serve to support prediction of the event and an assessment of the consequences. Some of these data were the same as considered in the flooding scenarios.

The main event studied during DP21 was the Achoma landslide on 18th June 2020. In this event, soil and rock on a hillside slipped loose and created a landslide affecting more than 40 hectares.

The landslide generated a dam in the Colca river, which caused flooding and was clearly visible using Sentinel-2 data as shown in Figure D.9.

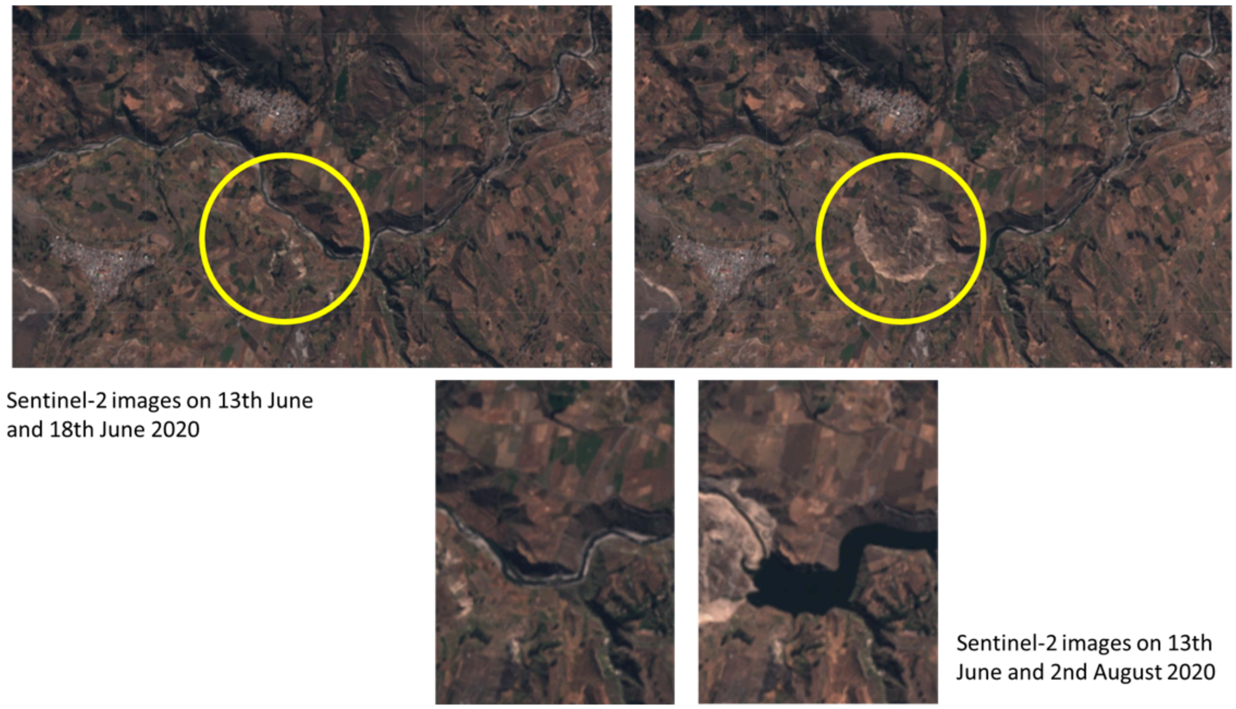

Figure D.9 — Sentinel-2 images over Achoma landslide.

Similar analysis to the flooding was carried out with Sentinel-1 (SAR) to detect changes. The preliminary products for visual assessment were the ACD and MTC.

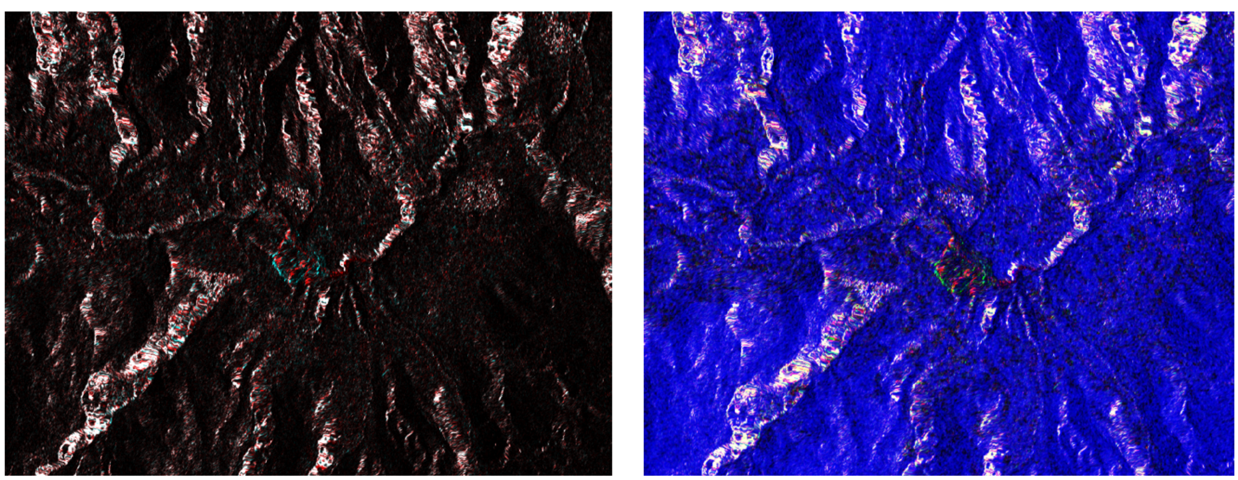

Figure D.10 — ACD (left) and MTC (right) generated with Sentinel-1 data over Achoma with images before and after the landslide.

The change in the terrain was visible in the ACD at the center of the image. The changes are highlighted in red and cyan (depending on the slope, the landslide increases or decreases, and the backscatter amplitude). But in the MTC, the change can be distinguished more precisely due to the loss of coherence. In the MTC composite, the blue band corresponds to the coherence. In Figure D.10, the coherence is high in all the images (blue and white color) except in the area affected by the landslide.

In particular, for this event, a time series of the coherence was computed using the Sentinel-1 SLC products.

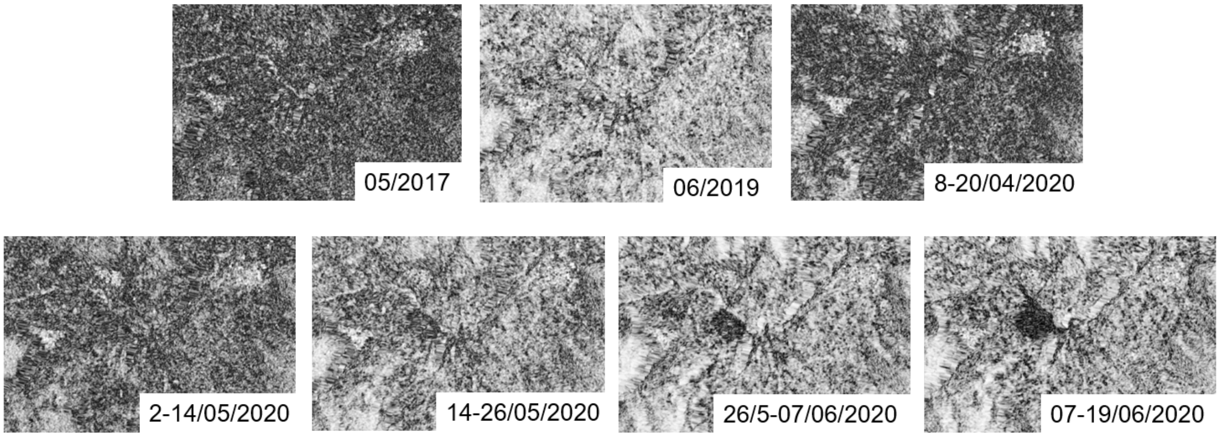

Figure D.11 — Time series of coherences generated with Sentinel-1 data over Achoma.

In the time series, the coherence in all the areas seemed uniform and is higher or lower depending on the specific pair of images (probably due to soil moisture), but always homogeneous. After the pair from 14th and 26th May 2020, the area where the landslide will happen can be distinguished because of the loss of coherence.

The loss of coherence was at its maximum in the last image (computed with a pair of images just before and after the landslide), and so the contour of the affected terrain could be delineated easily.

But the coherence in this example was not only useful to identify the affected area, it also seemed possible to use it to predict the event some days before it happens.

