A tool for dataset comparison: Observational Data at a point location

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Contents

jupyter: obsflow

### 0.1 Introduction

Here will be the introduction to our report on everything ‘climate data’ regarding their use in the electricity sector.

Overall it goes like this:

(This is an example of using [mermaid](https://mermaid.js.org/) to generate a flowchart in Quarto.)

flowchart LR  
 A[What data are out there] --> B(An Inventory)  
 B --> C{Interviewswith\nEnergy Sector\nChampions}  
 C --> D[Best practices]  
 C --> E[Gap analysis]

**A demo for including video:** <https://www.youtube.com/watch?v=KrWZmIQxUz8>

## 1 2. Literature Review

title: Demand jupyter: python3

Electricity demand is a vital component in the planning, operation, and resilience of power systems. Climate change is expected to alter electricity demand patterns by affecting not only patterns of temperature, such as mean temperature, number of temperature extremes, and seasonal variations, but also consumption behaviours across different sectors. Numerous studies project increased cooling demand during hotter summers and reduced heating demand during milder winters as this pattern have been consistently observed across multiple global regions ( @Amonkar2023, @Auffhammer2011, @Pilli-Sihvola2010, @Trotter2016, @Wood2015). The magnitude and direction of these changes are strongly dependent on the region and latitude; for example, countries in warmer climates are expected to see higher overall demand growth due to increased cooling loads (@Bonkaney2023, @Emodi2018, @Zachariadis2014). Climate change also affects electricity consumption by sector and temporal demand profiles, including daily and seasonal variations. The residential, commercial, and industrial sectors respond differently to climate drivers ( @Dirks2015, @Shaik2024, @Taseska2012). Meanwhile, the timing of electricity demand is shifting as well, with studies projecting changes in peak load hours and seasonal peaks due to rising temperatures and more frequent extreme heat events ( @Amonkar2023, @Fonseca2019, @Romitti2022).

To assess the impacts of climate change on electricity demand, different approaches have been employed. These include the use of climate projections from GCM and RCM combined with downscaling techniques to capture local climatic variability ( @Auffhammer2017, @Auffhammer2011, @Fonseca2019, @Lipson2019, @Trotter2016). Empirical models, such as regression-bases analyses, have been also used to estimate historical relationships between temperature and electricity use ( @Bonkaney2023, @Emodi2018, @Pilli-Sihvola2010) , while simulation tools and energy-climate models are applied to explore future scenarios under different socio-economic and climatic conditions ( @Dirks2015, @Lipson2019, @Taseska2012).

## 2 Climate change drivers and affected electricity demand parameters

### 2.1 Seasonal variations

Rising temperatures due to climate change have led to a significant in seasonal electricity demand, particularly by increasing cooling demand during summer and reducing heating needs during winter. This shifting trend has been widely documented across regional and global studies. For example, @Auffhammer2017 showed that electricity demand in the United States shows a strong nonlinear response to high temperatures, especially above 25-30 degC, driven mainly by demand for air conditioning. Similarly, @DeCian2019 also confirmed this global trend that there are steep increases in demand where air conditioning is rising due to climate change. Regional case studies, such as @Craig2020, have demonstrated that peak demand coincides more frequently with extreme heat days, stressing both power generation and distribution infrastructure. The anticipated rise in the frequency, intensity, and duration of heatwaves further amplifies this concerns, requiring investments in peak capacity, demand-side management, and adaptation strategies. @Taseska2012 projected increased summer cooling demand across European regions due to higher temperatures, while @Zachariadis2014 confirmed the similar rise in cooling demand in Cyprus. @Dirks2015 also found that seasonal peaks are shifting in the United States, with summer peaks becoming more dominant due to climate-induced changes in building energy use.

However, while winters are projected to be warmer, the demand responses are more variable. @Romitti2022 introduced a classification of demand response profiles: a “V”-shaped response which is common in mid-latitude temperated cities, such as North America and Europe where demand increases at both high and low temperatures; increasing response where demand rises steadily with temperature, which can be shown in tropical cities; and unresponsive profile where minimal or no correlation between temperature and electricity demand. @Pilli-Sihvola2010 used multivariate regression in Europe to estimate electricity consumption changes and found that Northern and Central Europe will experience reduced heating demand in winter while Southern Europe will face increased cooling demand and higher costs in summer. This results in an increased annual electricity demand in Spain while it will decrease in Finland, Germany and France. @Wood2015 analyzed how climate change could flatten winter peaks while enhancing summer peaks in the United Kingdom, suggesting that infrastructure planning should shift from winter-dominant to summer-dominant strategies.

### 2.2 Regional variations: by continents, by latitudes

The impacts of climate change on electricity demand show considerable regional heterogeneity, followed by geographic location, climatic baseline, economic development, and infrastructure characteristics. A clear latitudinal pattern exists: countries at lower latitude are projected to have higher increases in electricity demand for cooling, while higher latitude regions may observe mixed outcomes due to the opposing effects of warmer winters and hotter summers.

In tropical regions, where average temperature are already high, even modest increases in temperature can trigger substantial rises in electricity use. @Bonkaney2023 found that rising temperatures will affect electricity demand for all warming levels due to increasing air conditioning needs, with low adaptive capacity exacerbating system stress in Niger. @Emodi2018

### 2.3 Demand parameters

* Annual demand: generation capacity and/or storage capacity
* Size and timing of peak demand: maintenance and construction schedule, supply planning
* Spatial distribution of demand: topology and capacity of the electricity transmission networks.
* Sectors: ability to adapt or respond to climate change

## 3 Sectoral variations in demand

* Differences in demand patterns by sectors, such as residential, industrial, and commercial.
* Seasonal and hourly variations in demand and how these might evolve under climate change

## 4 Methodologies for assessing climate change impacts

* Climate data: GCMs, RCMs
* Downscaling method: dynamic, statistical
* Empirical methods: regression analysis
* Simulation models: energy-climate models

## 5 Adaptation strategies

* How to adapt changing demand patterns caused by climate change.
* Demand-side management, energy efficiency measures, grid flexibility.

