Investigating the Distribution of Residential Solar Panel Uptake in Christchurch

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GEOG309: Research for Resilient Environments and Communities
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1. Executive Summary

Research Context

- Residential solar panels are a key component of New Zealand's transition to renewable energy, enabling households to actively reduce carbon emissions.
- Observations by Dave Kelly suggested that Beckenham may have higher solar adoption than other Christchurch suburbs, prompting this study to explore local patterns of uptake.

Research Aim

- Investigate the distribution of rooftop solar panels across selected Christchurch suburbs.
- Identify which socioeconomic, housing and environmental factors most strongly influence residential solar adoption.

Study Area and Data Sources

- Six Christchurch suburbs were selected to represent a range of socioeconomic deciles.
- Data sources included 2023 Census information (Stats NZ-Tatauranga Aotearoa [Stats NZ], 2023) and high-resolution aerial imagery (Toitū Te Whenua - Land Information New Zealand [LINZ], 2023).
- Variables analysed encompassed property ownership, dwelling type, property size, education levels, commuting methods, and household income.

Methods

- Solar panels were detected using a deep learning model in ArcGIS Pro.
- Detection results were validated using manual checks on 10% of properties and corrected using the Rogan and Gladen method to account for false positives and false negatives.
- Pearson correlation analyses and scatterplots were created in RStudio to identify relationships between solar adoption and predictor variables.

Key Findings

- Beckenham showed the highest solar panel uptake (corrected prevalence 18.17%), confirming the initial observation.
- Strong correlations were observed between solar panel adoption and:
    - Economic factors: Property ownership, single dwelling homes, and property size
    - Education and environmental awareness: Proportion of residents with bachelor's degrees and residents commuting to work by cycling.
- Spatial patterns indicated consistently high adoption in Beckenham and lower uptake in Merivale and Sydenham South

Suggestions for Future Research

- Refine deep learning model to reduce false positives and false negatives.
- Increase the size of validation samples to improve model accuracy.
- Expand analysis to more suburbs and possibly nationwide to increase representativeness.
- Incorporate qualitative research (surveys, interviews) to understand household motivations.
- Inform targeted policy initiatives to support solar adoption in areas with low uptake using insights from correlations between adoption and predictor variables.

2. Introduction

Solar energy generation is a core component of the global transition towards decarbonisation, as it enables individuals to contribute directly to reducing fossil fuel reliance. This personal adoption capacity makes understanding the reasoning behind implementation significant, shaping effective government policy and private-sector business strategies. Accordingly, this report aims to investigate the distribution of solar panels across Christchurch and what factors are influencing their implementation.

Since the 1980s, advances in technology have seen improvement in materials, production scale, and efficiency, driving significant global price reductions (Kavlak et al., 2018). Consequently, solar energy is the second most implemented renewable energy source worldwide (Pourasl, et al., 2023), with New Zealand's local implementation mirroring the international trend; generation capacity has increased from 8W per person in 2014 to 108W per person in 2024 (Energy Efficiency and Conservation Authority [EECA], 2025).

This growth was observed locally by Dave Kelly of the Beckenham Neighbourhood Association, who noted a high concentration of solar panels in his suburb, Beckenham, (relative to Christchurch) following his own solar system installation. This observation guided our project development, alongside his additional interest whether solar panel implementation was driven by opportunity—regarding economic and environmental viability—or by interest, relating to environmental preferences.

While the financial and environmental benefits of solar energy are well established, there is little New Zealand-based research examining the local drivers of adoption. This project has sought to address this gap. The following sections outline the supporting literature, research methods, and key results, followed by discussion of limitations and recommendations.

3. Literature Review

Financial Analysis

A comprehensive understanding of the drivers behind solar panel implementation requires consideration of their financial viability. Technological developments have been the primary driver of global solar panel cost reductions (Kavlak et al., 2018), with retail prices falling by about 80% in the last 20 years, increasing the feasibility of implementation for many consumers (Lightforce Solar, 2025).

For most New Zealand households, solar panel systems typically save $800 - $1200 annually, with greater savings achieved through increased household electrification (EECA, 2025). Furthermore, the financial returns are influenced less by geographic location—which would otherwise favour northern regions—and more by household energy consumptions and effective electricity management aligned with demand timing (EECA, 2025; Miller et al., 2015)**.** The economic context shapes a consumer's likelihood to adopt solar, aiding the explanation behind residential solar panel implementation across Christchurch.