D.1.3. Conclusion

The work on Peru's Rimac and Puira rivers showed it was possible to deliver a value chain to create an example ARD and DRI, however, it also identified issues and limitations around automating the process that would need to be addressed.

D.2. Flooding hazards and pandemic impacts within the Red River basin in Manitoba, Canada

DP21 undertook the following steps in going from flood extent to traffic control.

- Calculation of ARD flood extent from the following.
  - Digital Elevation Model (DEM), e.g., from 5 m lidar, and Near-Real-Time (NRT) river gauge data to predict flooded areas. For example, Figure D.12 shows the output for the

2011 flooding as suitable 2020 gauge data were not accessible. This is the so-called "bathtub" approach, where the flood surface is projected onto the DEM by assuming a horizontal plane of predetermined height or elevation.

- Optical or radar satellite data combined with algorithms used to detect flooding. Figure D.12 shows flooding occurrence for April 2020 determined using Sentinel-1, Sentinel-2, and Landsat-8 data by Wuhan University which was overlaid on the same DEM as used for Figure D.13 but was for an area further north that overlaps with the modeled flood extent.

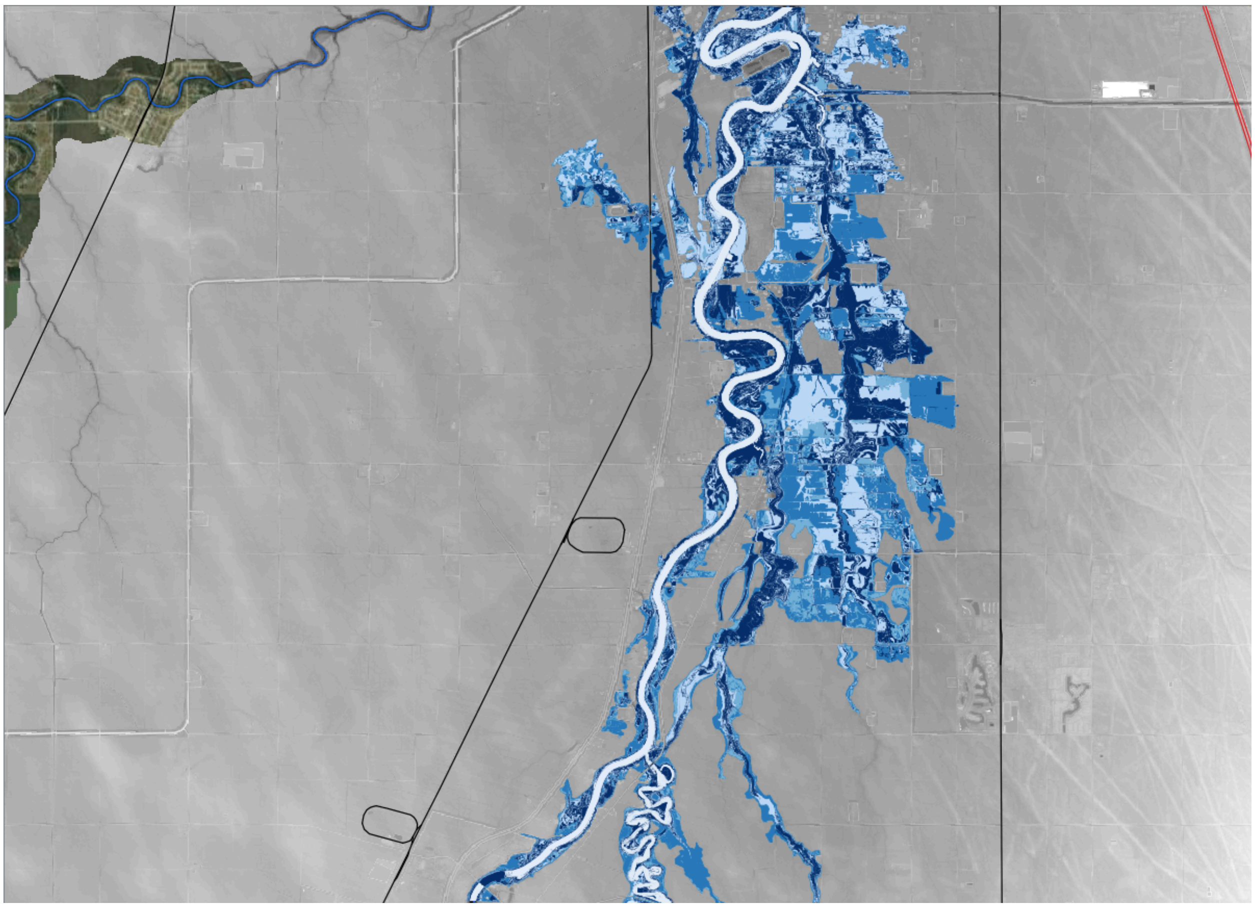

Figure D.12 — Area of 2011 flooding colored light to dark blue according to flood day (start to end) overlaid on lidar DEM (shades of gray), with railway lines as black lines, and motorways as a red lines and the flooding area from RSS Hydro using the "bathtub" approach.

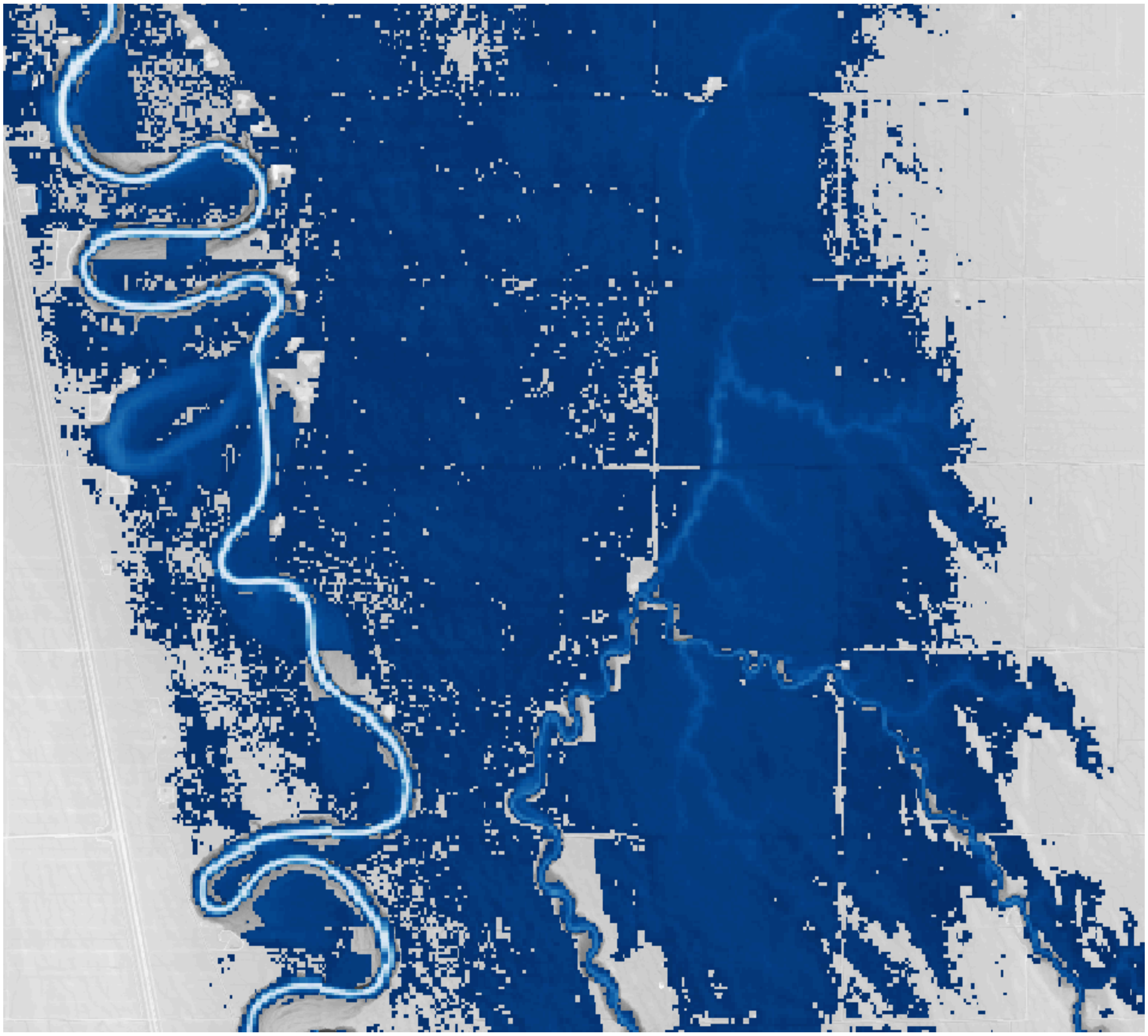

Figure D.13 — Section of the April 2020 flooding, colored dark to light blue according to the occurrence, developed by Wuhan University, overlaid on the lidar DEM.