## 6 References

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## 7 3. Electricity Sector Activities

title: Capacity Expansion Modelling jupyter: python3

## 8 Description

Modelling of growth in grid requirements taking demand, supply, costs, etc. as inputs to determine how to best meet demand in the lowest costs method [Power Sector Modeling 101](https://www.energy.gov/sites/prod/files/2016/02/f30/EPSA_Power_Sector_Modeling_FINAL_021816_0.pdf)

title: Construction jupyter: python3

## 9 Description

Plan and construct various assets including hydropower facilities, transmission/distribution lines, electrical stations. Some special consideration may be required for remote locations and seasonality of the construction season. (MV note: This needs to be refined, just wanted to get something as a placeholder)

title: Dam Safety Review jupyter: python3

## 10 Description

Includes assessments of PMP, PMF, IDF and other hydrotechnical aspects of dam safety. Also includes failure modes analysis which could include broader climatic indicators.

title: Demand Forecasting jupyter: python3

## 11 Description

Modelling daily, weekly and peak demands over short and long-term planning horizons (MV note: for MH, we typically have a separate load forecast for electrical energy, electrical peak, and natural gas volume… so we may want to capture that nuance).

## 12 Hydro

lorem ipsum, bla, bla, and blah

## 13 Nuclear

lorem ipsum, bla, bla, and blah

## 14 Solar

lorem ipsum, bla, bla, and blah

## 15 Thermal

lorem ipsum, bla, bla, and blah

## 16 Wind

lorem ipsum, bla, bla, and blah

title: Electrical System Operations jupyter: python3

## 17 Description

Operate the electrical system in real-time to manage several factors including load, generation, exports, imports, line losses, equipment ratings, and contingencies. (MV note: This needs to be refined, just wanted to get something as a placeholder)

title: Enterprise Risk Management jupyter: python3

## 18 Description

Understanding various exposure risks relative to other ERM/organizational risk profiles

|  |
| --- |
| Maybe consider this! |
| The following may need to become distinct sections! |

## 19 Infrastructure Condition Assessment

## 20 Investment Prioritization

## 21 Vegetation Management

title: ESG & Sustainability Reporting jupyter: python3

## 22 Description

Need to support disclosure requirements (voluntary and mandatory) related to risk and based on scenario analysis.

title: Forest Fire Monitoring and Awareness jupyter: python3

## 23 Description

Use of projections to inform future wildfire resilience investments (e.g. pole wrapping).

title: Generation Forecasting jupyter: python3

## 24 Description

Combination of fuel supply and outages to determine how much generation can be available over a given planning window (Short to Long)

## 25 Hydro

## 26 Nuclear

## 27 Solar

## 28 Thermal

## 29 Wind

title: Infrastructure Condition Assessment & Investment Prioritization jupyter: python3

## 30 Description

Based on existing condition of assets (scope to be expanded to include more robust vulnerabilities) and projected changes to hazard exposure, support in the development of investment prioritization.

title: Infrastructure Design jupyter: python3

## 31 Description

Parameters used to meet regulatory design criteria, beyond design basis criteria and develop and maintain these assets. Floodplain avoidance/mitigative design.

## 32 Hydro

## 33 Thermal & Nuclear

## 34 Transmission & Distribution

title: Innovation Investments jupyter: python3

## 35 Description

Use projections to support decision making on geographic needs for non-wire solution, microgrid, BESS, demand management.

title: Licensing & Impact/Environmental Assessments jupyter: python3

## 36 Description

Determines the impact of the project on surrounding areas and how these could interact in the climate change context. Also seeing need for this with CER/OEB emerging regulatory requirements.

title: Nuclear Safety Reviews jupyter: python3

## 37 Description

Includes assessments of PMP, PMF, IDF and other hydrotechnical aspects of dam safety. Also includes failure modes analysis which could include broader climatic indicators.

title: Outage Scheduling jupyter: python3

## 38 Description

Considerations for outage scheduling constraints due to predominately temperatures related events.

title: Proactive management of heavily loaded assets jupyter: python3

## 39 Description

Incorporation of temperature projections to support investment decisions for heavily loaded assets.

title: Resource Adequacy Planning jupyter: python3

## 40 Description

Planning for adequate resources to meet capacity for peak and energy demands. This might encompass several imbedded criteria such as a drought planning criterion.

title: Support supply chain decision-making jupyter: python3

## 41 Description

Where surplus equipment should be located.

title: Vegetation Management jupyter: python3

## 42 Description

Support the enhancement of vegetation management programs to include changes in vegetation growth.

title: Worker safety jupyter: python3

## 43 Description

Incorporate climate hazard evaluation and mitigation into job planning. For work environments imposing elevated risk to climate hazard exposure, this may include implementing appropriate administrative and/or engineering controls such as modifying work schedules to reduce exposure to extreme temperatures.

## 44 4. Datasets

title: Overview of Climate Data jupyter: python3

|  |
| --- |
| Note |
| The structure of this section may be organized by:   * Climate Variable * Datasets (Preferred!)   TBD |

## 45 Sources of Climate Data Hallo

Generally, climate data can be sourced from historical observation of climate using instrumentation or from climate model simulations. In the context of electricity system planning and design, future climatic conditions should be of primary interest, but observed historical climate data and products derived thereof may also be employed or used in the development of adequate future climate information.

Observed data is provided as point information at station locations. To provide continuous fields of climate information, station data can be interpolated spatially to produce gridded historical data. They provide a portrait of climate beyond the stations point locations but are impacted by potential interpolation errors, particularly in data sparce regions, or in regions of complex topography (e.g. mountainous areas). The approach that attempts to overcome these drawbacks is the reproduction of historical climate through the combination of a maximum of available climate information with a physical climate simulation approach known as climate reanalysis. [Reanalysis products](https://reanalyses.org) have substantially improved over recent years and are often used as surrogates for observational data in climate science and studies.

