A GIS-based open-source methodology using LiDAR digital surface models for estimating rooftop solar energy potential

Author: Shreyas Rama, student in the Master of Geospatial Data Science programme

Supervisor: Marwan Katurji, Associate Professor in Atmospheric Dynamics in the School of Earth & Environment

Abstract

Rewiring Aotearoa (RA) is an independent, non-profit organisation working on energy, climate, and electrification outreach and research. This report describes research work in collaboration with RA that develops and documents a reproducible and open methodology for estimating rooftop solar energy potential, in the form of a technical report.

The methodology uses publicly available Light Detection and Ranging (LiDAR) digital surface models (DSMs), solar radiation measurements from country-wide hindcasts, open-source geographical information systems (GIS) tools, scripts written in the Python programming language, and validation with a New Zealand-developed solar radiation estimation tool (SolarView), to accurately model solar radiation yield for building rooftops. It is developed and designed with replicability in mind, with a permissive open-source license to foster collaboration with a wide variety of groups interested in developing an open solar energy estimation model.

This research, development, and subsequent technical report contributes to the energy discussions across New Zealand at both local and regional scales. It helps to enables compelling economic arguments for the increased uptake of solar. Additionally, through an open-source and replicable methodology, this research contributes to the wider international work and literature on solar energy potential estimation using LiDAR and digital surface models.

1 Introduction

1.1 Background

Transitioning to renewable energy across many different industries is a critical step in New Zealand's decarbonisation and emissions reduction. Rewiring Aotearoa aim to identify pathways for electrification across households, communities, and industries, through research, public engagement and advocacy.

A key component of their electrification advocacy is the promotion of solar energy, in particular rooftop photovoltaic (PV) systems. Solar is a clean and renewable energy source, and presents significant savings for households in terms of price per kilowatt-hour (kWh) when compared to electricity provided from the grid, which is projected to continually increase (*New Zealand's Electricity Future*, 2022). Recent New Zealand Government energy strategies have not created much certainty as to whether grid prices will reduce. Increased uptake of solar and unused electricity exported back to the grid reduces the cost of electricity (i.e. the merit order effect) (Janda, 2018).

Additionally, non-residential buildings such as schools, community halls, and carparks, often feature large, flat roofs which are ideal for PV installations and solar energy generation. Accurately estimating the potential for this generation across different building types helps to highlight how communities and regions of New Zealand can contribute to local energy systems, which in turn helps planning at a local and even national level.

1.2 Problem statement

There is currently no open-source methodology for accurately estimating rooftop solar energy potential using high-resolution LiDAR data. This imposes limits for groups such as researchers, community organisations, local councils, and their ability to integrate solar potential data into their planning, as well as provide tools and information to promote awareness for their respective communities.

Interest in solar energy generation is increasing, as more retailers offer solutions for households and businesses, as well as better PV technology being developed to more efficiently convert solar radiation into usable energy. However, some of the available tools for estimating solar potential are proprietary, closed-source, or often require paid subscriptions. Other models may use coarse global climate models to estimate solar irradiation for a given area which does not take into account shading from local features such as buildings or trees.

To address these problems, there is a need for a reproducible, transparent and open-source methodology to accurately estimate solar energy potential at differing spatiotemporal scales.

1.3 Aim and objectives

The research described in this report aims to answer the following research question: how can a GIS-based and open-source workflow using LiDAR digital surface models be developed and validated to provide accurate estimates of rooftop solar energy potential?

Furthermore, the research aims to provide a technical report and accompanying source code for generating accurate building estimates for areas of New Zealand. The estimates will incorporate validation against measured solar radiation in order to provide estimates that are useful for both Rewiring Aotearoa and their electrification advocacy, as well as groups that do not have access to proprietary and commercial datasets.

2 Literature review

2.1 Workflows and methodologies

At a high level, the nature of estimating solar energy potential (in general, not just for rooftops) requires a series of data transformation steps (i.e. workflow, or pipeline) to produce a dataset which can be used to represent solar energy potential. Within this workflow, many software tools are utilised and assumptions made. Therefore, establishing a high-level workflow for this estimation (irrespective of software or tools) becomes important to understand the different transformations and assumptions that occur, and why the transformations are used at different stages – including things like input parameters and their purpose. This helps to enhance transparency, reproducibility, and understandability within the methodology.

Tro-Cabrera et al. (2025) established EHUkhi, a GIS-based modelling methodology that produces RPVP (rooftop photovoltaic potential) as well its associated energy return on energy investment. EHUkhi is clearly shown as a colour-coded diagram displaying the different steps and software tools utilised as well as calculations used along the way to arrive at RPVP – which is a complex calculation involving raster arithmetic and various other documented assumptions. They made use of a variety of different software tools and packages, notably utilising the *r.sun* tool from GRASS (Geographic Resources Analysis Support System) GIS to perform solar irradiation prediction. However, details about input parameters for *r.sun* and how they were derived, and any assumptions that were made when using the tool were omitted.

Similarly, Anselmo et al. (2024) and Nguyen & Pearce (2010) chose to use a GIS-based approach, also involving *r.sun* in their methodologies. However, their aims differ – with more of a focus on results validation and estimating potential for solar farms, respectively. Of note in Anselmo et al. (2024) is the use of QGIS' Graphical Modeller, which allows for a graphical representation of the overall workflow for estimating solar irradiation including the ability to change the input parameters. This was crucial as solar irradiance data for 28 years was required for analysis, and this aspect of automation enabled modelling the 28 years more efficiently. In Nguyen & Pearce (2010) a list of required data inputs is provided as part of a 'pre-simulation' stage which helps to establish not only the purpose of the data but also where it was sourced from.

Returning to rooftops, AdjiSki et al. (2023) opted to use the Urban Multi-scale Environmental Predictor (UMEP) set of tools written in Python – which includes the Solar Energy on Building Envelopes (SEBE) tool. Like *r.sun*, SEBE calculates pixel-wise solar energy potential and can even calculate irradiance on building walls. However, the input parameters for UMEP/SEBE are significantly more complex than *r.sun*. It requires data for a typical meteorological year to be processed into a certain format (using the UMEP MetProcessor tool) mandated by UMEP. In addition, and crucially for this research as it only focuses on rooftops, there is no mechanism to exclude building wall calculations from the process which adds more computational expense (*UMEP/SEBE - Any Options for Rooftop Only Solar Potential · UMEP-Dev/UMEP · Discussion #778*, n.d.).

Among these different workflows, there are many moving parts and assumptions, and some do not encompass an entire end-to-end process for solar energy potential estimation. Piecing together software tools may increase the methodology's overall complexity.

Commercial software can offer a more streamlined approach. A workflow using the proprietary software ArcGIS Pro is provided by Suomalainen et al. (2017). They make use of the solar radiation tools available in ArcGIS Pro software, which provides almost all of the tools and algorithms needed for estimating solar energy potential. Only two open-source tools are used (LAStools and Python) for constructing digital elevation models per Auckland neighbourhood.

2.2 Open-source software

Commercial (or proprietary) GIS tools can limit the potential user base and provide barriers to adoption, such as requiring one-off or recurring payments for access to the software. Open-source alternatives can provide free software and therefore reach a wider user base (Tro-Cabrera et al., 2025). Usage of the free and open-source QGIS over ArcGIS Pro, allows better dissemination of results by removing the technological barriers given by the licensing requirements of ArcGIS Pro (Anselmo et al., 2024).

Open-source software has the benefit of enabling experts across the world to contribute collaboratively to the development of effective software. The open-source license of GRASS GIS (which contains *r.sun*) makes the source code available to all and in turn creates opportunities for improvements to be made to the models (Hofierka & Kaňuk, 2009).

While using open-source software has the benefit of reaching a wider audience, it also means that any methodology employed and its outputs are more transparent, and in theory more reproducible.

Several of the studies in this review that used open-source software for solar radiation estimation mentioned which open-source software packages were used and how they were employed in an overall methodology, but often lacked specific detail about important parameters and their values, and no research paper provided external links to code that was developed as part of the research – Hofierka & Kaňuk (2009) talked about "shell-scripting within the Linux operating system" but did not provide examples. Having access to specific code (i.e. non-library code) or intermediate outputs enhances reproducibility. An enhancement in this sense, for example, would be to provide collated datasets as well as detailed technical information on how to process the data (through supplying scripts or programs) through an online code repository, like GitHub. Alternatively, in the context of using a graphical user interface (GUI), steps taken to achieve a certain outcome within the GUI can be placed in the appendix as done by Palmer et al. (2018).

Nguyen & Pearce (2010) mention "offering an algorithm that is applicable to other regions in Ontario and throughout the world, which utilizes open source and free software tools and data". As mentioned previously, in their research significant detail about input parameters into *r.sun* is provided, which makes it simple to visit the sources the authors listed in order to retrieve the same datasets and replicate their results.

2.3 LiDAR datasets

One of the key datasets used in this methodology is LiDAR data, and in particular digital elevation and surface models. These are important to produce accurate results for solar energy potential. In the case of Mujić & Karabegović (2023), a 30m x 30m DEM was used with the caveat that a LiDAR DSM at 1m x 1m resolution would result in more accurate solar potential results.