Australian Solar Implementation Framework: Case Study

Australia provides a successful example of how policies can promote residential solar panel implementation. Installed on more than 20% of all households, both state and territory governments utilised generous feed-in tariffs to drive implementation (Zander et al., 2019). These incentives demonstrated that reduced installation costs have the most significant influence on solar panel uptake, with highest implementation seen in populations of middle-range income with higher wealth (Best and Chareunsy, 2022). This finding aligns with Dave's motivation vs. opportunity hypothesis, which expected more economically-concerned (middle income), but opportunity-rich (higher wealth) populations to prioritise solar panels. Additionally, the Australian context also saw increased implementation in households with higher electricity requirements, aligning with the financial analysis (Wen et al., 2023). The Australian case reiterates the relevance of motivation vs opportunity drivers, demonstrating how financial incentives and household circumstances shape solar adoption.

Known Variables Linked to Solar Panel Implementation

The literature identified economic, social, and environmental factors linked to solar panel adoption. A higher net wealth, rather than income, was found to be more indicative of solar panel installation (Best et al., 2019), which again highlighted the relevance of including economic opportunity in this project. Home ownership was found to be a primary indicator for rooftop solar panel uptake, with installation being more common in rural and suburban areas than major urban centres (McCarthy and Liu, 2022; Best et al., 2019). This was considered when selecting suburbs, excluding built-up areas which may have skewed our analysis.

Notably, the literature also recognised that there is gender-based differences in solar panel uptake with women more likely to install larger solar systems, reducing the financial return, based on stronger environmental preferences (Pereira and O'Connell, 2025). While we were unable to carry out any gender-based analysis, it highlighted the relevance of environmental ideologies manifesting through renewable energy adoption. These variables demonstrate the range of influences shaping residential solar panel adoption, guiding the selection of variables which utilised in our analysis.

Methods for Solar Panel Identification

The methods for identifying solar panels in the literature was primarily achieved with advanced remote sensing and deep learning models (DLMs). There were limited alternatives for identification used, with an Australian-based article aggregating solar panel installation data by postcode (Lan et al., 2021), and Khakzad et al. (2024) noting the high labour demand when carrying out manual solar panel identification from imagery. This information guided the identification methodology, resulting in the decision to use a DLM to identify solar panels.

DLMs use semantic segmentation, a computer vision process which separates features within images—such as rooftop solar panels. These models are computationally intensive (Adke et al., 2021), a matter which was addressed in our project methods by downscaling the extent of areas analysed. Further limitations of DLMs lie in their training, which requires a degree of locality as regional differences affect the accuracy of identifications (Ren at al., 2022). These methodological considerations informed the development of our identification approach, ensuring that practical efficiency is balanced against the accuracy required for reliable solar panel detection.

4. Methods

Identifying Solar Panels in Our Chosen Areas

Solar photovoltaic (PV) installations across Christchurch were identified using deep-learning object detection within ArcGIS Pro. Manual identification from aerial imagery (Bradbury et al., 2016) was initially considered but dismissed due to inefficiency for large-area analysis. Object detection was conducted using ESRI's pre-trained model, applied to 2023 Land Information New Zealand (LINZ) aerial imagery.

Initial testing saw the LINZ aerial imagery broke into multiple JPEG files—approximately 30 per suburb following data sourcing. To address this issue, the 'Mosaic to New Raster' tool was used to stitch the images together to form one single JPEG file output. While automating the process with Model Builder was considered, the Mosaic tool was ultimately chosen for its simpler workflow and the groups limited experience with Model Builder.

Both the aerial imagery and property boundaries were clipped to the SA2 areas (Statistical Area 2) within Christchurch to improve processing efficiency. A SA2 area is a geographic unit used to represent communities that interact socially and economically, typically containing 3,000 to 25,000 people (Stats NZ, 2023). Detection times averaged about eight hours per suburb on lab computers, making citywide analysis unfeasible. Even on higher-capacity postgraduate computers, processing Aidanfield took three hours, leading to a reduced analysis extent. Reducing the study scope required selecting suburbs that would produce meaningful comparisons. Six suburbs were chosen using the deprivation index, which ranks areas from 1 (least deprived) to 10 (most deprived) based on factors like income, employment, and education. Because lower socio-economic areas often face barriers to solar uptake, deciles 8-10 were excluded, with two suburbs selected from deciles 1, 4, and 7.