Observational data and reanalysis data provide a representation of the actual evolution and sequence of events as they occurred and provide robust estimates of climate when averaged over climatic periods (usually 30 years). Note, however, that due to natural climate variability, climate estimates would shift with slight temporal shifts of the period, or the data being used.

Simulated data from climate models used for electricity system planning and design should be sourced from internationally coordinated ensembles of climate model simulations or products derived thereof. These simulations typically cover multiple decades and are available for historical and future periods. They are fully consistent in time and space and are provided on grids. The grid resolution depends on the model or the data product.

Like observational data, bias-adjusted historical climate simulations may be used to derive climate estimates of historical climate. These estimates will not be identical to climate estimates from observed data yet will generally fall into the range of natural variability of the observed climate. Since climate model simulations extend into the future, estimates for future climate may also be derived. It is important to note that the sequence of events produced by a historical climate simulation is distinct from the sequence of historically observed events, although their respective climate estimate is the robust characteristic they have in common.

## 46 Summary of Types of Climate Datasets

The datasets discussed here can be grouped into the following categories:

* **Observational data** are direct measurements from weather stations. These provide the most accurate and high-resolution temperature records, but their coverage is often limited to specific locations, leading to gaps in certain regions, particularly oceans and remote areas. Temporal gaps in the records may also be found in station data.
* **Gridded observational datasets** address the spatial limitation of station data by interpolating their data across a defined grid, providing more comprehensive spatial coverage. These datasets, such as those produced by national meteorological agencies, offer a balance between accuracy and spatial representation, though uncertainties arise in data-sparse regions.
* **Reanalysis datasets** combine historical observations with climate models to create consistent, long-term reconstructions of the atmosphere. They offer global coverage and high temporal resolution, making them valuable for analyzing past climate conditions and trends. However, reanalysis products rely on model-based data assimilation, which may introduce biases, especially in areas with limited observations.
* **Climate model data**, often from global climate models (GCMs), simulate temperature under different greenhouse gas scenarios. These projections are essential for understanding future climate patterns and assessing potential impacts. While models provide large-scale trends, they lack the precision of observational data due to their coarse spatial resolution and inherent uncertainties in modeling processes.

Together, these datasets enable a comprehensive view of both historical and future climate conditions, supporting a wide range of applications in the electricity sector.

### 46.1 4.1 Observational Data

title: Observational Datasets jupyter: python3

## 47 Definition of Observational Datasets

title: Adjusted and Homogenized Canadian Climate Data (AHCCD) jupyter: energy-data

## 48 Summary Description

The Adjusted and Homogenized Canadian Climate Data (AHCCD) dataset is a collection of quality-controlled and homogenized historical climate data from Environment and Climate Change Canada (ECCC). It provides long-term station-based observations for temperature and precipitation across Canada. The dataset corrects for non-climatic changes (e.g., station relocations, instrument changes) to ensure consistency and reliability in climate trend analysis.

**ToDo:** Add recent references

|  |
| --- |
| AHCCD Temperature Stations; blue: starting date prior to 1990, green: starting date from 1990, red: station closed but more than 30 years of data (Vincent et al., 2020) |

AHCCD Temperature Stations; blue: starting date prior to 1990, green: starting date from 1990, red: station closed but more than 30 years of data (Vincent et al., 2020)

## 49 Dataset Characteristics

* **Current version:** The dataset us updated annually with the most recent data.
* **Time period:** Varies per station and variable, data availability ranging between 1840 and 2019
* **Spatial resolution:** Point locations across Canada
* **Temporal resolution:** Annual, seasonal, monthly and daily values
* **Coverage:** Stations across all Canadian provinces and territories
* **Data type**: Historical observations from ECCC climate stations, adjusted and homogenized using statistical methods
* **Web reference:** Adjusted and Homogenized Canadian Climate Data (AHCCD)
* **Technical documentation:** Technical documentation: Adjusted and homogenized Canadian climate data (AHCCD)
* **Reference publications:** @Wan2007 @Wan2010 @Mekis2011 @Vincent2020

## 50 Key Strengths of AHCCD

* **Homogenized Time Series:** Adjustments remove artificial shifts due to non-climatic influences, enabling accurate trend analysis.
* **Long-Term Coverage:** Many stations provide over 100 years of data for studying climate variability and change.
* **National Consistency:** Standardized methodologies applied across the Canadian network.
* **Open Access**: Freely available for public, academic, and government use.
* **Supports Climate Indicators:** Used in the development of Canadian climate change indicators and official climate assessments.

## 51 Limitations of AHCCD

* **Station Coverage Gaps:** Sparse in some northern or remote regions, limiting spatial completeness.
* **Limited Variables:** Focused mainly on temperature and precipitation; does not include wind, humidity, etc.
* **Historical Instrumentation Issues:** Despite adjustments, some uncertainties remain from early observational practices.
* **Fixed Locations:** Station-based data may not represent broader regional conditions in complex terrain.
* **Limited temporal coverage:** The latest observation data may not have been processed. Daily data availability has not seen a recent update.

## 52 Available Variables in AHCCD

*For details click on variable group to uncollapse*

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| --- |
| **Homogenized surface air temperature**   * Daily minimum temperature * Daily maximum temperature * Daily minimum temperature * Monthly, seasonal, and annual mean temperature * 780 locations in Canada * Unit: ˚C |

|  |
| --- |
| **Adjusted precipitation**   * Daily liquid precipitation (rain) * Daily solid precipitation (snow) * Daily total precipitation (rain and snow) * Monthly, seasonal, and annual total precipitation * 467 locations in Canada * Unit: mm |

|  |
| --- |
| **Homogenized surface wind**   * Monthly, seasonal and annual means of hourly wind speed * Evaluated at standard 10 metre level * 156 locations in Canada * Unit: km/h |

|  |
| --- |
| **Homogenized sea level and station pressure**   * Monthly, seasonal and annual means of hourly sea level and station pressure (hectopascals) * 626 locations in Canada * Evaluated at standard 10 metre level for 156 locations in Canada |

## 53 Example Applications

*links to Electricity Sector Applications*

## 54 Data Access

* AHCCD station daily data on [ClimateData.ca](https://climatedata.ca/download/#ahccd-download)
* Climate data extraction tool (Monthly, seasonal and annual AHCCD station data)
* AHCCD station data on [PAVICS](https://pavics.ouranos.ca/datasets.html#b)

title: ANUSPLIN Canadian Gridded Climate Dataset (NRCanMET) jupyter: energy-data

## 55 Summary Description

The ANUSPLIN Canadian Gridded Climate Dataset (NRCanMET) is a high-resolution, station-based gridded climate dataset produced by Natural Resources Canada (NRCan) and Agriculture and Agri-Food Canada. It provides daily and monthly interpolated climate variables across Canada, utilizing the Australian National University Spline (ANUSPLIN) model. The dataset provides information coninuous in time and space for climate research and environmental studies.