DSMs at a 1m x 1m resolution (like the ones used in this methodology) aim to capture characteristics such as rooftops and their slope/orientation, as well as vegetation such as large trees which may cause a shading effect. LiDAR data with horizontal spacing larger than 1m is not sufficient to reflect fine-scale characteristics such as vegetation (Kodysh et al., 2013).

Gassar & Cha (2021), in a review of different photovoltaic potential estimation approaches at urban scales, stated that LiDAR data at higher resolutions has become more desirable for estimating rooftop potential. These datasets also enable automated computation, and as a result considered among the "best approaches for investigating and estimating the multiple parameters related to rooftop photovoltaic potential". They also found that LiDAR data in combination with rooftop prints and aerial imagery was a high-performance methodology with 95% accuracy, according to research that formed their overall review. A notable drawback they highlight is the computational expense required to obtain precise and reliable results. A LiDAR-based approach may be more suited to the scale of city districts or small cities. This highlights the importance of a reproducible workflow – while large regions may be computationally expensive, the ability to break said region into smaller, more quickly processable (and parallelizable) chunks and run them through a well-designed workflow offers a way to scale processing and reap the benefit of using a highly precise dataset such as LiDAR.

2.4 Validation of solar irradiation estimates

Numbers produced by solar irradiation algorithms such as *r.sun* or ArcGIS' Raster Solar Radiation tool are estimates, and for robustness and real-world applicability need to be validated. AdjiSki et al. (2023) developed a comprehensive methodology and applied it to several rooftops in Skopje, North Macedonia, to determine energy output based on provided solar panel characteristics. However, these numbers were not contextualised against real-world measurements to assess how accurate their model was.

Mujić & Karabegović (2023), who created a DEM as LiDAR data was not available, intended to validate the solar irradiation estimates that were generated from their DEM. However, due to a lack of nearby weather stations that measure solar radiation for their study area in Sarajevo, they were unable to. They noted that PVGIS (Photovoltaic Geographic Information System), an information system that provides data on solar radiation across the world, is often used as a basis for daily and monthly solar potential values – thereby providing values that can be used in validation of a model.

PVGIS, or in particular PVGIS-SARAH2 (the second Surface Solar Radiation Data Set - Heliosat), is a satellite-derived solar radiation database, whose values have been shown to be accurate compared to ground-based measurements (AlFaraj et al., 2024). It has a 5km resolution, and only covers certain areas of the world, not including New Zealand. For areas it does not cover, ERA5 (ECMWF (European Centre for Medium-Range Weather Forecasts) Reanalysis v5) is used to provide a global dataset.

Suomalainen et al. (2017) similarly used external tools to validate their solar irradiation estimates. NIWA (National Institute of Water and Atmospheric Research, now known as Earth Sciences New Zealand) SolarView is an online calculator that estimates solar energy at a given address and allows inputs such as panel direction and slope, using data from nearby climate stations (*Solarview*, n.d.). Used as a point of comparison, they found their annual estimates for solar irradiation were underestimating by approximately 5% compared to SolarView values. Section 3.4 of this report describes the SolarView dataset in more detail.

Palmer et al. (2018) focused on identification of suitable rooftops based on roof geometry and physical features, with accuracy determined by ground-truthing against a database of household PV installation data. Of note, however, was that LiDAR data used in the study was found in some cases to be more accurate than what was added to the database by panel installers – values for tilt and azimuth of panels were found to be transposed or estimated rather than measured, highlighting the importance of documenting any assumptions or findings of data used in validation.

3 Data

The methodology to estimate rooftop solar energy potential requires at minimum two datasets. The first is a DSM represented as a raster, and the second are building outlines represented as a vector dataset.

3.1 DSM

DSMs contain elevation data (measured in metres) in a gridded format, of surface features such as buildings and vegetation. They are derived from raw LiDAR point cloud data which contain a high density of point measurements which in turn offers detailed definition of surface features (Priestnall et al., 2000). DSMs are therefore highly useful for estimating solar energy potential, as shading is an important factor in solar energy production via PV installations. They are commonly used as an input parameter to solar irradiation estimation algorithms. Particular to this research, LINZ (Land Information New Zealand) offer DSMs at 1m x 1m resolution (*New Zealand LiDAR 1m DSM | LINZ Data Service*, n.d.). This is beneficial as it will help incorporate the aforementioned shading from terrain and tall structures into solar irradiation estimation. It can also be used to calculate roof slope and aspect which is another important factor in PV installation performance.

While 1m x 1m DSMs are appropriate for the purpose of estimating rooftop solar energy potential, there is currently no full nationwide LiDAR coverage. However, all urban centres with higher densities of rooftops are covered. Within the overall dataset for the country, aircraft performing LiDAR measurements were flown at different times. According to the New Zealand LiDAR 1m DSM Survey Index, aircraft for certain areas were flown as far back as 2010 (*New Zealand LiDAR 1m DSM Survey Index | LINZ Data Service*, n.d.). As a result, solar energy potential estimates may be inaccurate as vegetation would have grown or new buildings erected that may contribute to shading rooftops. This means the timeliness of the DSM is an important factor when attempting to accurately model solar energy potential on rooftops.

Figure 1 shows a visual representation of some University of Canterbury buildings in a DSM. The lighter-coloured pixels indicate higher elevation values (measured in metres above sea level), while darker pixels indicate lower elevation values.

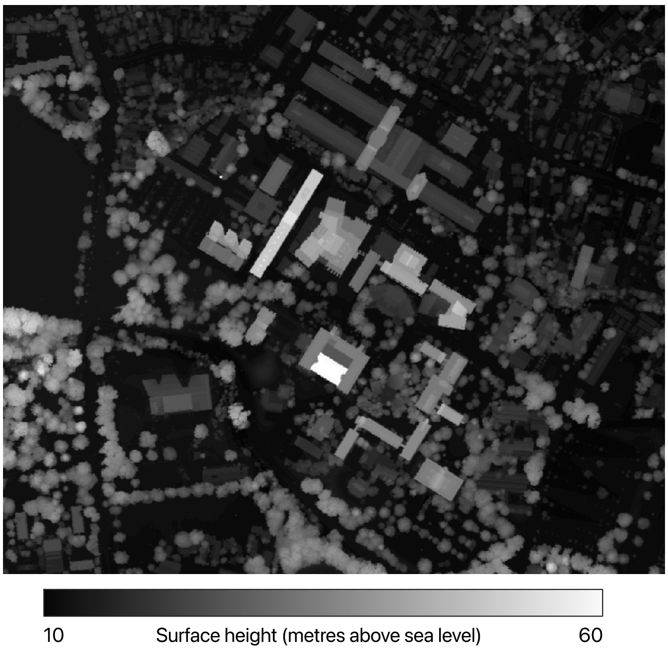


Figure 1: Visual representation of a digital surface model (DSM) for University of Canterbury buildings and surrounds

3.2 Building outlines

The second dataset required for rooftop solar energy potential estimation is building outlines. These are commonly distributed as a shapefile, a widely-used geospatial vector data format. LINZ provide building outlines across mainland New Zealand in this format. The outlines are extracted from LINZ's aerial imagery using both automated and manual processes, and only outlines greater than $10m^2$ are captured in the dataset (*NZ Building Outlines | LINZ Data Service*, n.d.).

Building outlines can be used to clip a solar irradiation raster that has been produced by an estimation algorithm. This produces a raster of only rooftops which has the benefit of a smaller file size, making region-scale processing (e.g. computing statistics for the study area) of rooftop solar energy potential faster than if terrain was included. However, this dataset runs into similar issues as DSMs. The overall dataset produced for New Zealand is the result of aerial imagery captured at various time points, going as far back as 2014. This again means not all buildings for an area may be covered, and there is also the drawback that it may not line up with when the LiDAR was captured for the given area.

Figure 2 shows building outlines (i.e. polygons) for some University of Canterbury buildings.

Figure 2: Building outlines for University of Canterbury buildings

3.3 WRF data

With an estimation of rooftop solar irradiation in the form of a raster, this estimate can be validated with two further datasets. The first of which is using MetService's WRF (Weather Research and Forecasting) data.

As mentioned in Section 2.4, PVGIS is a common information system providing raster data on solar radiation in different parts of the world. There are multiple organisations providing solar radiation data, at varying spatial and temporal resolutions, and timeframes (AlFaraj et al., 2024). However, a lot of these datasets are more focused on Europe, Africa, and parts of Asia.

In New Zealand, MetService is the national meteorological service. Through their Insights Platform, they offer a variety of weather-related products through observations recorded by their network of weather stations across the country (*MetService Insights Platform*, n.d.). The University of Canterbury has access to various WRF-related datasets for the past 20 years, including solar radiation. Some of this data has also been made available via the New Zealand Modelling Consortium's Open Environmental Digital Library, at varying resolutions and temporal scales (*New Zealand Modelling Consortium*, n.d.). For this research, solar radiation datasets (also known as shortwave down, or downward shortwave radiation) at a 4km pixel grid are provided in the netCDF (Network Common Data Form) format, which is used to store multidimensional scientific data (Rew & Davis, 1990).