- ARD raster area grid flood predictions converted to ARD flood contours, e.g., following an approach implemented by Safe Software using their FME platform (model based spatial ETL data transformation and integration tool); as shown in Figure D.14.
- Given the sensor and computational tools used, both EO and flood model output datasets tend to generate grid based observations or time series. However, many decision support tools are based on GIS approaches that are best adapted to work with vector datasets. This is why the ARD to DRI approach for flood impact analysis was designed to convert raster flood depth grids to vector flood contour polygons. Flood contours were used instead of flood extents because the rules associated with the transportation impact DRIs required flood depth estimates and not just flood state.
- In this example, a raster to vector conversion was performed, followed by the removal of the smallest polygons, generalization to reduce detail (e.g., by smoothing lines),

classification into five depth categories (0.1, 0.3, 0.5, 1.0, and 2.0+ m), and finally dissolving (aggregate touching features to further reduce complexity).

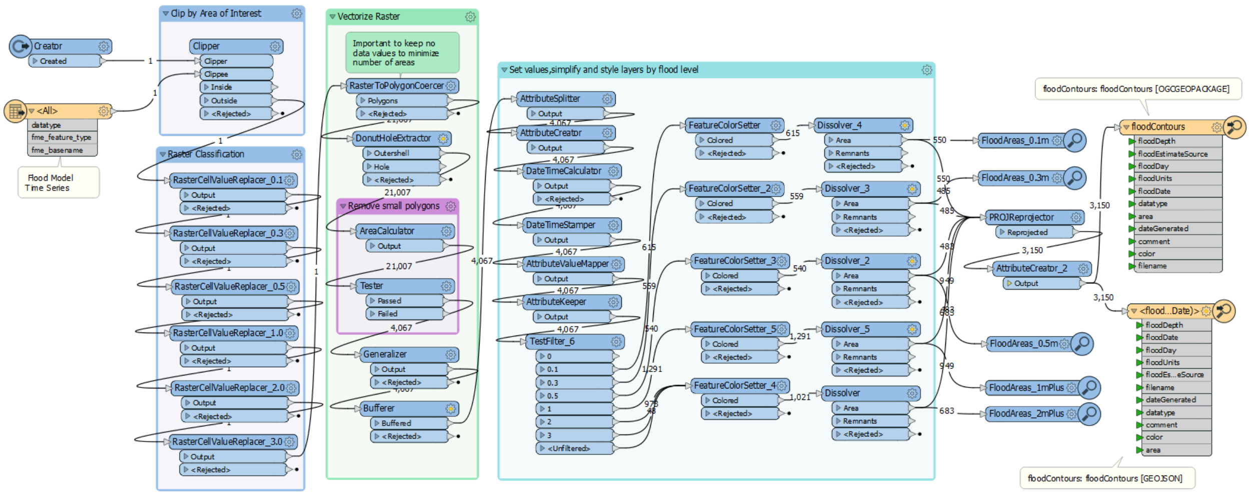

Figure D.14 — ETL approach for converting flooding areas to contours, using FME from Safe Software

- The result was saved as an OGC GeoPackage, which was easy to share with other components as well as use offline. To better support online integration, the vector flood contour time series provided to the HSR.health GeoNode instance which made these data available to other components via OGC services such as WMS and WFS. The data were also made available directly to users with web browsers via the GeoNode web map interface, see Figure D.15. The data were published with the flood date field used as a time series index so that the time slider can be used to explore the propagation of the flood over time.

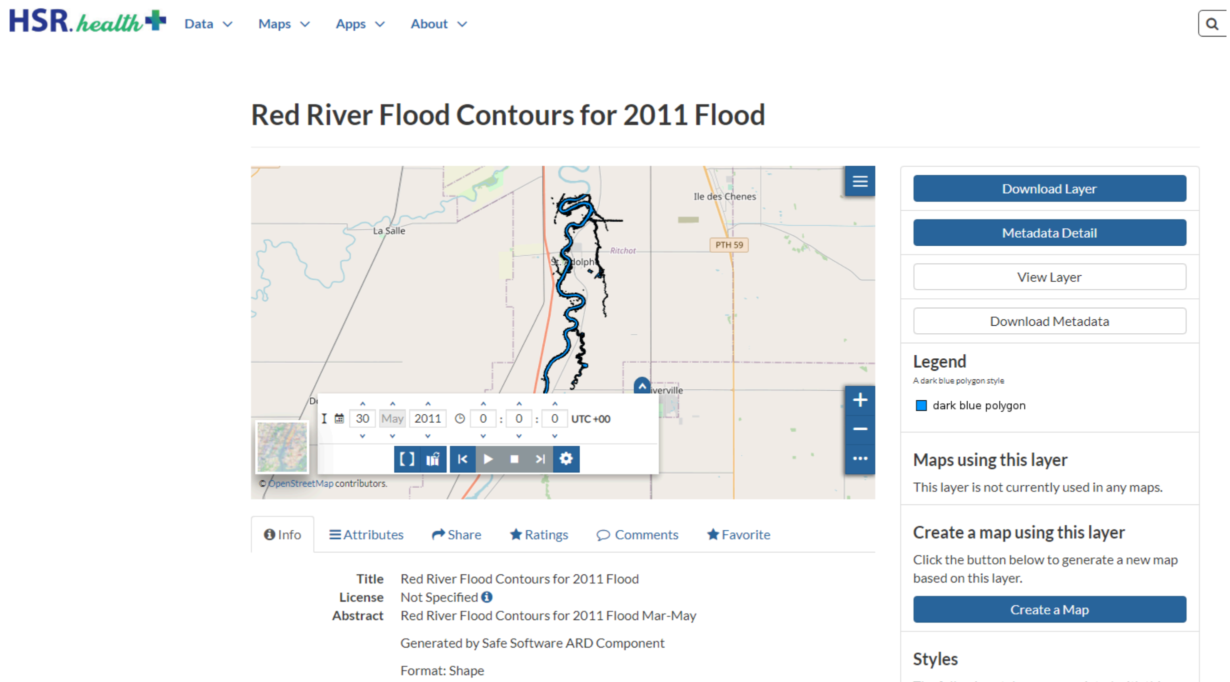

Figure D.15 — HSR.health GeoNode with Flood Contours for Red River flood from April 7 2011 loaded from FME workflow output.

- Flood contours were used to generate DRI routing information, e.g., following the approach outlined in Figure D.16 as designed by Skymantics.

Figure D.16 — Converting the flooding ARD inputs to DRI to support the management of flooded rivers, Skymantics

- The flood contours were used to determine the roads affected by flooding and the depth. The user specifies what depth of flooding is passable. Then, the routing determines the best route between two locations. See Figure D.17 that shows (from top to bottom) the route without flooding, routing parameters, and route with flooding. A full list of recipes and resulting DRIs is given in the Appendix to this section.