**ToDo:** Add PCIC Blend info, recent references

|  |
| --- |
| Percent difference in mean annual precipitation for NRCANmet minus PNWNAmet (from @Werner2019) |

Percent difference in mean annual precipitation for NRCANmet minus PNWNAmet (from @Werner2019)

## 56 Dataset Characteristics

* **Time period**: 1950–2015
* **Spatial resolution**: ~10 km grid spacing (0.1°)
* **Temporal resolution**: Daily and monthly
* **Coverage**: Canadian landmass
* **Data source**: Quality-controlled station observations interpolated using ANUSPLIN
* **Reference publications:** @Hutchinson2009, @McKenney2011,

## 57 Strengths and Limitations

### 57.1 Key Strengths of NRCanMET

* **High Spatial Resolution**: Provides detailed climate information at ~10 km resolution across Canada.
* **Long-Term Coverage**: Spans over six decades, enabling comprehensive climate trend analyses.
* **Quality-Controlled Data**: Utilizes quality-controlled station observations for interpolation.
* **Consistent Methodology**: Employs the ANUSPLIN model, ensuring consistency in data interpolation.
* **Accessibility**: Available through platforms like ClimateData.ca and the Pacific Climate Impacts Consortium.

### 57.2 Key Limitations of NRCanMET

* **Temporal Gaps**: Station density varies over time, potentially affecting data consistency in certain regions.
* **Interpolation Limitations**: Accuracy depends on the density and distribution of input stations.
* **Lack of Real-Time Updates**: Dataset extends only up to 2015, limiting its use for recent climate analyses.
* **Limited Variables**: Focuses primarily on temperature and precipitation; other climate variables are not included.

## 58 Available Variables in NRCanMET

*For details click on variable group to uncollapse*

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| --- |
| **Temperature Variables**   * Daily maximum temperature (°C) * Daily minimum temperature (°C) * Monthly maximum temperature (°C) * Monthly minimum temperature (°C) |

|  |
| --- |
| **Precipitation Variables**   * Daily total precipitation (mm) |

## 59 Typical Applications

*links to Electricity Sector Applications*

## 60 Data Access

* [ClimateData.ca](https://climatedata.ca/)
* [Pacific Climate Impacts Consortium](https://pacificclimate.org/data/daily-gridded-meteorological-datasets)
* [Open Government Portal - Canada](https://open.canada.ca/data/en/dataset/779ea77a-0ad1-42f2-853e-833e1cbb9a13)