The shortwave down WRF data is a hindcast driven off ERA5 (ECMWF (European Centre for Medium-Range Weather Forecasts) Reanalysis v5). This is the fifth generation of atmospheric reanalysis of the global climate (Setchell, 2020), which has then been downscaled to a 4km resolution over New Zealand. While this resolution will not show radiation changes on a fine-scale such as that of individual rooftops (or even small suburbs), the benefit is the ability to compare WRF numbers (which account for atmospheric conditions like cloud cover) for the past 20 years against the mostly clear-sky predictions made by the estimation algorithms, which can then indicate a typical loss due to the atmospheric conditions. Section 4.5 will describe how the WRF data can be adjusted via a 'solar coefficient', in order to conform it better to fine-scale rooftop characteristics.

ncview is a free and open-source software tool for visualising netCDF files (*Ncview | David W. Pierce, Scripps Institution of Oceanography*, n.d.). It allows for adjustment of the different variables contained within a netCDF file, as well as the ability to animate the data. Figure 3 shows a screenshot of viewing SWDOWN (shortwave down) radiation data for New Zealand in *ncview*. A mid-winter day (day 190) has been chosen, and a dotted, white outline of New Zealand can be seen.

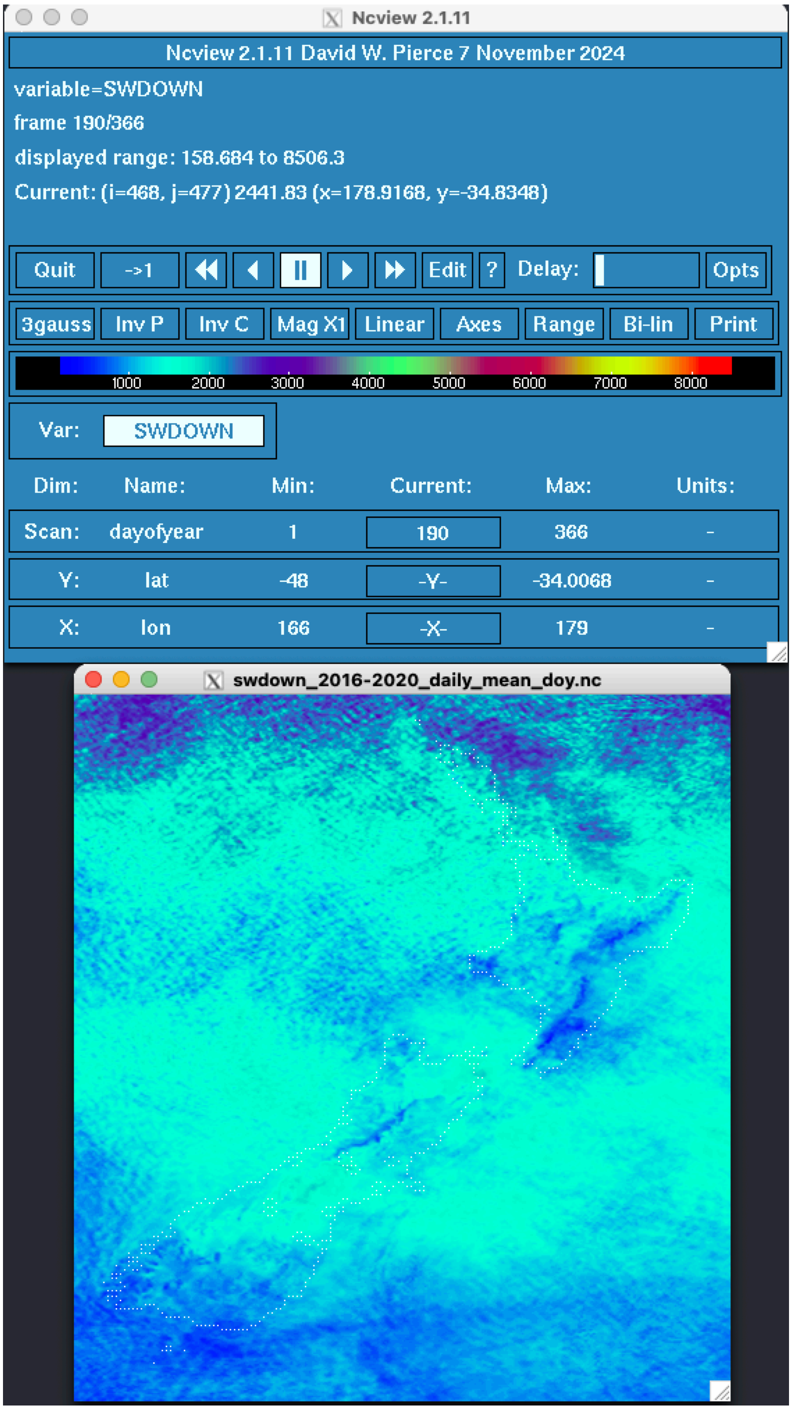


Figure 3: Viewing a netCDF file of WRF solar radiation data for New Zealand in *ncview* software

3.4 SolarView

The second validation dataset uses solar energy calculations generated with NIWA's SolarView. SolarView is an online calculator that provides estimates of solar irradiance at a given location, allowing inputs such as panel direction and slope (*Solarview*, n.d.). It uses a combination of the local landscape and irradiance data from the nearest climate station to provide solar energy estimates. Notably, it does not account for more localised features such as shading from nearby buildings or trees as it uses a 100m digital elevation model (*SolarView Help | Earth Sciences New Zealand | NIWA*, n.d.).

The web tool is free to use for non-commercial purposes after registering an account, but for programmatic access through APIs, NIWA need to be contacted to discuss options.

While SolarView does not provide estimates for rooftops, it does provide values in kWh/m² which can be used as a point of comparison for the rooftop solar energy potential estimates, which can be converted to kWh/m² easily due to the 1m² resolution. These come in the form of cumulative kWh/m² and cloudless W/m², both on an hourly basis. Importantly,by default these values represent sunlight received on a panel positioned optimally, i.e. panel tilt reflects the latitude of the location.

In summary, given estimates from clear-sky prediction algorithms that utilise DSMs, WRF irradiance data can then be used to understand a typical loss due to atmospheric conditions, as well as compute a solar coefficient raster, capturing fine-scale characteristics of rooftops in order to adjust the WRF data accordingly. Furthermore, with SolarView estimate data, it is possible to get an idea of how the model performs and whether the results are acceptable. This can inform improvements to the model and better predict rooftop solar energy potential.

3.5 WRF vs. NIWA climate data

Both WRF and SolarView's underlying dataset measure solar radiation. Given that SolarView's dataset uses NIWA's electronic weather stations (EWS) and are observed values of radiation, it can be useful to compare WRF data to it to see if there are any biases which may influence estimates.

A CSV for NIWA's downtown Christchurch EWS on Kyle Street was used to represent SolarView data – this is the same dataset that SolarView would use when creating estimates for a chosen location in the Christchurch CBD area. The nearest grid cell containing the EWS in the WRF data was chosen.

3.5.1 Annual total radiation

Across the three years chosen for comparison, as shown in Figure 4, WRF consistently overestimates annual total radiation compared to the Kyle Street EWS.

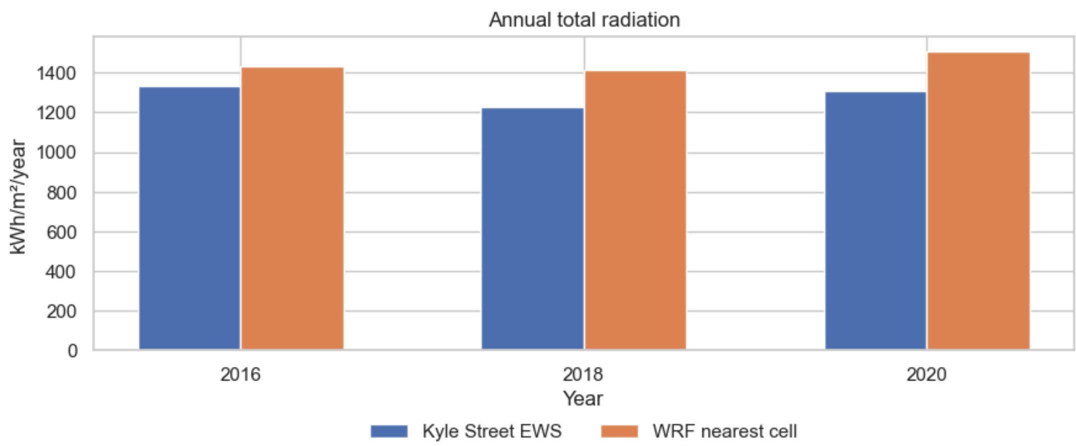


Figure 4: Annual total radiation measurements from WRF compared with Kyle Street EWS

3.5.2 Monthly percent bias

At a more granular level, Figure 5 shows a breakdown by month and by percentage to understand the relative differences.