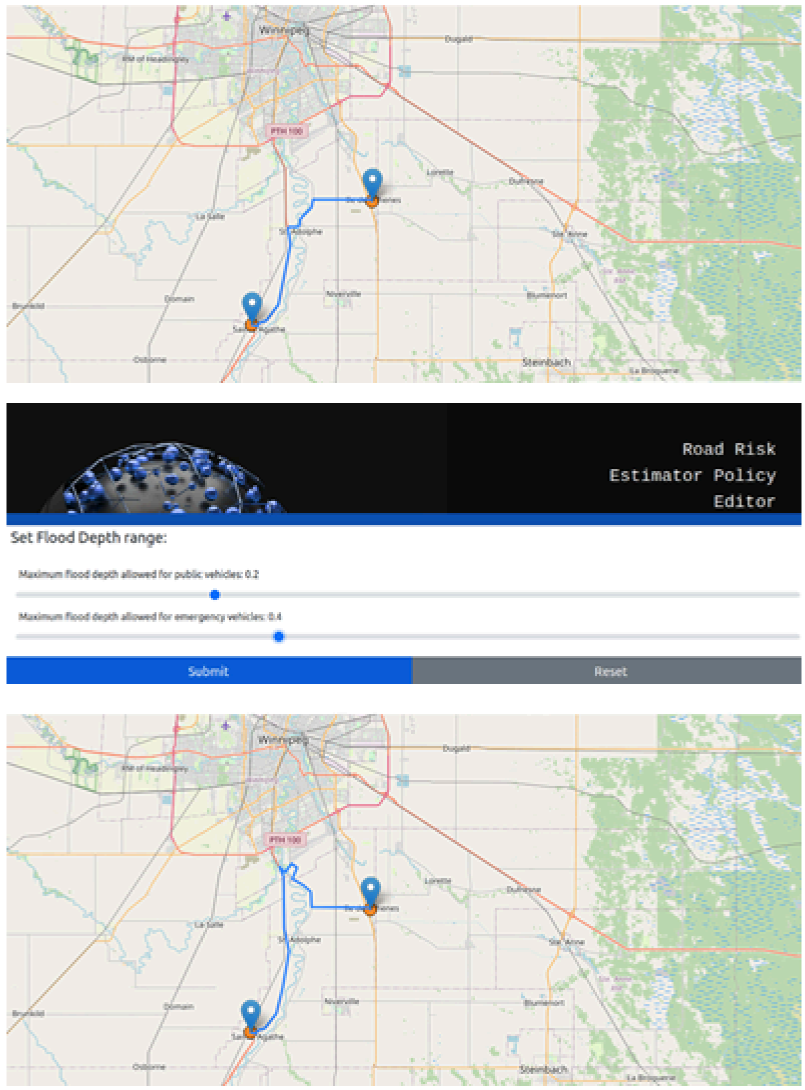

Figure D.17 — Route determination without (top) and with (bottom) flooding overlaid on OSM, and the routing parameters (middle); Skymantics

D.2.1. Conclusion

This activity focused on flooding within the Red River basin, Canada. DP21 generated ARD data and then converted the data to DRI following a recipe that focused on the routing of emergency vehicles. The ARD data included numerical modeling and EO sources (Sentinel-1, Sentinel-2, and Landsat-8) that were first generated as raster (image) products and then converted to vector (point, line, polygon) products to better support downstream impact analysis components.

The transfer of data between the different players was primarily through manual transfer in a GeoPackage, with the addition of web service support once the flood contours were published to GeoNode. The flooding figures were generated using QGIS, but could have used another visualization package that supports geospatial information.

It was recognized there was a need to deal with the encountered size and scaling limitations of GeoNode. Therefore, further work was identified as being needed to bring all components together via cloud computing, so that manual data transfer is removed wherever possible.

Also, when data are provided as a service with a REST endpoint, technologies such as GeoCollaborate can access and share those data products in a real-time collaborative environment, connecting all decision-makers immediately and enabling interactivity across the collaborative participants. Therefore, a reasonable goal for data providers is to offer data as a service to put the data to work more rapidly.

D.2.2. References

- Lindenschmidt et al. 2010
- Manitoba, 2020, Red River Floodway Operation Report Spring 2020
- NASA, 2020, Another Flood on the Red River

D.2.3. Appendix: Flooding DRI Recipes

Routing recipes for a flood scenario

Table D.1

RECIPE DESCRIPTION	INPUT ARD	PROCESS	OUTPUT DRI	THRESHOLDS	EXPLANATION	SUGGESTED ACTIONS
Sentinel-1 Change Detection Algorithm	Sentinel-1 GRD	Satellite algorithm	Change detection map (Geo TiFF); Change detection mask (Geo JSON); Flood mask / extension, change maps			
Update road estimated speeds due to precipitation	Current precipitation area and intensity; Roads dataset	Find roads affected by precipitation	Light rain occurring in road X; Heavy rain occurring in road X	0.25–6.4 mm/h; >6.4 mm/h	Common thresholds and impacts in observational studies.	Reduce estimated road speed by 10%; Reduce estimated road speed by 25%

RECIPE DESCRIPTION	INPUT ARD	PROCESS	OUTPUT DRI	THRESHOLDS	EXPLANATION	SUGGESTED ACTIONS
					Considerable regional variations	
Update estimated speeds from traffic cameras	Real-time traffic cameras live-stream	Find jammed roads	Road X average speed	<50% speed limit))	((Successfully tested in OGC SCIRA pilot	Mark road as jammed and notify it; Reduce estimated road speed
Manage flooded roads	Extension & depth of current flooding; Terrain topography (road elevation); River and flood gauges (water level); Inputs from public and first responders (water level); Roads dataset	Find roads affected by flooding	Road X flooded but passable; Road X flooded and only passable by special vehicles; Road X flooded and impassable	<150mm flood depth; 150-300 mm flood depth; >300 mm flood depth	With 150 mm depth, water can enter a small car's exhaust pipe. With 300 mm depth, cars can start floating. Several articles point to a traffic speed reduction based on depth.	Reduce estimated road speed to 70-20 km/h; Reduce estimated road speed to 20-2 km/h; Block road for public; Notify traffic apps; Block road for all transit
Forecast flooded roads during night time	Extension & depth of future flooding (during night time); Terrain topography (road elevation); Roads dataset	Find roads affected by future flooding during night time	Road X flooded and only passable by special vehicles; Road X flooded and impassable	150-300 mm flood depth; > 300 mm flood depth	Roads that are expected to get flooded during the night should be closed in advance. Somerset road closure gates are an example.	Block the road for the public. Notify traffic apps; Block road for all transit

E

ANNEX E (INFORMATIVE) INTEGRATION OF HEALTH & EARTH OBSERVATION DATA FOR PANDEMIC RESPONSE

E

ANNEX E (INFORMATIVE) INTEGRATION OF HEALTH & EARTH OBSERVATION DATA FOR PANDEMIC RESPONSE

E.1. Integration of Health and EO data and services for pandemic response in a region of the United States

In advance of the Disaster Pilot 2021 (DP21), the world become very familiar with the word 'pandemic,' but it is important to understand what it means. When a known or unknown disease affects a large number of people within a community or population it is classed as an epidemic. It becomes a pandemic when the disease spreads to multiple countries, whereas an epidemic is an unexpected increase in the number of disease cases in a specific geographical area. The reference to geography in both definitions is a useful indication of why geographic information and Earth Observation (EO) data can offer help when integrated with health data to support the response to pandemic situations.

COVID-19 is an infectious disease caused by a coronavirus named SARS-CoV-2. Most people infected experience mild to moderate respiratory illness and recover without requiring special treatment. Some experience no symptoms at all. However, older people and those with some underlying medical conditions are more likely to develop serious illness and may require medical attention, and sadly, many people died due to COVID-19.

This activity focused on how health and EO data can be integrated to improve the pandemic response within Louisiana, United States.

The fact that Hurricane Ida struck Louisiana during the pandemic indicates the need to be able to monitor and respond to other disaster events that might occur at the same time as a pandemic. Therefore, the aim was to demonstrate how integrating health and EO data can add value and provide support and assistance within a pandemic response.

E.1.1. What is there now?

Before the COVID-19 pandemic, there was no integration of health and EO data for a pandemic response within Louisiana. Once the pandemic began, datasets began being produced to look at the disease spread and its impact. These datasets tended to be produced in isolation, rather than integrated, as described below.

For health, together with the data already collected by the State, various analyses looked at the spread of the disease. For example, the Louisiana Coronavirus Data Dashboard includes a Parish risk index displayed in a Geographic Information System (GIS).

For EO, existing datasets were applied to the pandemic situation, however, most of the analysis focused on the impact of the pandemic rather than health issues. For example, there was a lot of work looking at the reduction in carbon dioxide emissions due to the large-scale reductions in the number of planes flying, or looking at a reduction in thermal energy and light pollution in urban centers as factories and offices were not operating due to government directions that people should stay at home.