### 60.1 4.2 Reanalysis Data

title: Reanalysis Datasets jupyter: python3

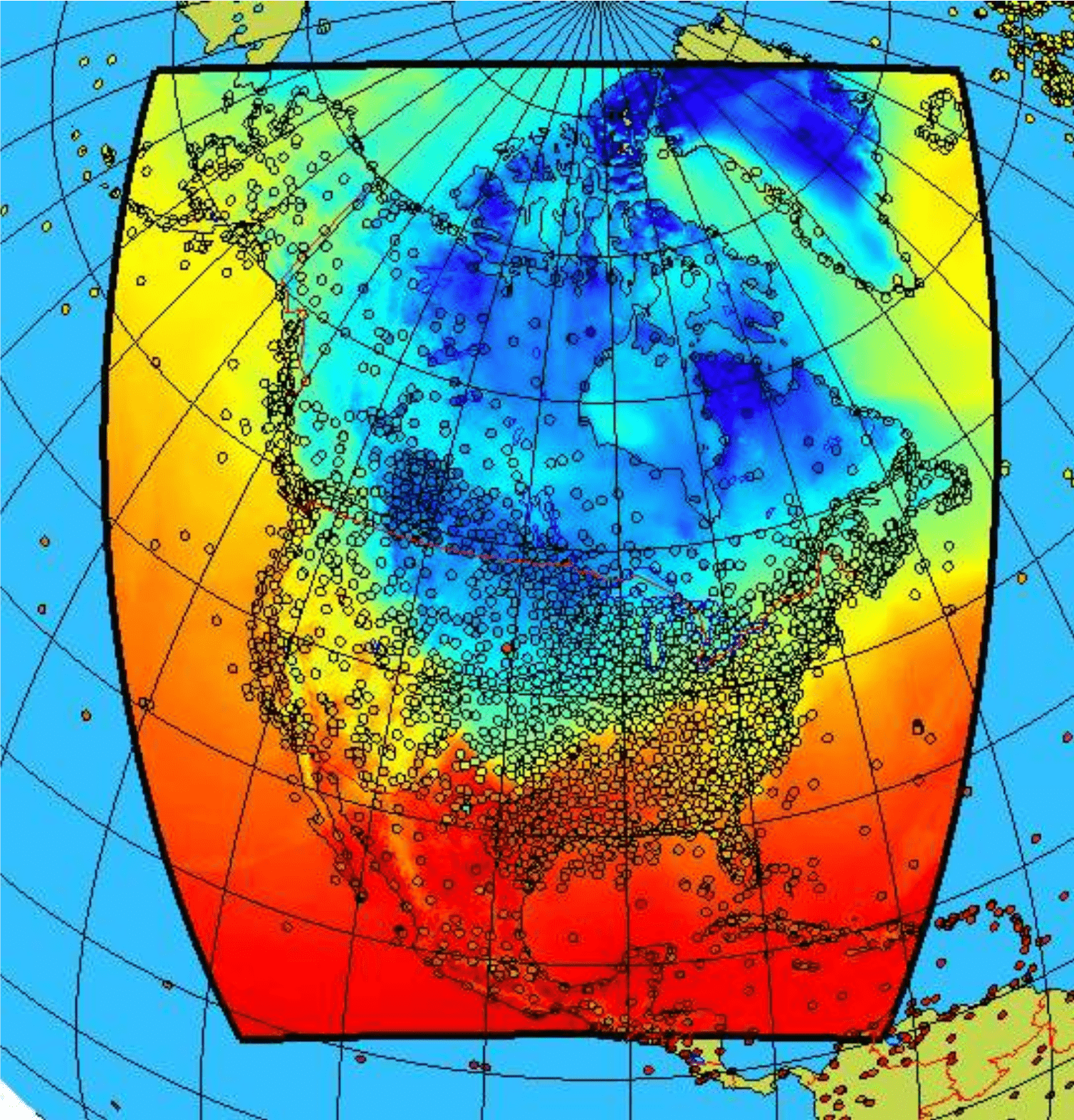
## 61 Definition of Reanalysis Data

title: Canadian Surface Reanalysis - CaSR jupyter: energy-data

(previously: Regional Deterministic Reforecast System - RDRS v2.1)

## 62 Summary Description

The Canadian Surface Reanalysis (CaSR) is a high-resolution atmospheric reanalysis dataset produced by Environment and Climate Change Canada (ECCC). It provides historical, high-resolution climate and weather data over North America, with a focus on Canada. CaSR is based on the Global Deterministic Reforecast System (GDRS) and refined with the Canadian Regional Reforecast System (RDRS) to better capture local variations.



CaSR simulation domain with station locations

## 63 Dataset Characteristics

* **Current version:** v3.1
* **Time period:** 1980–2023
* **Spatial resolution:** ~10 km grid spacing
* **Temporal resolution:** Hourly and daily outputs
* **Spatial coverage:** Canada and U.S.
* **Data type:** Reanalysis model assimilating observations (satellites, surface stations, radiosondes, etc.)
* **Web references:** ECCC CaSR Web Site, Northern Climate Data Report and Inventory (NCDRI) Web Site
* **Reference publications:** @Gasset2021

## 64 Strengths and Limitations

**ToDo:** Upcoming discussion with Nicolas Gasset, include known more issues & strengths with CaSR

Discussion avec Nicolas:

Avantages:

* Precip c’est une Analyse (ERA5 c’est que le modèle!!!)
* PRecip en montagne pareil ERA5(-Land) CaSR
* Nicolas travaille sur une comparaison
* Neige est mieux dans ERA5-Land que dans CaSR (Est: trop de neige dans CaSR)
* Comparaison min/max de CaSR contre ERA5-Land et MERRA2
* Extrêmes Vent pas assez fort

Desavantages:

* pas operationnelle (on y travaille) (ERA5-Land le fait)
* 1970-2024!
* CaSR meilleur forcage pour modèle surface et hydro: Le sol est pas bon, drainage, ruissillement
* CaSR Land

### 64.1 Key Strengths of CaSR

**High Resolution:** ~10 km grid spacing provides detailed spatial variability, better than global reanalyses.  
**Assimilation of Diverse Observations:** Uses satellite, surface, and upper-air data for accuracy.  
**Hourly Data Availability:** Useful for high-frequency climate and weather analysis.  
**Canadian-Specific:** Optimized for Canadian climate conditions, including extreme cold and snow processes.  
**Convidence Index:** A confidence index for precipitation informs on the weight of observations in the analysis.  
**Detailed Precipitation:** Precipitation types are distiguished (ice pellets, freezing precipitation, liquid water equivalent of snow, liquid precipitation) and modeled as well as reanalysis precipitation are provided.  
**Active Development:** New versions and longer temporal record in preparation.  
**~~Consistent Historical Record:~~** ~~Spans over four decades, allowing for trend analysis and climate studies.~~

### 64.2 Key Limitations of CaSR

**~~Limited Coverage:~~** ~~Primarily focused on Canada, with partial U.S. coverage.~~  
**Model Biases:** Errors may exist due to model physics and parameterizations, especially in complex terrain (e.g., mountains).  
**Limited Suitability for Trend Analysis:** For the current version, gaps in observation data and model errors may skew trends found in the dataset. **ToDo:** Check with Nicolas, Hélène/Marilyn’s results.  
**Uncommon Georeference:** The data are made available on a rotated grid which may be difficult to handle.  
**Precipitation Uncertainties:** Like all reanalyses, CaSR precipitation estimates may deviate from observed values in localized regions.  
**Limited to Land surface:** Primarily land-focused, no information over oceans is available.  
**Computationally Intensive:** Relatively high-resolution data requires significant storage and processing power for analysis over larger areas.

## 65 Available Variables in CaSR

*For details click on variable group to uncollapse*

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| **Temperature**   * Temperature [˚C] * Dew point temperature [˚C]   Temperature variables are provided at 1h & 3h frequency and at levels 1.5 m, ~20m, and ~40m. For more details see the respective [table on the CaSR web site](https://hpfx.collab.science.gc.ca/~scar700/rcas-casr/dataset_specifics.html#available_variables) |

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| **Precipitation**   * Quantity of daily precipitation (CaPA 24h) [m] * Confidence index of daily precipitation * Quantity of hourly precipitation (model) [m] * Quantity of hourly precipitation (hourly disagregated CaPA 24h/6h) [m] * Quantity of ice pellets (liquid water equivalent) (model) [m] * Quantity of freezing precipitation (liquid water equivalent) (model) [m] * Quantity of liquid precipitation (model) [m]   Precipitation variables are provided at 1h and 24h frequency at the surface level. For more details see the respective [table on the CaSR web site](https://hpfx.collab.science.gc.ca/~scar700/rcas-casr/dataset_specifics.html#available_variables) |