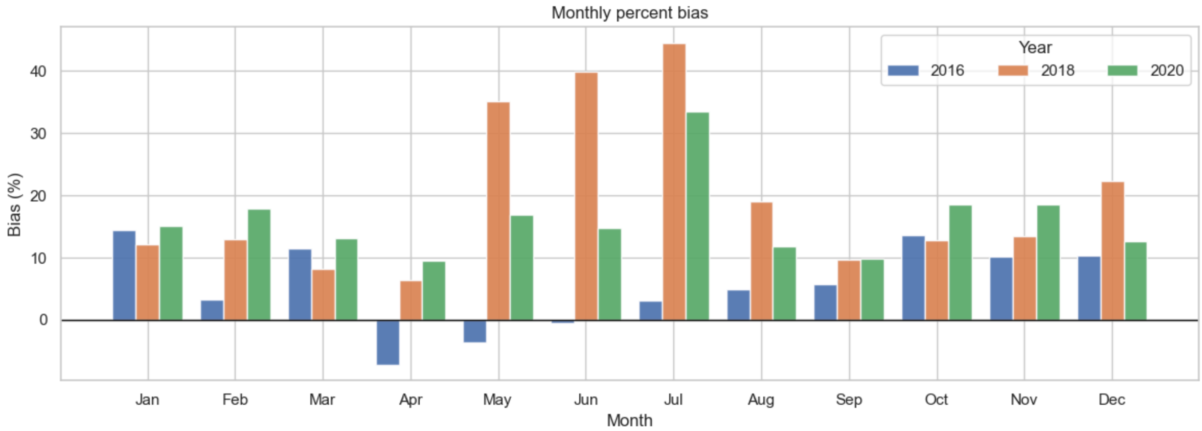


Figure 5: Monthly percent bias for WRF against Kyle Street EWS

Conclusions that can be drawn:

- Biases in the three warmer seasons seem to be more consistent between years compared to winter. This may mean cloud cover is more difficult to predict during winter months as it varies a lot more in its intensity than in summer
- Christchurch City in particular is more sensitive to swings in winter solar radiation due to pollution and its inversion layer, which has shown larger attenuations in shortwave radiation (Tapper, 1976). This means the hindcast that WRF is derived from may not capture this localised effect compared to direct measurements within the city
- Large biases in winter may be more impactful due to a likely undersupply of significant radiation for solar energy generation

In order to produce values that could be used to adjust estimates to account for bias, a more detailed and longitudinal analysis is required. Alternatively, a gridded product may be requested from NIWA (or constructed from existing regional gridded datasets) and used directly within the methodology in place of WRF data.

The benefit of using WRF data is that it is a gridded product across New Zealand on an hourly basis (and is therefore more convenient and flexible for a variety of use cases), whereas NIWA provides gridded solar radiation on a daily basis at a region level and would require more processing.

4 Methodology

The methodology employed in this research has been designed with open-source and automation in mind. The source code and documentation can be viewed at the *solar-estimates* repository on GitHub (*Rewiring-Nz/solar-Estimates*, 2025).

4.1 Data processing

DSMs downloaded from LINZ via their data portal, come in an archived format containing several GeoTIFF raster files representing tiles that make up the overall DSM. In order to produce an input raster used by the estimation algorithm, these need to be mosaicked, or combined together. The GDAL (Geospatial Data Abstraction Library) set of tools, which are available as a Python package, are utilised to build a virtual dataset of the mosaicked input DSMs via `gdal.BuildVRT`. From there, the virtual raster can be used by GIS software.

With a single raster representing the DSM, aspect and slope rasters can be calculated, which are important when estimating solar irradiation – the estimation algorithms measure the sun's angle at different points in the day and require slope and aspect to understand how sunlight may hit a surface at any given point. As the remainder of operations in this methodology rely on the GRASS GIS software, the mosaicked virtual raster is loaded into GRASS via its Python scripting module. Aspect and slope rasters are then calculated via the *r.slope.aspect* module in GRASS.

4.2 Solar radiation modelling with *r.sun*

With three rasters now generated, the GRASS *r.sun* module used to estimate solar irradiation can be run. *r.sun* utilises a variety of parameters that cover things like latitude, surface and atmospheric conditions, and time of day. The following inputs for a single invocation of *r.sun* form the basis of this step:

- DSM, with calculated slope and aspect rasters
- Individual day to estimate for
- Time step of 1 hour (can be adjusted for more fine-grained analysis)
- Daily Linke values that measure atmospheric turbidity are interpolated via numbers produced by Remund et al. (2003)

Repeated calls to *r.sun* can produce estimates over any time period. However, computation can be quite expensive. Execution time will scale with factors such as the extent of the DSM and chosen time step.

r.sun works in two modes – one for calculating solar irradiance values (Watts per m^2) for a set local time, and the other for sums of solar irradiation (Watt-hours per m^2 for the provided day) (*R.sun - GRASS GIS Manual*, n.d.). The second mode is used here, and is called in a loop to calculate irradiation across a time period represented as either a range of days or a list of days to interpolate between. Interpolation using key days (e.g. solstices, or mid-month days) will help to reduce computation time at the cost of potentially less accurate results. The resulting rasters for computed days are then summed together to produce a single raster that contains total solar irradiation for the time period.

Figure 6 and Figure 7 shows the resulting solar irradiation rasters for January and June, respectively.

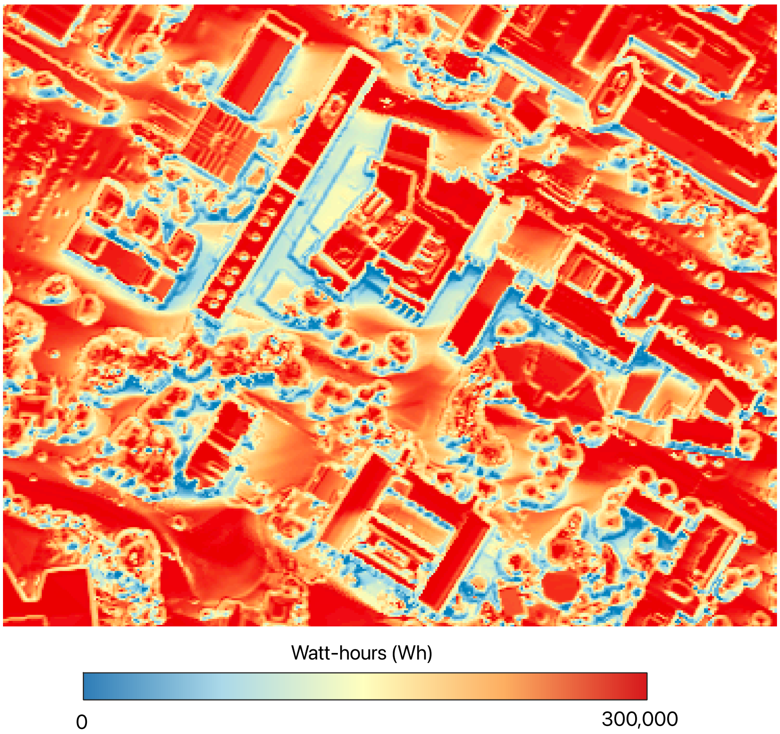


Figure 6: Solar irradiation raster of University of Canterbury buildings for the month of January produced by GRASS' *r.sun* module

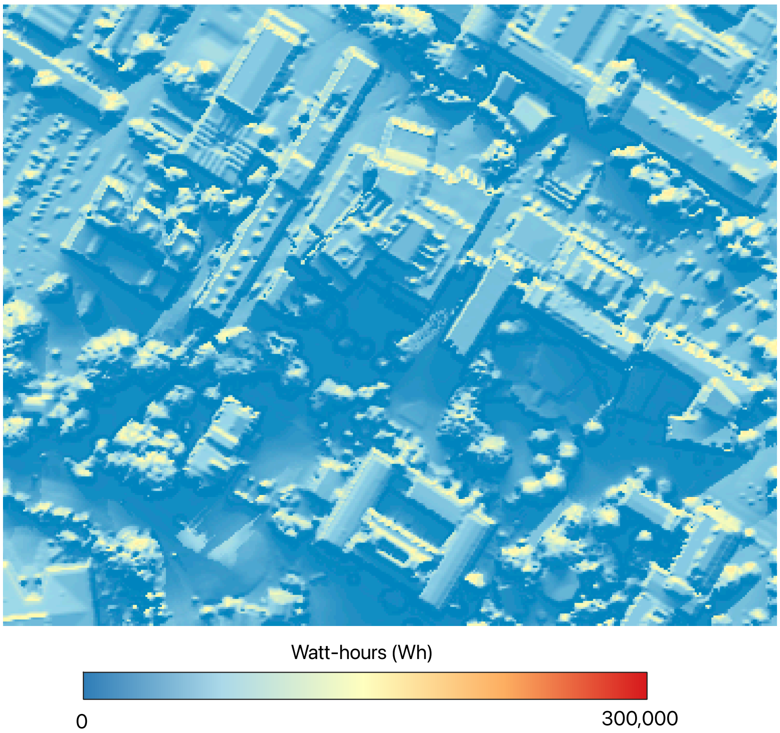


Figure 7: Solar irradiation raster of University of Canterbury buildings for the month of June produced by GRASS' *r.sun* module

In June, only a portion of the rooftops that face north receive any significant solar radiation.