Some examples, although not all, of the use of EO data to look at the pandemic, include:

- NASA's EarthData COVID Dashboard was an experimental dashboard looking at 10 areas across the globe and focusing on 7 indicators, demonstrating the changes in the environment that were observed as communities around the world changed their behavior.
- European Space Agency & European Union's Rapid Action on Coronavirus and EO Dashboard demonstrated how EO data can support the monitoring of societal and economic changes due to the pandemic using data from the Copernicus Sentinel satellites and other Copernicus Contributing Missions. The Dashboard also included case and vaccination health data on the diseases, although these were not integrated with the EO data. The GeoGlam Crop Monitor (https://cropmonitor.org/) provided information on global agriculture conditions and crop conditions, and how COVID-19 might impact food markets and the knock-on effects of this on food insecurity.
- GIS COVID-19 Dashboard from the BEYOND Centre of Earth Observation Research and Satellite Remote Sensing, National Observatory of Athens gave details on the COVID-19 worldwide spread, plus additional air quality and environmental indicators.

Whilst there were other dashboards across the world, many were focused only on a particular area of the world, focusing on specific data indicators or producing reports available to access. This review concluded that there was not a good example of the integration of health and EO data to support the pandemic response, which is why DP21 could add value to the current experience at that time.

E.1.2. What did the 2021 Disaster Pilot Do?

Following the data model developed in DP21, the work focused on developing a set of potential Analysis Ready Datasets (ARD) and Decision Ready Indicators (DRI) that could be used to support a pandemic response and identify those health indicators which could be supported by EO data.

As an example of how this might work, the activity showed how health data could be used within a GIS to support pandemic response through a Medical Supplies Index and routing map developed by HSR.health and Skymantics, together with EO examples images that could be integrated to create, develop, or improve the ARD or DRI.

E.1.2.1. Foundation Layers

As highlighted in Step 1 of Clause 6, it is recognized that a number of foundation data layers of local geospatial information need to be established and developed into which health and EO data can be integrated.

The following Foundation Layers for pandemic response were identified, and most could be achieved from national or local information:

- habitation layers (villages, homes, farms) including building footprints;
- health infrastructure including hospitals, clinics, medical offices, health centers, pharmacies, labs, dental clinics, nursing homes, long-term care centers, diagnostic testing centers, emergency dispatch centers, health supply manufacturers and warehouses, and drug manufacturing plants, etc.;
- critical infrastructure including power, telecommunications including wireless network, water, sanitation, etc.;
- transport network including road network, freight train route, helicopter, and aircraft landing zones;
- address databases and geocoding applications; and
- critical supply chain facilities and routes for key medical, food, etc.

The EO specific Foundation Layers would include the following.

- Satellite Imagery of the area the disaster response team is responsible for, with coordinates or addresses.
- Land Use and Land Cover maps identifying how the land is being used, e.g., urban centers, agriculture, woodland, lakes, and rivers, etc.
- Digital Elevation Models to understand the height of land.
- Potential Hazard and Vulnerability (High Risk) Areas for natural hazards such as flood risks, tornado risk, etc., based on models and developed using EO data.

As highlighted in Step 2 of the User Readiness, all of these data layers need to be collected and presented using agreed standards for data to ensure that the data can be easily integrated.

E.1.3. Pandemic Response

This section focuses on how EO data could potentially be used to support the development of ARD and DRI datasets by integration with health data. Although the focus is on the pandemic, the summary listed below is equally applicable to other disaster response scenarios. Some of the datasets are simply downloadable from the relevant satellite data provider, others may require some pre-processing by a data provider to turn the raw satellite data into the datasets listed here. Of course, all satellite datasets will need processing into integration-ready datasets with relevant data standards applied.

E.1.3.1. Analysis Ready Datasets (ARD)

- **Optical & Synthetic Aperture Radar (SAR) Satellite Imagery -**

Both of these types of imagery are used for observing, giving a snapshot of what was happening at the time the image was acquired and can be useful for detecting how things change over time. Images normally take at least a couple of hours from acquisition to delivery, and so this will always be a near past viewpoint.

+ Several satellites can provide similar data: examples that offer optical imagery include NASA's Landsat missions, European Space Agency's (ESA) Copernicus Sentinel-2 satellites, PeruSAT, Planet's constellations, and Satellogic's Newsat constellation. Examples offering SAR imagery include Canada's RADARSAT, ESA's Sentinel-1, Japan Aerospace Exploration Agency's (JAXA) ALOS PALSAR, and commercial missions such as the ICEYE constellation.

These data would support the following.

- *Land Cover Overview* - Give an overview of a wide area in a disaster situation, which can be useful to compare to the foundation layers to identify any changes as a result of the disaster scenario.
- *Pandemic tracking worldwide* - Using the imagery to identify the frequency of transportation, where there are ship movements, lorries on roads, cars in car parks, etc., all of which will give an indication of economic activity where vehicle and construction activity slowed during COVID-19, and when it increases as countries resume. This imagery can give a useful insight into how the pandemic might be spreading.
- *Crushing Trauma* - If damage is significant enough (using very high-resolution satellite imagery), the images can be used to pinpoint the location of building damage which would give an indicator of potential crush injuries.
- *Incidents of Panic Buying and Looting* - If using very high-resolution satellite imagery, it would be possible to see crowds or damage from looting.
- *Deaths Above Normal* - Tracking increased activity in graveyards and cemeteries through high-resolution imagery can also be a measure of mortality about normal due to the pandemic.
    - **Air Quality -** The concentration of pollutants in the air such as nitrogen dioxide and carbon dioxide reduced significantly across the globe due to the COVID-19 pandemic due to a reduced burning of fossil fuels. Example satellites offering these types of data include the Copernicus Sentinel-5P and the commercial GHGSat satellites.

This data would support the following.

- *Pre-existing conditions* - Air pollution such as smoke, particulates, ash, etc., could cause people with existing respiratory, cardiovascular, and other conditions to experience worsening symptoms.

- *Population in Area of Dangerous Air Pollution* - Risk models of pollution movement in the air can be developed or enhanced, alongside actual pollution levels that can be monitored.

- *Respiratory Illnesses* - Air pollution such as smoke, particulates, ash, etc., could cause an increase in respiratory symptoms amongst sufferers, or increase the number of people suffering from respiratory issues.

- *Dangerous Chemicals in the Air* - Some chemicals in the air, such as nuclear radiation, can't be monitored directly, but satellites can provide wind speed measurements and precipitation to support dispersion modeling.

  - **Water Quality -** Satellites can measure several elements of water quality, such as temperature, phytoplankton levels (microscopic algae), and turbidity, which individually, and combined, can offer an indication of water quality. Example satellites that offer these data include Copernicus Sentinel-3, NASA's MODIS, and JAXA's GCOM-C.

These data would support:

- *Predicted Increases in Illnesses* - Identification of drinking water or standing water that became contaminated, which can lead to an increase in gastric illnesses which can cause dehydration;

- *Pathogen Identification In Water* - Indicators of pathogens in water can be indirectly identified by satellites, for example, high turbidity can be linked to sewage in the water, or cholera predicted by increases in phytoplankton during dry seasons as the aquatic animals that carry cholera feed on phytoplankton. (https://earthobservatory.nasa.gov/features/disease-vector);

- *Dangerous Chemicals in Water* - Chemicals in water can be indirectly identified by satellites, for example, mine waste in water shows up as brightly colored; and

- *Population with Compromised Water Systems* - Identification of contaminated drinking water, which can lead to an increase in gastric illnesses which can cause dehydration.

  - **Thermal Imagery -** Thermal Imagery measures the amount of heat being generated by a location and can measure everything from the temperature of the ground through heat loss from buildings to wildfires. Example satellites that offer these types of data include NASA's Landsat-8, -9 & MODIS; Copernicus Sentinel-3 and JAXA's GCOM-C. These data would support the following.

- *Population of Power Outage Area* — Drop-in thermal activity in urban centers can indicate a loss of power.

- *Pandemic response tracking worldwide* - Drop in thermal activity across countries due to offices and factories having fewer lights on and less machinery and heating operating.

Whilst not a direct indicator of the pandemic's spread, this drop in thermal activity could be an indicator of the spread of quarantine measures across countries and how populations are abiding by quarantine measures.

- *Deaths Above Normal* - For cultures that use funeral pyres or similar burial rituals, the increase in small fires would indicate the increase in deaths above normal.

- *Exposure (Cold, Heat)* - For any communities living outside, or forced to be outside, from a disaster scenario this will measure the temperatures the communities are facing and will indicate the additional support potentially needed.

    - **Air Temperature & Relative Humidity -** Whilst these two elements are not measured directly by satellites, water vapor can be determined by the delay in the return of satellite signals passing through the atmosphere, or by assimilating satellite data into numerical weather forecasting models. Air temperature is the temperature 2 meters above the ground, and relative humidity is the concentration of the water vapor present in the air. The signals from positioning satellites can be used to support these datasets, alongside data from the commercial SPIRE satellites.