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| **Wind**   * U-component of the wind (along the grid X axis) [kts] * V-component of the wind (along the grid Y axis) [kts] * Corrected U-component of the wind (along West-East direction) [kts] * Corrected V-component of the wind (along South-North direction) [kts] * Wind Modulus (derived using UU and VV) [kts] * Meteorologial Wind direction (derived using UU and VV) [degree]   Wind variables are provided at 1h frequency and at levels 10m, ~20m, and ~40m. For more details see the respective [table on the CaSR web site](https://hpfx.collab.science.gc.ca/~scar700/rcas-casr/dataset_specifics.html#available_variables) |

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| **Humidity**   * Relative humidity [%] * Specific humidity [kg/kg]   Humidity variables are provided at 1h frequency and at levels 1.5 m, ~20m, and ~40m. For more details see the respective [table on the CaSR web site](https://hpfx.collab.science.gc.ca/~scar700/rcas-casr/dataset_specifics.html#available_variables) |

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| **Radiation**   * Downward solar flux [W/m2] * Surface incoming infrared flux [W/m2]   Radiation variables are provided at 1h frequency at the surface level. For more details see the respective [table on the CaSR web site](https://hpfx.collab.science.gc.ca/~scar700/rcas-casr/dataset_specifics.html#available_variables) |

|  |
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| **Snow**   * Water equivalent of snow depth over land subgrid tile [kg/m2] * Snow depth over land subgrid tile [cm]   Snow variables are provided at 24h frequency at the surface level. For more details see the respective [table on the CaSR web site](https://hpfx.collab.science.gc.ca/~scar700/rcas-casr/dataset_specifics.html#available_variables) |

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| **Other Meteorological Variables**   * Surface pressure [mb] * Sea level pressure [mb] * Geopotential height [dam]   These meteorological variables are provided at 1h frequency and (depending on variable) at surface level, ~20m, and ~40m. For more details see the respective [table on the CaSR web site](https://hpfx.collab.science.gc.ca/~scar700/rcas-casr/dataset_specifics.html#available_variables) |

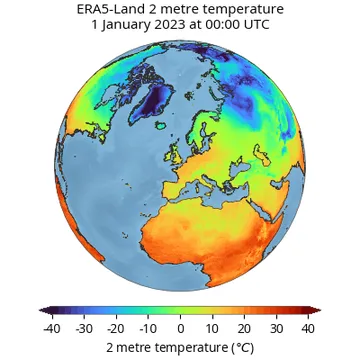
## 66 Example Applications

*links to Electricity Sector Applications*

## 67 Summary Description

ERA5-Land is a high-resolution global land surface reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). It provides detailed historical climate and weather data, focusing on land surface variables with enhanced spatial and temporal resolution compared to the standard ERA5 dataset. ERA5-Land is generated using the same land surface model as ERA5 but with higher resolution and no atmospheric data assimilation to improve consistency in land-related processes.

**ToDo:** Add referencec, data access



ERA5-Land Example, Source: Copernicus Climate Change Service (C3S) Climate Data Store (CDS))

## 68 Dataset Characteristics

* **Current version:** ???
* **Time period**: 1950–present
* **Spatial resolution:** ~9 km grid spacing
* **Temporal resolution:** Hourly and daily outputs
* **Spatial coverage:** Global land area
* **Data type:** ECMWF land surface model forced by ERA5 atmospheric conditions
* **Web references:** ERA5-Land on ECMWF web site, ERA5-Land data documentation, ERA5-Land on Copernicus Climate Change Service (C3S) Climate Data Store (CDS), ERA5-Land on Northern Climate Data Report and Inventory (NCDRI) Web Site,
* **Reference Publications:** @Muñoz2019, **ToDo** Figure out how to add: “Accessed on [date]

## 69 Strengths and Limitations

### 69.1 Key Strengths of ERA5-Land

* **High Spatial Resolution**: ~9 km grid improves detail over land compared to ERA5 (~31 km).
* **Long-Term Consistency**: Extends back to 1950, enabling long-term climate studies.
* **Hourly Data Availability**: Supports high-frequency climate and hydrological applications.
* **Improved Land Surface Processes**: Enhanced representation of soil moisture, snow, and vegetation dynamics.
* **Global Coverage**: Provides consistent land surface data across all continents.

### 69.2 Limitations of ERA5-Land

* **No Atmospheric Data Assimilation**: Unlike ERA5, does not assimilate atmospheric observations, which may introduce biases.
* **Precipitation Uncertainties**: Forced by ERA5 atmospheric fields, which can lead to regional biases in precipitation estimates.
* **Limited Ocean Representation**: Focuses on land; coastal interactions may be less accurate.
* **Computationally Intensive**: High-resolution data requires significant storage and processing resources.
* **Lack of Direct Observations**: Some variables are entirely model-based, potentially differing from ground-based observations.

## 70 Available Variables in ERA5-Land

*For details click on variable group to uncollapse*

|  |
| --- |
| **Atmospheric & Surface Variables**   * 2m air temperature * 2m dew point temperature * Surface pressure * 10m wind speed and direction * Surface (skin) temperature |

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| **Precipitation & Moisture Variables**   * Total precipitation * Rainfall rate * Snowfall rate * Snow water equivalent (SWE) * Evaporation * Soil moisture content (multiple layers) |

|  |
| --- |
| **Radiation & Energy Balance**   * Surface net solar radiation * Surface net thermal radiation * Latent heat flux * Sensible heat flux |

|  |
| --- |
| **Land Surface & Snow Variables**   * Snow depth * Soil temperature (multiple layers) * Soil moisture (multiple layers) * Surface runoff * Ground heat flux |

|  |
| --- |
| **Other Meteorological Variables**   * Albedo * Surface roughness length * Vegetation fraction |