4.3 Rooftop clipping and pixel filtering

The next step is to produce a raster that contains only rooftops as this is the focus of this research. The building outline dataset can be used alongside the *r.mask* GRASS module to clip the raster and preserve just the rooftops as they correspond to the building outlines.

At this point, a clear-sky estimate of rooftop solar potential for individual buildings has been produced in the form of a raster. Each 1m x 1m pixel of the raster corresponds to the sum of Watt-hours of solar irradiation it receives for the entire specified period. These pixels can then be filtered, for example using the slope raster to remove pixels that exceed a degree threshold where panels cannot be installed on them, or eliminating south-facing pixels that fall within an aspect range, or removing pixels that don't meet a certain Watt-hour threshold for the time period. This step needs to be conducted with experts in the PV industry as advancements in technology may make even south-facing panels viable.

Figure 8 shows the resulting rooftop-only raster after clipping the solar irradiation raster to building outlines.

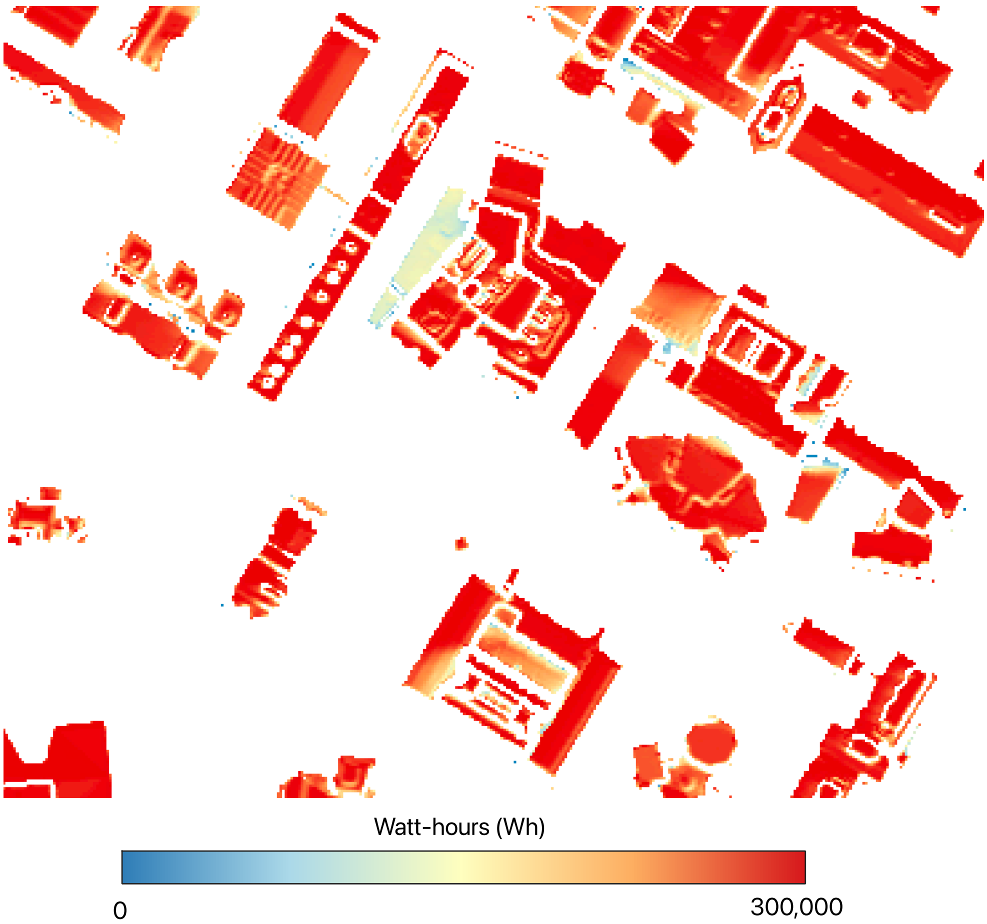


Figure 8: Resulting raster after clipping a solar irradiation raster to building outlines

After filtering, univariate statistics (i.e. the *v.rast.stats* GRASS module) can then be calculated to produce outputs such as a table that records each building and their associated solar energy potential.

4.4 Solar coefficient raster

A further raster can be derived from the previously created irradiation rasters. By normalising the values in the solar irradiation raster to a percentage of the 1m² pixel that receives the most radiation on a given rooftop, a 'solar coefficient' raster can be produced. This raster is representative of how well or how poorly certain areas of the rooftop perform in terms of irradiance, and can then be used to enhance the WRF raster to reflect these characteristics.

Similarly to the estimation described in Section 4.2, solar coefficient rasters are produced per-day of the study time period.

4.5 Incorporating WRF data

r.sun's predictions are mostly clear-sky estimates – there is some accounting for atmospheric conditions via the Linke turbidity values, however cloud cover is not explicitly modelled. Therefore, to validate the rooftop solar energy potential estimates, WRF solar radiation data can be used as a point of comparison.

In order for the WRF data to be used as part of the methodology, it requires processing as it is in the netCDF format – this is achieved by using the *xarray* Python library to form a raster of solar radiation values for any time period and extent encompassed by the netCDF file. As the WRF raster is a much coarser resolution than the rooftop raster, only a few pixels may cover the extent of a given study area.

For this report, five years of WRF data (2016 to 2020) were averaged and resampled to daily values. This provides a 'typical' weather profile for all of New Zealand while maintaining a reasonable filesize.

WRF rasters are produced for each day, and are then adjusted using the daily solar coefficient rasters. These WRF rasters are then summed and can provide a comparison to the clear-sky estimates which match the same time period.

4.6 Validation against SolarView data

SolarView data was collected for select locations in New Zealand to compare against estimates from the *r.sun* and WRF methodology. This has the benefit of using an existing pipeline developed within New Zealand and using climate data specific to New Zealand.

As mentioned in Section 3.4, values from SolarView represent sunlight received on a panel positioned in accordance with its latitude. Therefore, SolarView estimates may be higher or not totally applicable when used in combination with area measurements for a rooftop.

Despite this, SolarView estimates can still provide a point of comparison for the rooftop solar energy potential estimates, and can help to validate whether the model is performing adequately.

The hourly cumulative and cloudless SolarView data are summed to produce annual values in kWh/m^2 for comparison against the methodology's estimates.

4.7 Diagram

Figure 9 summarises at a high level the data and methodology in this report, and references the relevant sections from Section 4. While estimates are typically given for a year, this workflow can be applied on any time scale.