These data would support the following.

- *Exposure (Cold, Heat)* - For any communities living outside, or forced to be outside from a disaster scenario, this will measure the temperatures faced and the support they might need.

- *Pandemic Spread* - Scientific research indicated that humidity may be a useful supporting indicator of COVID-19 transmission — although this needs more research as it was not uniform across the different States in the US study.

- *Weather Forecasts* - Give indications of future temperature and humidity and the impact on both the disaster response efforts and those vulnerable people suffering from the disaster.

    - **Light Pollution -** Monitoring the lights of the world can give indications of what is happening in the terms of economic activity and transportation. Light pollution measurements can only be acquired at night. Example satellites that offer these datasets include the NASA/NOAA Suomi NPP Visible Infrared Imaging Radiometer Suite (VIIRS) and JPSS-1/NOAA-20. Light pollutin monitoring would support the following.

- *Population of Power Outage Area* - Reduction of light pollution in urban centers can indicate a loss of power.

- *Pandemic tracking worldwide* - A drop in light pollution in urban areas across the world can indicate a slowdown of economic activity as factories and offices reduce their working hours.

    - **Precipitation -** This is the measurement of the amount of water falling from the sky in all forms, including rain, hail, snow, or other particles. Example satellites with these datasets include EUMETSAT's Meteosat and SEVERI, JAXA's GCOM-C, NOAA's AVHRR, and NASA's GPM. These data would support the following.

- *Vector (Disease Carrying Mosquitoes) & Pathogen Identification in Vectors (e.g., Mosquitoes)* - Mosquito breeding favors standing water that can be caused by heavy rainfall.
- *Water Extent & Floods* - Heavy precipitation fall can be an indicator of flooding, whether this is flash flooding, rivers bursting banks from rainfall upstream, potential snowmelt, or additional water falling onto the already sodden ground.
- *Weather Forecasts* - An indication of current and future precipitation and how this might impact both the disaster response efforts and those vulnerable people suffering from the disaster.
    - **Water Extent & Flood Modelling -** Measurements of water extent are useful to map water bodies, particularly flooding. Combined with elevation models, water body mapping can also be useful to understand depths of water and be used to predict floods. The satellites that offer these types of data would include the optical and SAR missions highlighted above. These data would support the following.

- *Vector (Disease Carrying Mosquitoes) & Pathogen Identification in Vectors (e.g., Mosquitoes)* - Mosquito breeding favors standing water that can be caused by heavy rainfall.
- *Drownings/Suffocation* - Dramatic increases in water extents or depths would also give an indication of potential drownings.
- *Transportation* - Flooding and changes in water extents or depths impacts the transport network in terms of understanding the open medical supply routes, flooded areas to avoid, distance to medical care, safe routes to the care, and safe evacuation routes

E.1.3.2. Decision Ready Indicators (DRI)

EO data can also contribute directly to the Hazard and Vulnerability Areas (High Risk) DRI through the various risk modeling tools, such as Flood Risk Modeling, Flood Forecasting, and Hurricane/Tornado Forecasting.

These would utilize various datasets identified above to contribute towards the model. More details on the flood risk model can be found in Annex D.

E.1.4. Showing How Data Can Be Used

The Medical Supply Needs Index, developed by HSR.health, gives an estimate of the number of medical supplies a medical facility may need in order to deal with the anticipated patient load during the pandemic and/or a disaster situation.

The calculation of the Medical Supply Needs Index for the COVID-19 pandemic began with the calculation of the Pandemic Risk Index, which combines both Mortality Risk and Transmission Risk Indices.

- Mortality Risk Index utilizes data on population demographics and the prevalence of comorbidities to identify the risk to the underlying population of severe illness or mortality due to the COVID-19 pandemic.
- Transmission Risk Index utilizes data on population, case counts, geographical area, and human mobility to identify the risk of the spread of COVID-19.

Both of these indices were normalized so that the output falls between 0 and 100, where 100 is high. The current generalized recommendations from those indices were that 0-25 is low risk, 25-75 is moderate risk, and 75-100 is high risk.

The two indices were combined to create the Pandemic Risk Index, which represented both the spread of the pandemic and the health risk that the pandemic poses. Similar to the indices that make it up, the Pandemic Risk Index was normalized and used the same generalized recommendations such that 0-25 is low risk, 25-75 is moderate risk, and 75-100 is high risk creating an ARD.

The Medical Supply Needs Index calculated the usage level of Personal Protective Equipment (PPE) — in this case, gowns, gloves, and masks — by combining the number of COVID hospitalizations, the number of those hospitalizations in the Intensive Care Unit (ICU), number of healthcare workers, first responders, and other users of PPE and the current PPE usage rates. This gave a second ARD of the high and low estimates of current PPE needs.

These two ARD's were combined to produce the supply level which was based on the spread of the pandemic and the health risk to the underlying population. Once compared to the current supplies of PPE by hospital location, this supply level created a DRI on the difference between current PPE supplies and forecasted need. Figure E.1 shows the workflow for the Medical Supply Needs Index.

Stockpile Managers, Emergency Operation Managers, Supplier Chains, and Government agencies can use the DRI generated by the Medical Supply Needs Index to determine when and how much PPE supply needs to be delivered to ensure the location has sufficient PPE to continue to operate effectively.

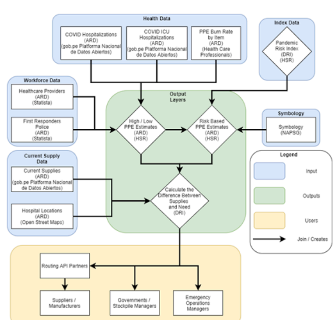

Figure E.1 — Medical Supply Needs Index Workflow Courtesy of HSR.health

Figure E.2 shows the Medical Supply Needs at a small census district level, with each color indicating a different level of Medical Supply Needs; purple as the highest, followed by red, orange, yellow, green, blue, and the white areas, which have the lowest level of need. Overlaid are the first hospital locations shown by the red crosses, and distribution locals for the medical supplies with green stars which allows users to easily identify the areas that need supplies and the closest distribution depots.

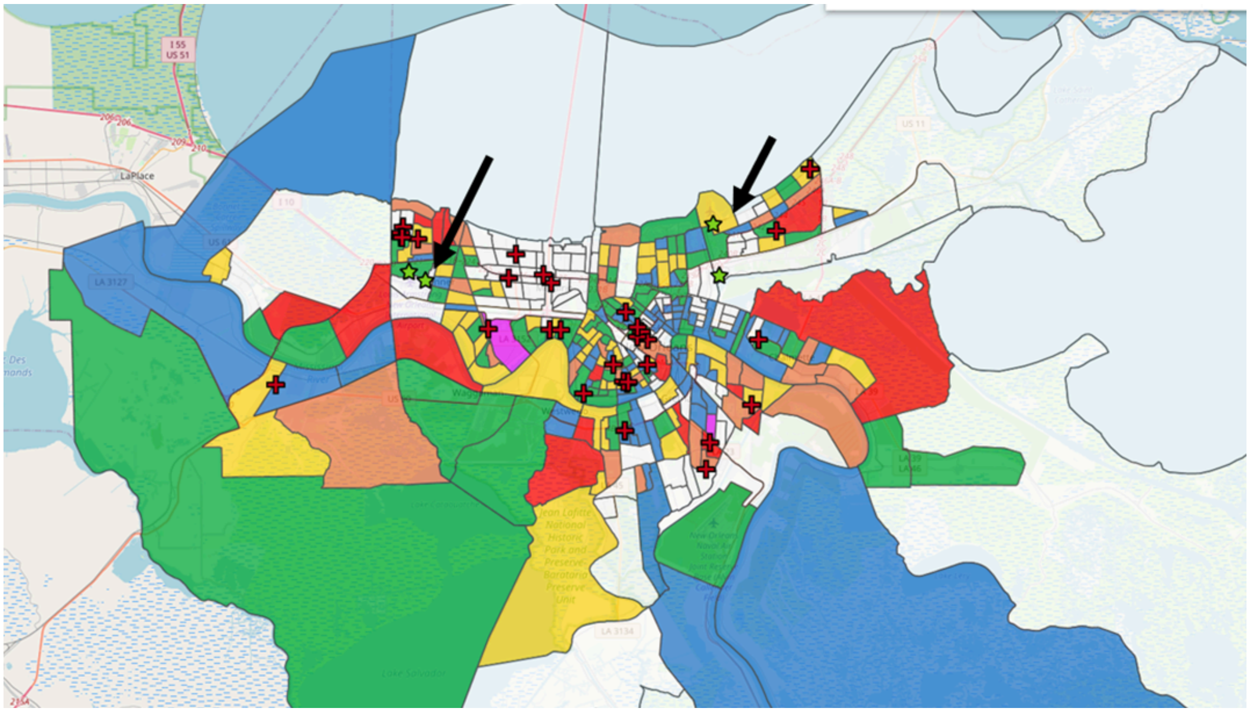

Figure E.2 — Medical supply needs index with hospital and distribution location. Courtesy of HSR.*health*

As a part of DP21, Skymantics developed a dynamic routing solution that could be utilized to identify the quickest or best route to transfer the supplies from the distribution centers (such as warehouses, airports, or ports) to the hospitals and clinics. This would include dealing with road closures for any reason. This solution will enable decision-makers to improve ordering for Medical Supplies taking into account changing utilization, delays in delivery, etc.