In ArcGIS, the deep-learning-essentials package was installed to run the ESRI Object Detection model. The 'Detect Objects Using Deep Learning' tool was applied with the imagery file and the model file (*NZ_solarPanels.dlpk*). Most settings were left as default, except the detection threshold. Higher thresholds improved accuracy but missed panels, while lower thresholds increased false positives. A threshold of 0.6 was chosen to balance accuracy and efficiency, as verifying detections was faster than finding missed panels.

Property and SA2 boundaries were sourced from LINZ along with the aerial imagery. These layers were used to count detections within individual properties and, at a broader scale, to identify properties with solar installations in each SA2 unit. Given the model's limited accuracy, our focus was on identifying properties with PV installations rather than counting individual panels. Following detection, a 'count' field was added with a value of 1 to the output attribute table. Using the 'Summarise Within' tool, these identifications were input alongside the property boundary layer. Summing the 'count' field produced the total number of PV detections within an individual property.

Due to inaccuracies in the model's detections, selection conditions were applied to refine the properties classified as having PV installations. Properties with four or more detected panels were retained, as most PV systems exceed this number, eliminating 1-3 panel false positives. Additional filters removed misclassified property types, such as roads, hydro, and shared land titles (e.g., apartments). Properties over 4000 m^2 were also excluded, as these went beyond the scope of typical residential property size.

Once refined, the 'Summarise Within' tool was applied to the selected properties and the LINZ SA2 boundaries. The output provided the count of qualifying properties within each suburb.

Validating Counts

Inaccuracies observed during testing and suburb runs led us to question the model's reliability. To evaluate its accuracy, a Cohen's Kappa index assessment was calculated for Beckenham by manually reviewing all properties to verify detections. True positives were marked green, false positives orange, and missed panels (false negatives) pink (Figure 1).

Figure 1. *Map of Beckenham showing manual checks of solar panel detections. Green = true positives (manual + software detection), orange = false positives (software detection only), pink = false negatives (manual detection only). True negatives are not shown. Kappa index values were used to assess detection agreement.*

Running the Kappa index (K) produces a value between 0 and 1, where higher values indicate stronger agreement between the model and the manual verifications. Counts from both datasets (Table 1) were used to create a Kappa calculation which returned a value of 0.54 (see Appendix 1 for calculation), indicating moderate agreement (Kumar, 2022).

Table 1. *Manual vs software detections in Beckenham for Cohen's Kappa index calculations.*

	Manual Detection	**No Manual Detection**	**Total**
Software Detection	30 True Positive	33 False Positive	63
No Software Detection	14 False Negative	858 True Negative	872
Total	44	891	935

While the model showed moderate agreement beyond random chance, notable inaccuracies remained. To ensure comparability, we needed to confirm that the model's reliability was consistent across all areas. If the model performed consistently, we would be confident comparing our results with census data, despite only achieving moderate overall agreement.

Due to time and resource limits, a full Kappa analysis wasn't feasible for each selected SA2. Instead, 10% of properties in each suburb were randomly sampled (with replacement) for manual checking, and 100% of detected properties were verified. Results showed clear variation in true, false, and missed detections, so correction factors were applied using the 10% samples.

Correcting Counts

To account for misclassification error in the automated detection of solar panels, the apparent prevalence (the proportion of houses identified as containing panels) was adjusted using the method proposed by Rogan and Gladen (1978). This correction method uses the sensitivity (true positive rate) and specificity (true negative rate) of the detection model, allowing estimation of the true prevalence of solar panels in each suburb. The true prevalence was calculated as:

$$True\ Prevalence = \frac{(Apparent\ Prevalence + Specificity - 1)}{(Sensitivity + Specificity - 1)}$$

This formula corrects for both false positives and false negatives, providing a more accurate representation of the actual number of solar-equipped houses. The corrected count was then obtained by multiplying the true prevalence by the total number of houses in each suburb:

$$Corrected\ Count = True\ Prevalence * Total\ House\ Count$$

Corrected counts were calculated for each SA2 based on misidentification rates (see Appendix 2). Although this increased confidence in the results, discrepancies persisted, likely due to the limited 10% validation sample. For instance, Beckenham exhibited low sensitivity (0.25) and moderate specificity (0.98), indicating the model missed numerous true positives and slightly overestimated negatives, resulting in inflated corrected prevalence estimates. Expanding the validation sample would likely enhance the stability of sensitivity and specificity estimates, reduce random error, and produce corrected values more closely aligned with manual counts (Appendix 3; Dobbin & Simon, 2011).