## 71 Example Applications

*links to Electricity Sector Applications*

## 72 Data Access

* ERA5-Land hourly data from 1950 to present are available on the [Copernicus Data Store](https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=download). ECMWF has a web site with [Instructions to download ERA5-Land](https://confluence.ecmwf.int/display/CKB/How+to+download+ERA5).
* Hourly and daily temperature and precipitation ERA5-Land data are available on [PAVICS](https://pavics.ouranos.ca/datasets.html#c)

### 72.1 Instructions for Data Access on PAVICS

To access ERA5-Land data hosted on [PAVICS](https://pavics.ouranos.ca/datasets.html#c) via a Python script, locate the the OpenDAP Data URL of the dataset by clicking on the Threads Catalog link. Using the [Xarray Python Library](https://xarray.dev/) the dataset can be easily read. The output from the following code allows to interactively browse the content of the dataset:

import xarray as xr  
  
# the OpenDAP URL for hourly ERA5-Land data  
url = "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/reanalyses/day\_ERA5-Land\_NAM.ncml"  
  
# open the dataset  
ds = xr.open\_dataset(url, chunks={'time': -1, 'lat': 50, 'lon': 50}, decode\_timedelta=False)  
print("The ERA5-Land dataset:")  
ds

A quicklook visualization of the data is shown below.

ds.tas.sel(time="2019-01-16").plot()

### 72.2 4.2 Climate Projection Data

## 73 Definition

Climate projection datasets are collections of climate model outputs that simulate future climate conditions based on various greenhouse gas emission scenarios. These datasets are used to assess potential impacts of climate change on various sectors, including agriculture, water resources, and ecosystems.

### 73.1 4.4 Analysis Support Tools

This section contains pages with Python code that can be used to support the analysis and selection of climate datasets for applications in the electricity sector.

## 74 Overview

This page contains Python code that can extract and display historical climate data from different sources at a point location for comparison. The code can be run on the PAVICS platform or a locally configured Python environment with [Jupyter Notebook or Jupyter Lab](https://jupyter.org/) functionality enabled. It relys on the data available on PAVICS, but other data from other sources may be introduced.

Two versions are shown:

* A simple script that may be modified by the user to control the output figure.
* A script that generates an interactive dashboard with widgets for the user to control the output of the figure.

|  |
| --- |
| Note |
| The code sections below can not be executed on this web page. For them to be run they will need to be copied to a Jupyter Notebook on PAVICS or a local Python environment. |

## 75 A simple script

This script generates a figure to compare datasets of historical climate.

### 75.1 First we need to import libraries and define the data

The following section determines the content of the figure in terms of the datasets, the point location, the time period and the frequency.

import xarray as xr  
import xclim as xc  
from xclim.core import units  
from clisops.core.subset import subset\_gridpoint  
import matplotlib.pyplot as plt  
from datetime import date  
from dask.diagnostics import ProgressBar  
import warnings  
warnings.filterwarnings(action='ignore')  
# plt.style.available  
plt.style.use('seaborn-v0\_8')  
  
# Inputs  
lat\_in = 45.0  
lon\_in = -72.0  
  
start\_date = date(1991,1,1)  
end\_date = date(2020,12,31)  
  
freq = 'year'  
  
datasets = {  
 "ECCC\_AHCCD\_gen3\_temperature": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/station\_obs/ECCC\_AHCCD\_gen3\_temperature.ncml",  
 #"ECCC\_AHCCD\_gen2\_precipitation": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/station\_obs/ECCC\_AHCCD\_gen2\_precipitation.ncml",  
 "NRCANMet\_v2": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/gridded\_obs/nrcan\_v2.ncml",  
 "RDRSv2.1": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/reanalyses/day\_RDRSv2.1\_NAM.ncml",  
 "ERA5-Land": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/reanalyses/day\_ERA5-Land\_NAM.ncml"  
 }  
  
def aggregate(ds, var, freq='annual'):  
 freqs={  
 'month': 'MS',  
 'season': 'QS-DEC',  
 'year': 'YS'  
 }  
 functs = {  
 'pr': xc.indicators.atmos.precip\_average,  
 'tasmin': xc.indicators.atmos.tn\_mean,  
 'tasmax': xc.indicators.atmos.tx\_mean,  
 }  
 return functs[var](ds=ds, freq=freqs[freq])

### 75.2 In the second step we create the figure

The next section of code will load the data for the selected location, time period, location and frequency and generate the figure.

fig, ax = plt.subplots(1,1, figsize=(15,5))  
for idx, (name, url) in enumerate(datasets.items()):  
 ds = xr.open\_dataset(url, chunks={'time': -1, 'lat': 50, 'lon': 50}, decode\_timedelta=False)  
 print(f"Loading {name} ...")   
 #display(ds)   
 ds\_pt = subset\_gridpoint(ds,  
 lat=lat\_in,  
 lon=lon\_in,  
 start\_date=start\_date.strftime('%Y-%m-%d'),  
 end\_date=end\_date.strftime('%Y-%m-%d'),  
 add\_distance=True)  
   
 dist = f"dist = {ds\_pt.distance.values/1000:0.1f} km"  
 #print(dist)  
   
 # Style  
 color = f"C{idx}"  
 line\_styles = {"tasmin": ":", "tasmax": "--"}  
   
 tmp\_vars = ['tasmin', 'tasmax']  
 if all(var in ds.data\_vars for var in tmp\_vars):  
 for var in tmp\_vars:  
  
 ds\_var = aggregate(ds=ds\_pt, var=var, freq=freq)  
  
 if 'units' in ds\_var.attrs and ds\_var.units == 'K':  
 ds\_var = units.convert\_units\_to(ds\_var, "degC")  
 #display(ds\_pt)  
  
 ds\_var.plot.line(ax=ax,  
 linestyle=line\_styles[var],  
 color=color,  
 label=f"{name} - {dist}" if var == 'tasmin' else None,  
 add\_legend=False  
 )  
plt.legend(bbox\_to\_anchor=(1.05, 1.0), loc='upper left')  
ax.set\_ylabel(f"Minimum and maximum\n{freq} temperature [˚C]")  
plt.title(f"{freq.capitalize()} Minimum and Maximum Temperatures from Multiple Datasets between {start\_date.year} and {end\_date.year}");

Modifying the two code sections above allows the user to adjust the content of the figure.