Figure E.3 shows an example of distance to the closest hospital calculated for all districts in New Orleans, with districts colored according to their time to care: less than 5 minutes are green and less than 30 minutes are yellow. The data are visualized using an API microservice based on OGC API — Features developed within the OGC Testbed-17 API experiment scenarios. OGC API — Features provides API building blocks to create, modify, and query features on the Web [2].

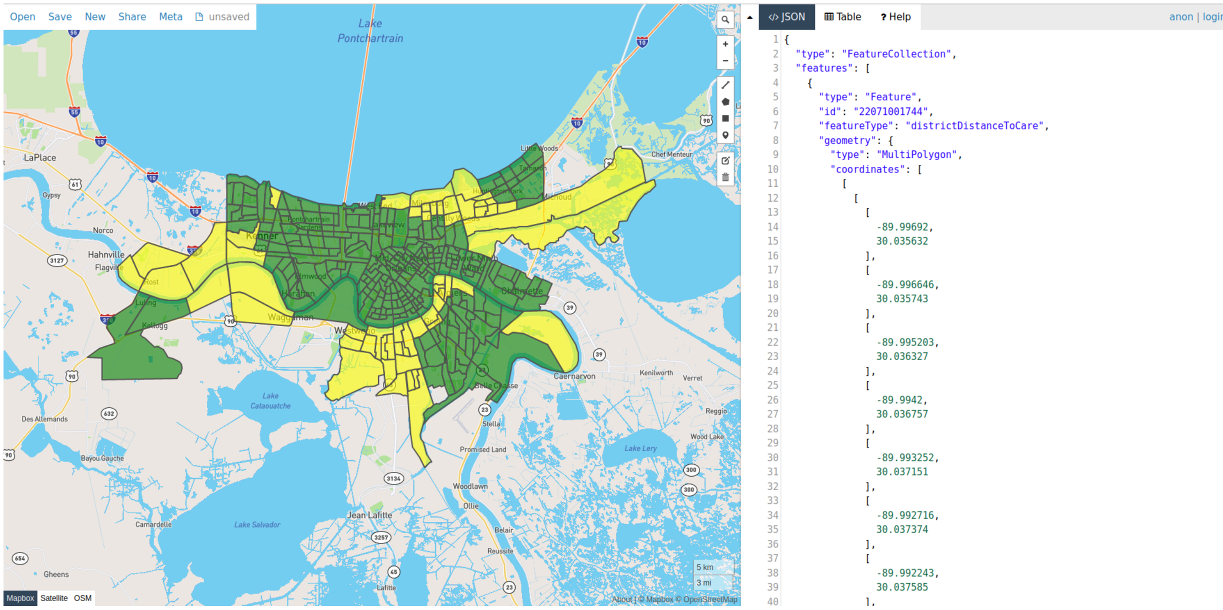

Figure E.3 — Distance to the closest hospital calculated for all districts in New Orleans, colored according to time to care. Visualization courtesy of Skymantics.

E.1.4.1. Earth Observation

A local EO example for Louisiana can be seen in Figure E.4, which includes the 2017 USGS Lidar DEM overlaid on the 2019 US National Land Cover Database (NLCD) layer with OpenStreetMap (OSM) data for waterways shown as blue lines. As the NLCD is a large dataset, for the whole of the US, rather than downloading, it was pulled from the Multi-Resolution Land Characteristics (MRLC) consortium, a group of US federal agencies, using the Web Map Service (WMS). The DEM was developed based on a horizontal projection/datum of NAD83 (2011) — Universal Transverse Mercator (zone 15N) with a vertical datum of NAVD88 (GEOID12B). Heights are shown in meters above/below this datum, and the parts of New Orleans that are below this datum that would be confusing to users. So, when fully used, the dataset needs to be converted to a meaningful height.

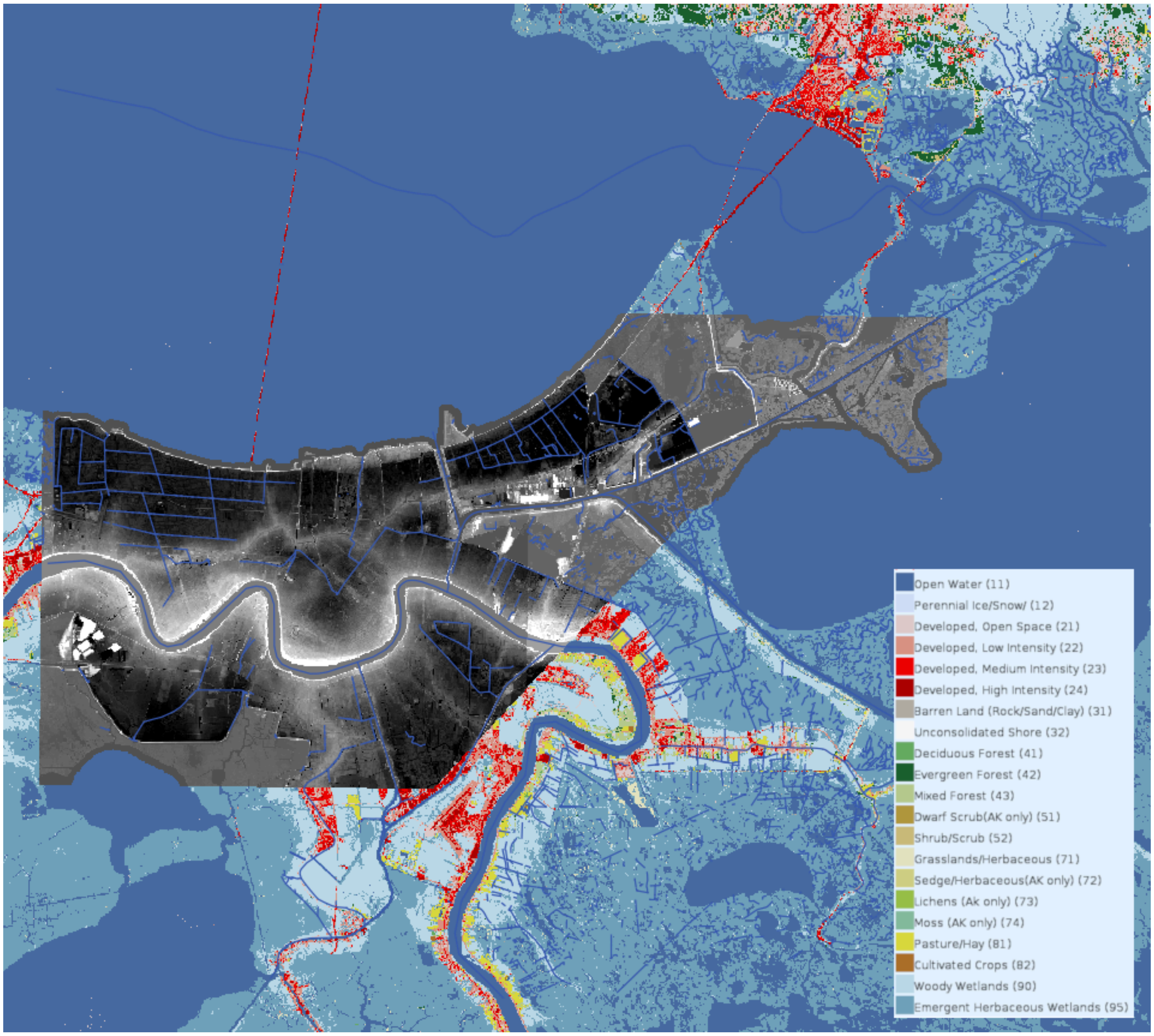

Figure E.4 — 2017 USGS Lidar DEM overlaid on the US National Land Cover Database layer with OpenStreetMap data for waterways shown as blue lines for the wider New Orleans area, Louisiana.