Variable Selection

To analyse factors influencing solar panel uptake, a dataset was compiled using 2023 Census data from Statistics New Zealand (Stats NZ, 2023). The aim was to explore the socioeconomic and environmental variables that might shape household decisions to install solar panels. By identifying which factors have the strongest relationship with solar adoption, we can better understand the social landscape of renewable energy uptake and potentially inform targeted outreach or policy initiatives.

Variables that were focused on reflected wealth, education, lifestyle, and environmental awareness, all of which are likely to influence solar investment. For example, we examined home ownership, capturing the percentage of households that owned their home, held it in a family trust, or rented, providing insight into housing stability and capacity to invest in solar technology.

Modes of travel to work was also analysed, representing the usual transport method of employed residents aged 15 and over. This variable can act as a proxy for environmental awareness, as households with more sustainable commuting patterns may be more receptive to renewable energy technologies (Ghosh & Prasad, 2024).

Workplace address data was used to assess whether residents work locally or commute, reflecting lifestyle and disposable income. Education was measured by the proportion of residents aged 15 and over with Bachelor's or Level 7 qualifications, as higher education is often linked to greater environmental awareness and access to resources for renewable energy adoption.

Property size was sourced from Land Information New Zealand imagery (LINZ, 2023), providing an estimate of the average property area in each SA2 area. Larger properties generally have greater roof space and higher energy consumption from increased electrification (Wen et al., 2023), making PV installation both feasible and economically attractive. Dwelling type was also considered, with standalone houses offering more flexibility for solar installations than joined dwellings. Lastly, household income was considered, which is a key indicator of a household's financial capacity to invest in solar technology. Together, these variables provide a well-rounded picture of the conditions that may either encourage or limit solar adoption.

Some potentially influential variables, such as electric vehicle ownership, political preferences, roof orientation, or property age were unfortunately unavailable at the SA2 level. Their absence represents a limitation of this analysis, as they could offer additional insight into environmental attitudes and investment capacity.

All collected data was grouped by SA2 area and compiled. The percentage of properties with solar installations was used as the response variable, while the variables described above served as predictors.

Data Analysis in R

The statistical analysis was carried out using R (RStudio, 2025). To assess the strength of the relationships between predictors and solar uptake, a Pearson correlation heatmap was generated. This visualisation clearly illustrates the direction and magnitude of linear relationships between variables. Pearson's correlation coefficient (r) ranges from -1 (indicating a strong negative correlation) to 1 (a strong positive correlation), with values near zero reflecting weak or no linear relationship.

To further explore these relationships, scatterplots were produced for the variables with the strongest correlations to solar uptake. The scatterplots allowed observation of patterns more closely and comparison of trends between the original and corrected solar panel datasets.

5. Results & Discussion

In the following results section, any reference to percentages relates to the respective suburb's proportion of each variable; "Corrected Solar Panel %" is the proportion of homes with identified solar panels from the entire suburb's property number.

Correlation Overview

The correlation heatmap generated in R (Figure 2; Appendix 4) displays the Pearson correlation coefficients between each variable in our dataset. The two rows of this heatmap represent the correlations between the solar panel data (original and corrected) and the other socio-economic variables. Row one illustrates the corrected solar panel data, and the second row illustrates the original data.