## 76 A script to create an interactive dashboard

### 76.1 Preparations for the dashboard

The following section of code defines functions that will be used by the dashboard to update the figure based on user input.

# Callback function to create the Matplotlib plot  
def create\_plot(xlim, freq, var):  
   
 start, end = xlim  
 start = date(start,1,1)  
 end = date(end,12,31)  
   
 fig, ax = plt.subplots(figsize=(9,3))  
   
 for idx, (name, file) in enumerate(data\_files.items()):  
 # Style:  
 color = f"C{idx}"  
 line\_styles = {"tasmin": ":", "tasmax": "--"}  
  
 tmp\_vars = ['tasmin', 'tasmax']  
 ds = xr.open\_dataset(file)  
 dist = f"dist = {ds.distance.values/1000:0.1f} km"  
 if all(var in ds.data\_vars for var in tmp\_vars):  
 for var in tmp\_vars:  
  
 ds\_var = aggregate(ds=ds, var=var, freq=freq)  
  
 if 'units' in ds\_var.attrs and ds\_var.units == 'K':  
 ds\_var = units.convert\_units\_to(ds\_var, "degC")  
 #display(ds\_pt)  
  
 ds\_var.sel(time=slice(start, end)).plot.line(ax=ax,  
 linestyle=line\_styles[var],  
 linewidth=1,  
 color=color,  
 label=f"{name} - {dist}" if var == 'tasmin' else None,  
 add\_legend=False  
 )  
 ax.set\_ylabel(f"Minimum and maximum\n{freq} temperature [˚C]")  
 ax.xaxis.label.set\_fontsize(8) # Update x-axis label font size  
 ax.yaxis.label.set\_fontsize(8) # Update y-axis label font size  
 ax.tick\_params(axis='x', labelsize=6) # Update x-axis tick labels font size  
 ax.tick\_params(axis='y', labelsize=6) # Update y-axis tick labels font size  
 plt.legend(bbox\_to\_anchor=(1.05, 1.0), loc='upper left', fontsize=6)  
 plt.title(f"{freq.capitalize()} Minimum and Maximum Temperatures from Multiple Datasets between {start.year} and {end.year}", fontsize=8);  
   
 plt.close(fig) # Prevent Matplotlib from displaying the figure immediately  
 return fig  
  
# callback function to exract data for point location.  
def extract\_data(lat, lon):  
   
 # ToDo: delete old points data!  
 data\_files = {}  
 for idx, (name, url) in enumerate(datasets.items()):  
 ds = xr.open\_dataset(url, chunks={'time': -1, 'lat': 50, 'lon': 50}, decode\_timedelta=False)  
 print(f"{10\*'-'} Reading {name} {10\*'-'}")   
 #display(ds)   
 ds\_pt = subset\_gridpoint(ds,  
 lat=lat,  
 lon=lon,  
 add\_distance=True)  
 # we need to remove 0D variables (applies to AHCCD data only)  
 ds\_pt = ds\_pt.drop\_vars([k for k in ds\_pt.variables.keys() if ds\_pt[k].dtype == 'O'])  
 #display(ds\_pt)  
 file = f'tmp/{name}\_lat{lat}\_lon{lon}.nc'  
 #print(f"Writing {file} ...")  
 ds\_pt.to\_netcdf(file)  
 data\_files[name] = file  
 return data\_files

### 76.2 Loading the data

The next block of code loads data from a default grid point.

# ToDo: load with AHCCD data  
datasets = {  
 "ECCC\_AHCCD\_gen3\_temperature": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/station\_obs/ECCC\_AHCCD\_gen3\_temperature.ncml",  
 #"ECCC\_AHCCD\_gen2\_precipitation": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/station\_obs/ECCC\_AHCCD\_gen2\_precipitation.ncml",  
 "NRCANMet\_v2": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/gridded\_obs/nrcan\_v2.ncml",  
 "RDRSv2.1": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/reanalyses/day\_RDRSv2.1\_NAM.ncml",  
 "ERA5-Land": "https://pavics.ouranos.ca/twitcher/ows/proxy/thredds/dodsC/datasets/reanalyses/day\_ERA5-Land\_NAM.ncml"  
 }  
  
with ProgressBar():  
 data\_files = extract\_data(lat\_in, lon\_in)  
  
print(data\_files)

### 76.3 Creating the interactive dashboard

The following code section uses the panel library to create a user interface to interactively modify the figure. It uses the above functions to update the figure accordingly.

import numpy as np  
import pandas as pd  
import matplotlib.pyplot as plt  
import panel as pn  
  
# Initialize Panel  
pn.extension()  
  
# Widgets  
xlim\_slider = pn.widgets.RangeSlider(name="Years", start=1950, end=2025, value=(1950, 2025), step=1)  
lat\_input = pn.widgets.TextInput(name="Latitude", placeholder="Enter Latitude", value=str(lat\_in), width=125)  
lon\_input = pn.widgets.TextInput(name="Longitude", placeholder="Enter Longitude", value=str(lon\_in), width=125)  
freq\_dropdown = pn.widgets.Select(name="Frequency", options=['month', 'season', 'year'], value='year', width=100)  
var\_dropdown = pn.widgets.Select(name="Variable", options=['Temperature', 'Precipitation'], width=150)  
var\_stats = pn.widgets.Select(name="Statistic", options=['mean', 'maximum', 'minimum'], width=150)  
  
# Dynamic Matplotlib plot  
dynamic\_plot = pn.bind(create\_plot, xlim=xlim\_slider, freq=freq\_dropdown, var=var\_dropdown)  
  
# Layout  
controls = pn.Row("### Controls", xlim\_slider, lat\_input, lon\_input, freq\_dropdown, var\_dropdown, var\_stats)  
dashboard = pn.Column(controls, pn.pane.Matplotlib(dynamic\_plot, tight=True))  
  
# Serve the dashboard  
dashboard