For water quality, Figure E.5 shows an example Copernicus Sentinel-2 image as a pseudo-color composite. Lake Pontchartrain is turbid with the mixing of different water masses shown by the different colors. On the southwestern area of the lake, there appears to be an algal bloom as the water is green in color. From analyses by the NOAA Harmful Algal Bloom Monitoring System, using Copernicus Sentinel-3 imagery, the algal bloom is cyanobacteria that form a surface floating accumulation. Cyanobacteria blooms can grow rapidly and produce toxins that cause harm to animal life and humans.

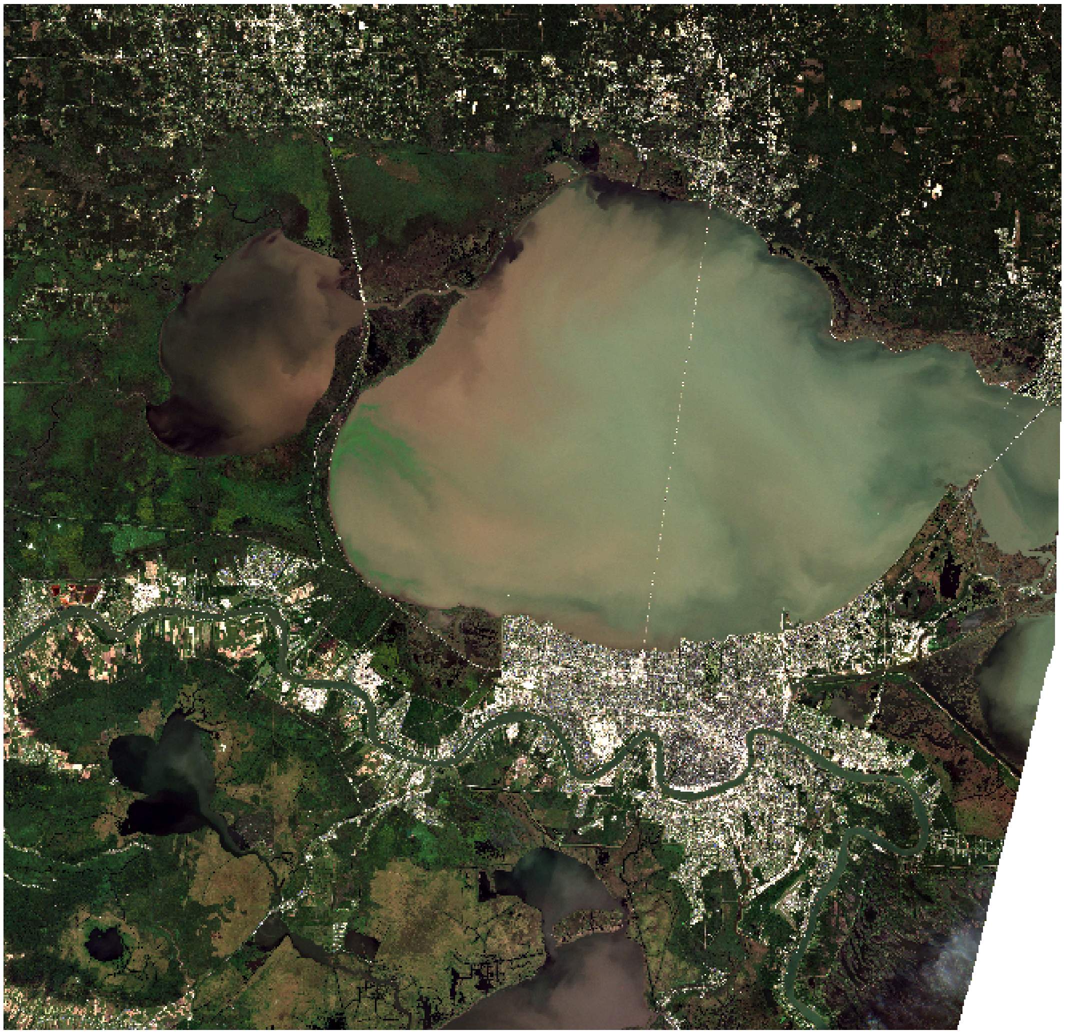

Figure E.5 — 2017 Sentinel-2 from 01 November 2021 shown as a pseudo-true color composite with a cyanobacteria bloom in the south-western area for the wider New Orleans area, Louisiana.

The World Health Organization (WHO) reports on six major air pollutants, namely particle pollution, ground-level ozone, carbon monoxide, sulfur oxides, nitrogen oxides, and lead. The Copernicus Atmosphere Monitoring Service (CAMS) provides both global and European focused air quality parameters as both reanalysis and predicted data. Figure E.6 shows an example predicted for 03 November 2021 as the total column carbon monoxide (CO), further real-time parameters can be seen on the CAMS website. CO is a colorless, odorless, gas that can be harmful when inhaled in large amounts and is released when something is burned like gasoline or during forest fires. New Orleans has a higher than the background value, but is not a hotspot (green to yellow colors).

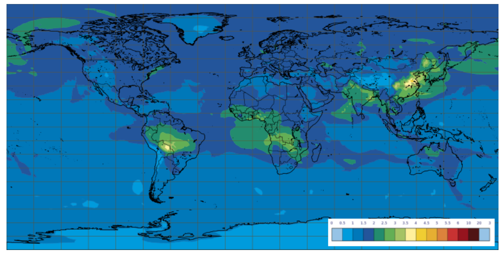

Figure E.6 — Total column (total amount in a column of air extending from the surface of the Earth to the top of the atmosphere) Carbon Monoxide [10^18 molecules / cm2] for the 03 November 2021, provided by CAMS.

E.1.5. Conclusions

The COVID-19 pandemic conclusively demonstrated that health data, EO data, and GIS solutions can play a crucial role in mitigating and managing a healthcare crisis. For DP21, time was spent developing the approach from a standing start. Using the outputs and recommendations of DP21, it will be possible to create a better opening position that will help respond to similar disasters and pandemics in the future.

The Medical Supply Needs Index, developed by HSR.health, gives an estimate of the number of medical supplies a medical facility may need to deal with the anticipated patient load during the current pandemic and/or disaster situation. Its combination with EO could be applied in a flooding scenario where the EO data are converted to flood maps that support routing, see Annex D for further details.

A range of EO data visualizations were generated by Pixalytics that showcased potential EO-derived products.

- Within Annex D, a Lidar DEM was used to support the modeling of floodwater height, and for New Orleans, a detailed (1 m spatial resolution) DEM was available to download in GeoTIFF format. These data were visualized in QGIS alongside the Land Cover that was accessed using a WMS feed.
- The Sentinel-2 image of Lake Pontchartrain shows the presence of a cyanobacteria bloom — a species of phytoplankton that can be associated with health issues in animals and humans. The data was downloaded from the Copernicus Open Access Hub and can be visualized using ESA's SNAP Toolbox.
- The Sentinel-5P visualization was accessed from the CAMS website, with the data also accessible for download and access via Application Programming Interfaces (APIs).

Future work will investigate bringing EO and Health data together with the EO data manipulated within a cloud-computing environment and provided to the Health (GeoNode) platform web services.

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ANNEX F (INFORMATIVE) REVISION HISTORY

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ANNEX F (INFORMATIVE) REVISION HISTORY

DATE	RELEASE	AUTHOR	PRIMARY CLAUSES MODIFIED	DESCRIPTION
October 29, 2021	0.1	S. Lavender	all	Initial version for comment
November 18, 2021	0.2	S. Lavender	all	Improved version integrating comments for submission to the OGC member meeting
January 17, 2022	0.3	S. Lavender	all	General review and update of the new setup, including consistent approach to figure referencing
March 14, 2022	0.4	S. Lavender	all	Inputs received via the website in parallel with the public presentation
April 25, 2023	0.5	S. Lavender	all	Rearranged version for the 2023 Disaster Pilot
October 28, 2023	0.6	A. Lavender	all	Disaster Pilot 2023 final draft for review by EDM working group

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