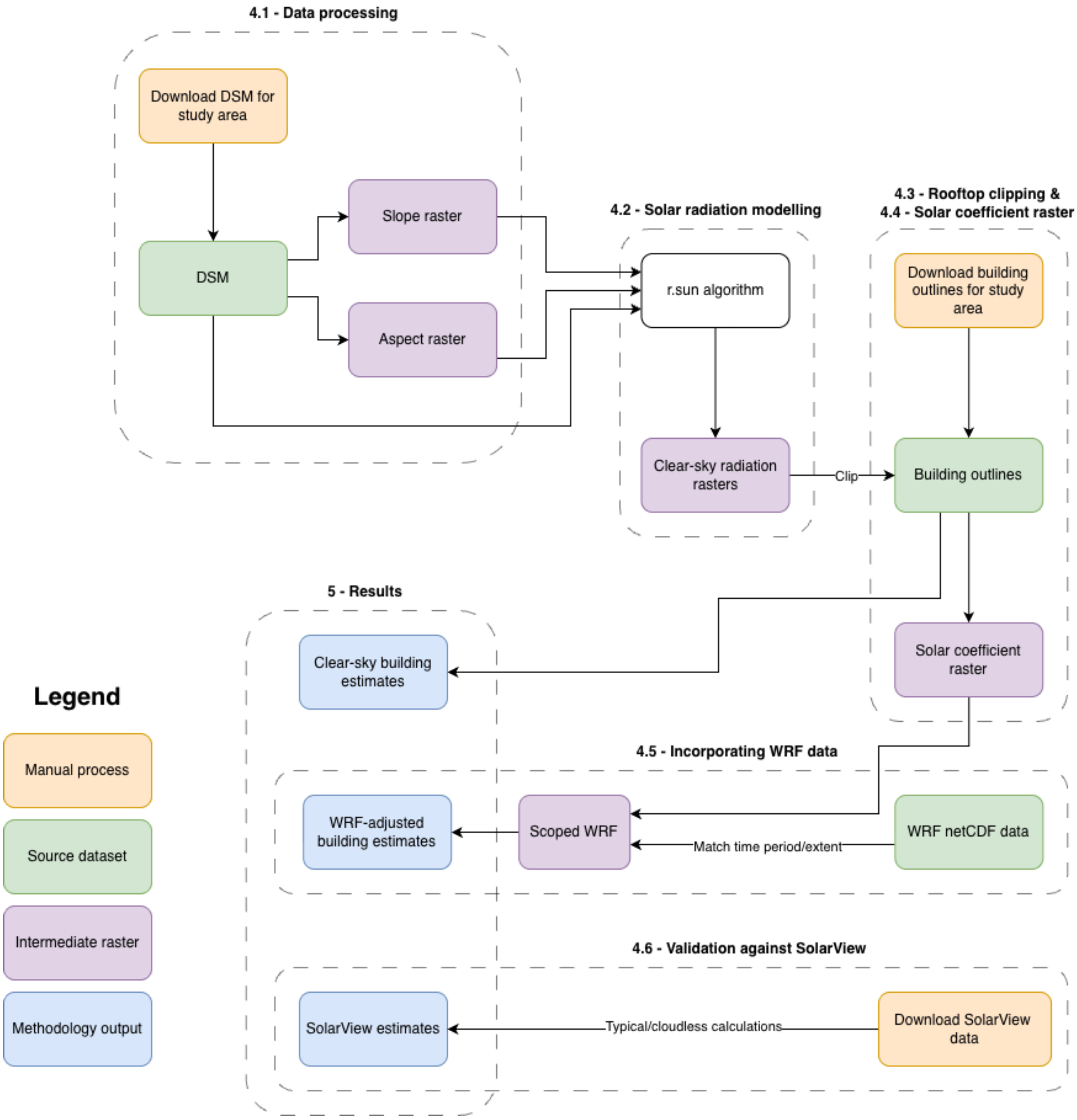


Figure 9: High level diagram of data sources and methodology flow

5 Results

The methodology was performed on three houses across New Zealand, with any significant geographical features that may affect solar energy potential mentioned. Methodology parameters and details for each house are described as follows:

- 14 key days throughout the year to calculate for and then interpolate between
- 4 hour time step
- <1MB LiDAR raster filesize

For each house, the following estimate types are generated (all values in annual kWh/m²):

- *r.sun* clear-sky: using the GRASS module with mostly default values following the methodology
- WRF-adjusted: creating solar coefficient rasters and adjusting the WRF solar radiation values accordingly
- SolarView: estimates from NIWA's online tool with default parameters
- SolarView cloudless: assumes cloudless conditions (i.e. maximum solar energy potential at the location)

5.1 Methodology outputs

In its current state, the methodology produces several outputs, some of which are optional.

5.1.1 CSV and GeoPackage

Estimates from *r.sun* and incorporating WRF data are merged with building outline data to provide both CSV and GeoPackage vector files. The CSV provides a quick way to understand, for example, total generation of the study area, whereas the GeoPackage allows integration with mapping software and GIS tools for analysis.

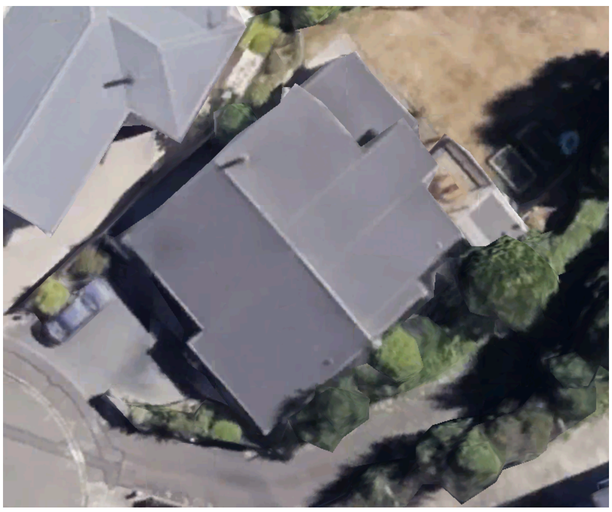
5.1.2 Intermediate rasters

As the methodology is designed to be flexible in its parameters, an option is provided to output a set of intermediate rasters. These include rasters for:

- solar irradiance for the entire area (pre-building clip)
- solar irradiance on buildings
- the WRF-adjusted solar irradiance for the area

Exporting the intermediate rasters is useful for more fine-grained analysis, i.e. investigating different rooftop shapes and their solar irradiance patterns.

5.2 House 1: Wellington



The first house is located in the Island Bay suburb of Wellington. There is minor hill obstruction to the south, as well as minimal shading from nearby trees and buildings. It features a typical gabled roof.

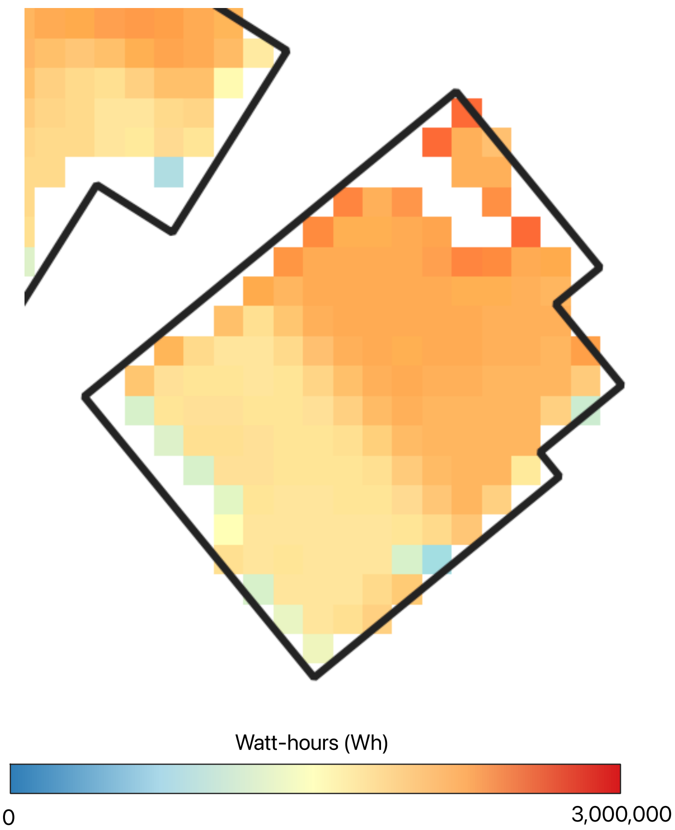


Figure 11: Annual irradiation for House 1

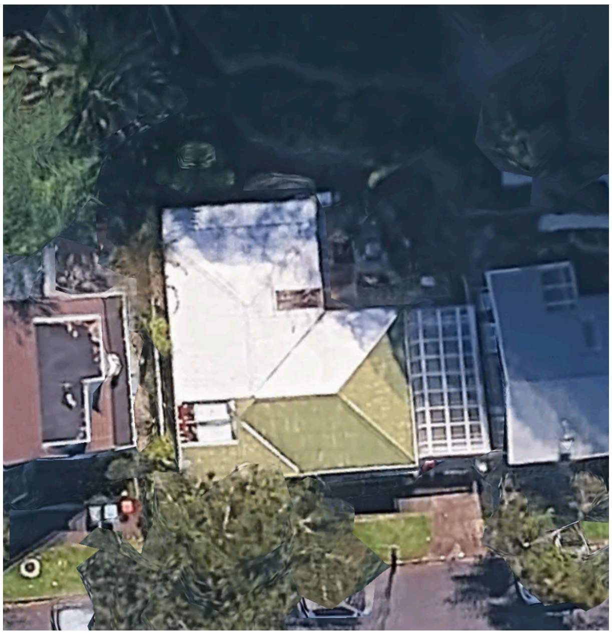
A screenshot of the annual irradiation raster is presented in Figure 11. Due to its gabled roof, the predominantly north-facing side of the roof receives more sunlight (darker shade of orange) than the other side.

Estimate	**Value (annual kWh/m²)**
r.sun clear-sky	1956
WRF-adjusted	1403
SolarView	1431
SolarView cloudless	2538

Table 1: Estimation results for House 1

Irradiance estimates for House 1 shown in Table 1 indicate that both the WRF-adjusted and SolarView estimates are relatively close to each other (1403 kWh/m² vs. 1431 kWh/m²). This may be due to SolarView using an optimal, north-facing panel position when providing its kWh/m² estimates, with most of the roof area also facing north.

5.3 House 2: Auckland



The second house is located in the Mount Eden suburb of Auckland. To the north the dormant volcano Maungawhau / Mount Eden and nearby trees contribute significantly to shading, but is otherwise relatively free of obstruction east-west.

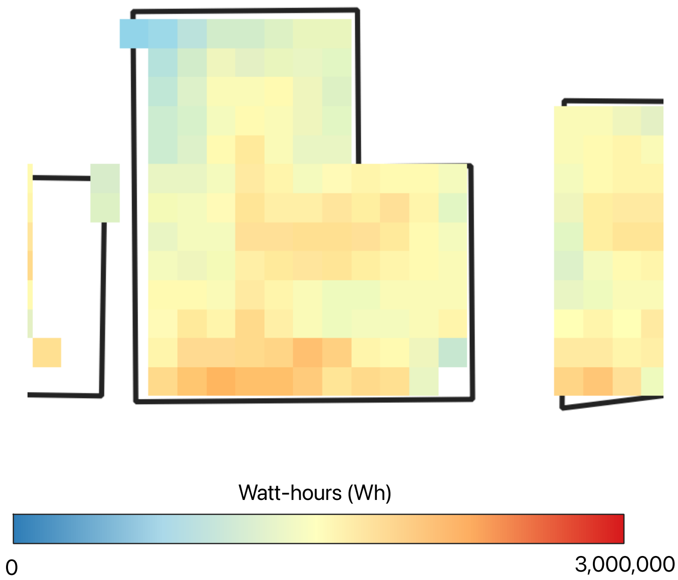


Figure 13: Annual irradiance for House 2

Figure 13 shows a screenshot of an annual irradiance raster for House 2. Pixels on the northern part of the roof (which would be expected to have the most solar radiation) receive less solar radiation due to shading from terrain and vegetation.

Estimate	Value (annual kWh/m²)
r.sun clear-sky	1507
WRF-adjusted	1052
SolarView	1489
SolarView cloudless	2586

Table 2: Estimation results for House 2

The results from House 2 shown in Table 2 highlight the benefit of using LiDAR data for rooftop solar energy potential estimation. SolarView uses digital elevation models at a fairly coarse 100m resolution, i.e. hills but not vegetation and buildings unlike DSMs. The WRF-adjusted estimate shows a much lower result for House 2 compared to SolarView (1052 kWh/m² vs. 1489 kWh/m²) - there are significantly tall trees that surround the base of Maungawhau / Mount Eden that are not accounted for in SolarView's estimate. Nearby houses with less obstruction (i.e. further away and less shaded from trees) are closer to SolarView's estimate for the area.

5.4 House 3: Christchurch

The third house is located in Lyttelton, south of Christchurch. The house is built up against the surrounding Port Hills, obscuring sunlight from the west. Notably, this house's roofs are mostly flat with a slight negative tilt from west to east.

Estimate	Value (annual kWh/m²)
r.sun clear-sky	2154
WRF-adjusted	1779
SolarView	1361
SolarView cloudless	2256

Table 3: Estimation results for House 3

The results from House 3 shown in Table 3 appear misleading at first. Both estimates derived from the methodology (*r.sun* clear-sky and WRF-adjusted) are significantly higher than estimates from previous houses. This is likely due to the house's flat roofs, which year-round receive more solar radiation compared to sloped roofs due to a higher exposure to sunlight in summer months. A comparison of solar radiation for an entire year between the target house and a nearby house with a more traditional gabled roof is shown in Figure 15:

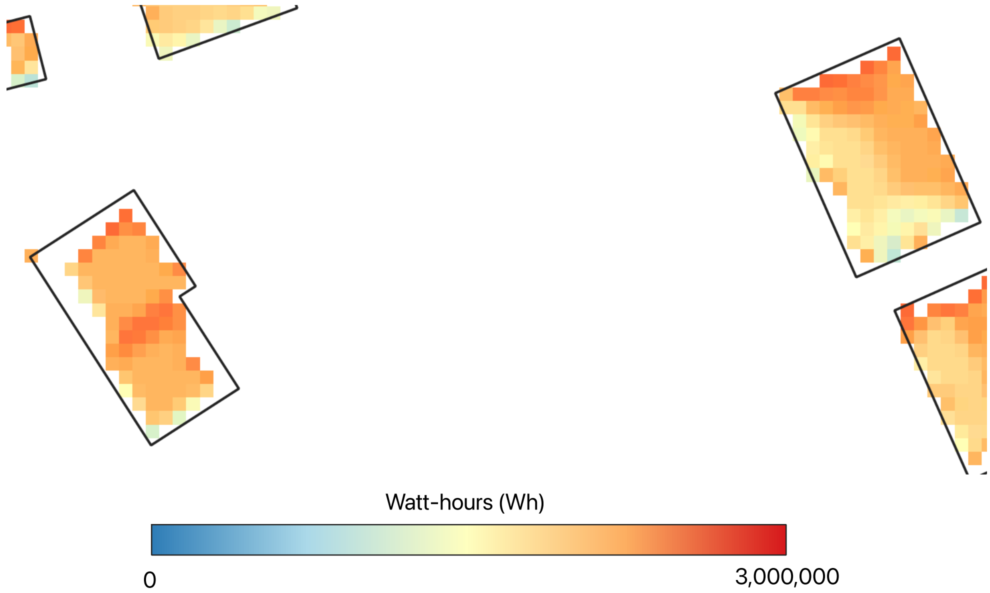


Figure 15: Annual solar radiation for House 3

On the left of Figure 15, House 3 with its flat roofs shows more radiation across its roof in comparison to a house to the right with a gabled roof where only the northern section of the roof is darker. Similarly, the slope can be analysed for both houses in Figure 16:

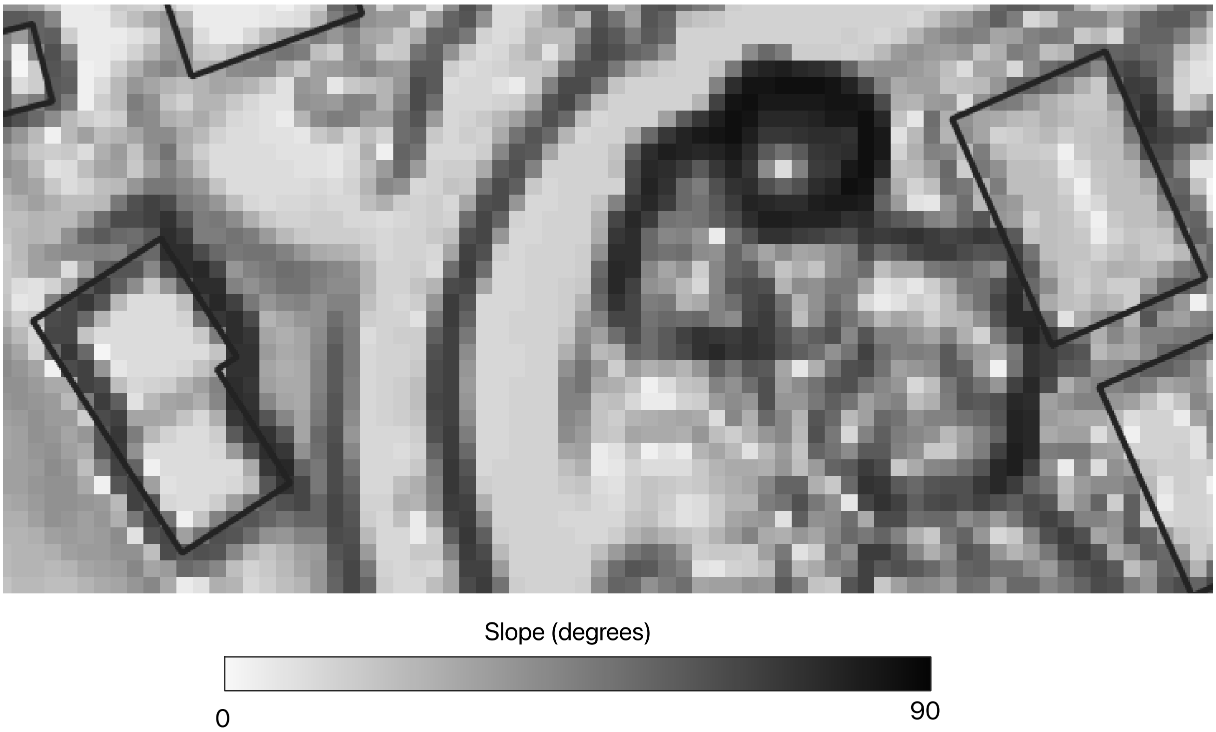


Figure 16: Slope for House 3 and a nearby house with a gabled roof

Lighter colours indicate a slope closer to flat, with darker colours closer to 90 degrees. This highlights the benefits of using DSMs along with *r.sun*, as roof slope is captured which has a significant impact on solar energy potential estimates. Results, in comparison to SolarView, are therefore more nuanced.

5.4.1 Monthly analysis

To investigate flat roof performance further, irradiance rasters were produced for January and June, and daily kWh/m² values calculated for each estimate type.

Estimate	January daily kWh/m²	June daily kWh/m²
r.sun clear-sky	8.97	2.81
WRF-adjusted	9.04	0.83
SolarView	5.32	1.43
SolarView cloudless	7.88	3.52

Table 4: January and June estimation results for House 3

Table 4 shows that in January, both the *r.sun* and WRF-adjusted estimates are significantly higher than SolarView's estimates. However, in June, the WRF-adjusted estimate is lower than SolarView's estimate. This is likely due to the flat roof receiving more sunlight in summer months, but in winter months panels that are tilted (i.e. SolarView's default of using the optimal tilt angle) perform better.

6 Conclusion

This project report outlines the development of a novel, reproducible, open-source methodology for estimating rooftop solar energy potential using LiDAR digital surface models and GIS tools, primarily GRASS GIS. By utilising publicly available datasets and open-source software, the methodology aims to provide an alternative to current proprietary and closed-source approaches, making solar potential estimation more accessible and transparent for a wider range of stakeholders.

The methodology aims to contribute to the growing literature around rooftop solar potential estimation using LiDAR digital surface models. It also provides replicable and automated methods for incorporating historical, measured solar radiation values as a means of improving upon clear-sky estimates, as well using a tool developed in New Zealand (SolarView) to help validate the estimates. Combining these methods with documented assumptions to produce a clear and replicable workflow, this report aims to further contribute to the field of solar energy modelling as electricity generation from solar increases in New Zealand and across the world.

However, the methodology is not without its limitations. Most notably, estimates are only as accurate as the input datasets. DSMs that were produced years ago may fail to accurately portray growth in vegetation or newly established buildings that contribute to shading.

Rooftop shape also significantly affects solar energy potential estimates. Flat roofs, in this methodology, appear to receive more sunlight compared to sloped or gabled roofs in summer. However, this benefit does not necessarily translate in winter months – panels that follow an optimal tilt angle for their latitude (SolarView default) tend to perform better. Additionally, the methodology currently has no way to specify tilt of a roof – using the values from these estimates would imply panels are installed flat against the roof without hardware to adjust the tilt.

Processing power is another limitation. Estimating for large raster extents (an entire town or city) and/or specifying granular time steps can be computationally expensive and time consuming. As the methodology allows for the study area and time steps to be changed (i.e. provide a smaller study area or change the time step) in order to reduce processing time, ensuring enough local features are captured, or that the time step is not too large, is important to maintain accuracy.

Finally, this research helps support Rewiring Aotearoa and their conversations around New Zealand's continued transition to renewable energy, by providing solar energy data that can then be developed into visualisations and calculators developed by RA (or the wider public) to help promote solar energy uptake.

6.1 Future work

6.1.1 Modelling PV systems

Estimating solar energy potential is a core step in the process of determining how much energy a rooftop PV installation can generate. In order to be more useful for end consumers that are looking to install a PV system, further steps are required such as simulating different panel sizes, types, and configurations (e.g. tilt and aspect). Future work could extend the workflow and incorporate open-source methodologies for simulating PV installations, similar to paid software like PVSyst (*PVsyst | Overview of PVsyst Version 8*, n.d.).

6.1.2 Lowering computation time

Optimisations such as parallel processing, cloud computing, and leveraging GPU capabilities are methods that could be explored to help reduce computation time for large study areas or more granular time steps.

6.1.3 Using coefficient rasters for real-sky estimation

r.sun's parameters include rasters that represent beam and diffuse radiation components in the form of coefficients (*R.sun - GRASS GIS Manual*, n.d.). These rasters are intended to be supplied when attempting to create real-sky estimates, and will adjust radiation values accordingly during the algorithm's execution. This provides a potentially quicker way to simulate multiple weather scenarios, by avoiding the usage of WRF or historical data. Another advantage this provides is that rasters are stored within GRASS' database, making use of any optimisations GRASS provides for raster operations.

References

AdjiSki, V., Kaplan, G., & MiJalkovski, S. (2023). Assessment of the solar energy potential of rooftops using LiDAR datasets and GIS based approach. *International Journal of Engineering and Geosciences*, *8*(2), 188–199. https://doi.org/10.26833/ijeg.1112274

AlFaraj, J., Popovici, E., & Leahy, P. (2024). Solar Irradiance Database Comparison for PV System Design: A Case Study. *Sustainability*, *16*(15), 6436. https://doi.org/10.3390/su16156436

Anselmo, S., Safaeianpour, A., Moghadam, S. T., & Ferrara, M. (2024). GIS-based solar radiation modelling for photovoltaic potential in cities: A sensitivity analysis for the evaluation of output variability range. *Energy Reports*, *12*, 4656–4669. https://doi.org/10.1016/j.egyr.2024.10.031

Gassar, A. A. A., & Cha, S. H. (2021). Review of geographic information systems-based rooftop solar photovoltaic potential estimation approaches at urban scales. *Applied Energy*, *291*, 116817. https://doi.org/10.1016/j.apenergy.2021.116817

Hofierka, J., & Kaňuk, J. (2009). Assessment of photovoltaic potential in urban areas using open-source solar radiation tools. *Renewable Energy*, *34*(10), 2206–2214. https://doi.org/10.1016/j.renene.2009.02.021

Janda, K. (2018). Slovak electricity market and the price merit order effect of photovoltaics. *Energy Policy*, *122*, 551–562. https://doi.org/10.1016/j.enpol.2018.07.021

Kodysh, J. B., Omitaomu, O. A., Bhaduri, B. L., & Neish, B. S. (2013). Methodology for estimating solar potential on multiple building rooftops for photovoltaic systems. *Sustainable Cities and Society*, *8*, 31–41. https://doi.org/10.1016/j.scs.2013.01.002

MetService Insights Platform. Retrieved September 26, 2025, from https://www.metocean.co.nz/products/insights-platform

Mujić, N., & Karabegović, A. (2023). Calculating and Comparing Solar Radiation Results Using GIS in the City Sarajevo Area. *2023 18th Conference on Computer Science and Intelligence Systems (FedCSIS)*, 285–290. https://doi.org/10.15439/2023F6245

Ncview | David W. Pierce, Scripps Institution of Oceanography. Retrieved January 31, 2026, from https://cirrus.ucsd.edu/ncview/

New Zealand LiDAR 1m DSM Survey Index | LINZ Data Service. Retrieved September 26, 2025, from https://data.linz.govt.nz/layer/122149-new-zealand-lidar-1m-dsm-survey-index/

New Zealand LiDAR 1m DSM | LINZ Data Service. Retrieved September 26, 2025, from https://data.linz.govt.nz/layer/122082-new-zealand-lidar-1m-dsm/

New Zealand Modelling Consortium. Retrieved September 26, 2025, from https://www.envlib.org/

New Zealand's electricity future: generation and future prices. (2022, April 22). https://www.ea.govt.nz/news/eye-on-electricity/new-zealands-electricity-future-generation-and-future-prices/

Nguyen, H. T., & Pearce, J. M. (2010). Estimating potential photovoltaic yield with \textit{r.sun} and the open source Geographical Resources Analysis Support System. *Solar Energy*, *84*(5), 831–843. https://doi.org/10.1016/j.solener.2010.02.009

NZ Building Outlines | LINZ Data Service. Retrieved September 26, 2025, from https://data.linz.govt.nz/layer/101290-nz-building-outlines/

Palmer, D., Koumpli, E., Cole, I., Gottschalg, R., & Betts, T. (2018). A GIS-Based Method for Identification of Wide Area Rooftop Suitability for Minimum Size PV Systems Using LiDAR Data and Photogrammetry. *Energies*, *11*(12), 3506. https://doi.org/10.3390/en11123506

Priestnall, G., Jaafar, J., & Duncan, A. (2000). Extracting urban features from LiDAR digital surface models. *Computers, Environment and Urban Systems*, *24*(2), 65–78. https://doi.org/10.1016/S0198-9715(99)00047-2

PVsyst | Overview of PVsyst Version 8. Retrieved January 26, 2026, from https://www.pvsyst.com/en/products/pvsyst-8/

r.sun - GRASS GIS manual. Retrieved September 26, 2025, from https://grass.osgeo.org/grass-stable/manuals/r.sun.html

Rew, R., & Davis, G. (1990). NetCDF: an interface for scientific data access. *IEEE Computer Graphics and Applications*, *10*(4), 76–82. https://doi.org/10.1109/38.56302

rewiring-nz/solar-estimates. (2025, September 24). Rewiring Aotearoa. https://github.com/rewiring-nz/solar-estimates

Setchell, H. (2020, February 19). *ECMWF Reanalysis v5*. https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5

Solarview. Retrieved September 14, 2025, from https://solarview.niwa.co.nz/

SolarView help | Earth Sciences New Zealand | NIWA. Retrieved January 24, 2026, from https://niwa.co.nz/renewable-energy/solarview-help

Suomalainen, K., Wang, V., & Sharp, B. (2017). Rooftop solar potential based on LiDAR data: Bottom-up assessment at neighbourhood level. *Renewable Energy*, *111*, 463–475. https://doi.org/10.1016/j.renene.2017.04.025

Tapper, N. J. (1976). *An investigation of incoming short and long wave radiation over Christchurch*. http://hdl.handle.net/10092/17792

Tro-Cabrera, A., Lago-Aurrekoetxea, R., Martínez-de-Alegría, I., Villamor, E., & Campos-Celador, A. (2025). A methodology for assessing rooftop solar photovoltaic potential using GIS open-source software and the EROI constraint. *Energy and Buildings*, *331*, 115401. https://doi.org/10.1016/j.enbuild.2025.115401

UMEP/SEBE - any options for rooftop only solar potential · UMEP-dev/UMEP · Discussion #778. Retrieved September 14, 2025, from https://github.com/UMEP-dev/UMEP/discussions/778