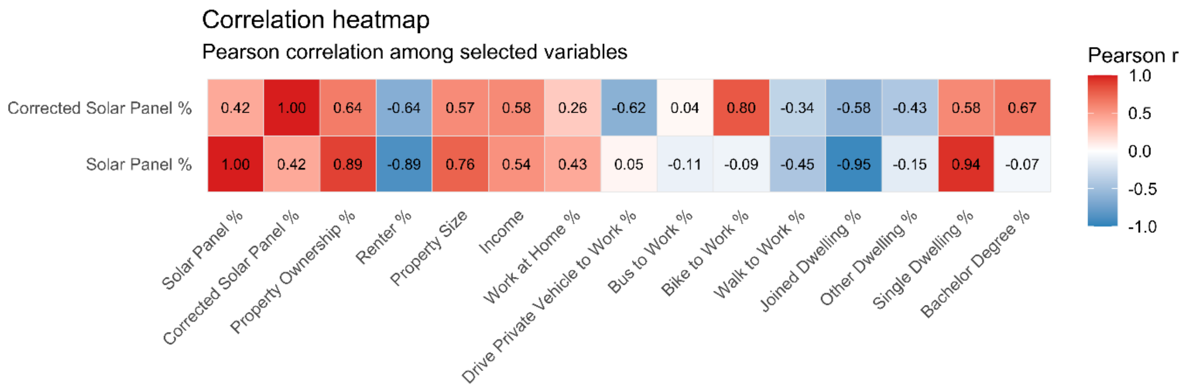


Figure 2. *Correlation heat map generated in RStudio illustrating the relationships between key predictor variables and the percentage of residential solar panel installations across suburbs. The figure includes both the original and corrected datasets, highlighting how variable correlations have changed after data correction.*

Original Dataset

In the original dataset, the variables most strongly correlated ($|r| > 0.6$) with solar panel adoption were:

- Percentage of single dwellings ($r = 0.94$)
- Percentage of property ownership ($r = 0.89$)
- Median property size ($r = 0.76$)
- Percentage of renters ($r = -0.89$)
- Percentage of joint dwellings ($r = -0.95$)

Scatterplots (Figure 3a and 3b) illustrate the two strongest correlations. Beckenham and Aidanfield exhibited higher proportions of solar panels, single dwelling properties, and property ownership, whereas Merivale and Sydenham South had lower values across these variables. These trends suggest that home ownership and dwelling type are key enabling factors for residential solar uptake; similar findings were identified in the literature with urban centres and rental occupancy reducing solar panel implementation (McCarthy & Liu, 2022; Best et al., 2019).

Figure 3a. *Scatterplot illustrating the relationship between solar panel presence and property ownership rates across suburbs. Each suburb is represented by a distinct point colour. Property ownership (%) reflects the proportion of residents who own their homes compared to those who rent or occupy through other arrangements.*

Figure 3b. *Scatterplot showing the relationship between solar panel presence and the percentage of single-dwelling homes across Christchurch suburbs. "Single dwelling" refers to standalone houses as opposed to attached or joined dwellings.*

The percentage of solar panels across the original dataset ranged from 3.76% to 6.38% (Table 2). Beckenham and Aidanfield, both decile 1 suburbs, recorded the highest values, while Merivale (decile 4) and Sydenham South (decile 7) were lowest. Notably, New Brighton (decile 7) recorded unexpectedly high solar panel presence. Manual inspection revealed that this result was due to false detections by the DLM, which was misidentifying polycarbonate roofs and significant shadows in the imagery. As noted by the literature, aerial imagery quality and localised model training is essential to DLMs' accuracy (Ren et al., 2022).

These preliminary results suggest a strong relationship between financial stability and solar panel adoption, supporting the hypothesis that opportunity, rather than ideological motivation, is a dominant driver for implementation.

Table 2. *Original and corrected solar panel presence (%) for six Christchurch suburbs.*

Suburbs	Original Solar Panel Presence %	Corrected Solar Panel Presence %
Beckenham	6.38	18.17
Aidanfield	6.33	7.04
Merivale	4.99	2.41
St Martins	5.78	7.68
Sydenham South	3.76	4.27
New Brighton	6.15	1.01

Corrected Dataset

Following correction using the Rogan and Gladen (1978) method, several correlations changed substantially. The strongest relationships ($|r| > 0.6$) were now observed with:

- Percentage of people who bike to work ($r = 0.80$)
- Percentage of people with bachelor's degrees ($r = 0.67$)
- Percentage of property ownership ($r = 0.64$)
- Percentage of people who drive a private vehicle to work ($r = -0.62$)
- Percentage of renters ($r = -0.64$)

Scatterplots (Figure 4a and 4b) illustrated the relationships between biking to work and education level and solar panel presence. Beckenham exhibited the highest levels in both variables, but Aidanfield recorded low in both variables, contrary to what may have been expected from the literature. Likely, biking to work is not a suitable proxy for environmental preferences for Aidanfield residents due to the increased distance from the Christchurch CBD. With the lowest education level across all the analysed suburbs, Aidanfield may be more influenced by the financial benefits of solar panels, or this matter may relate to the area's relatively young age (compared to other Christchurch suburbs). Testing these hypotheses behind solar implementation would require additional qualitative research with Aidanfield residents, better informing this analysis.

Figure 4a. *Scatterplot showing the relationship between solar panel presence and the percentage of residents who commute to work by bicycle across Christchurch suburbs.*

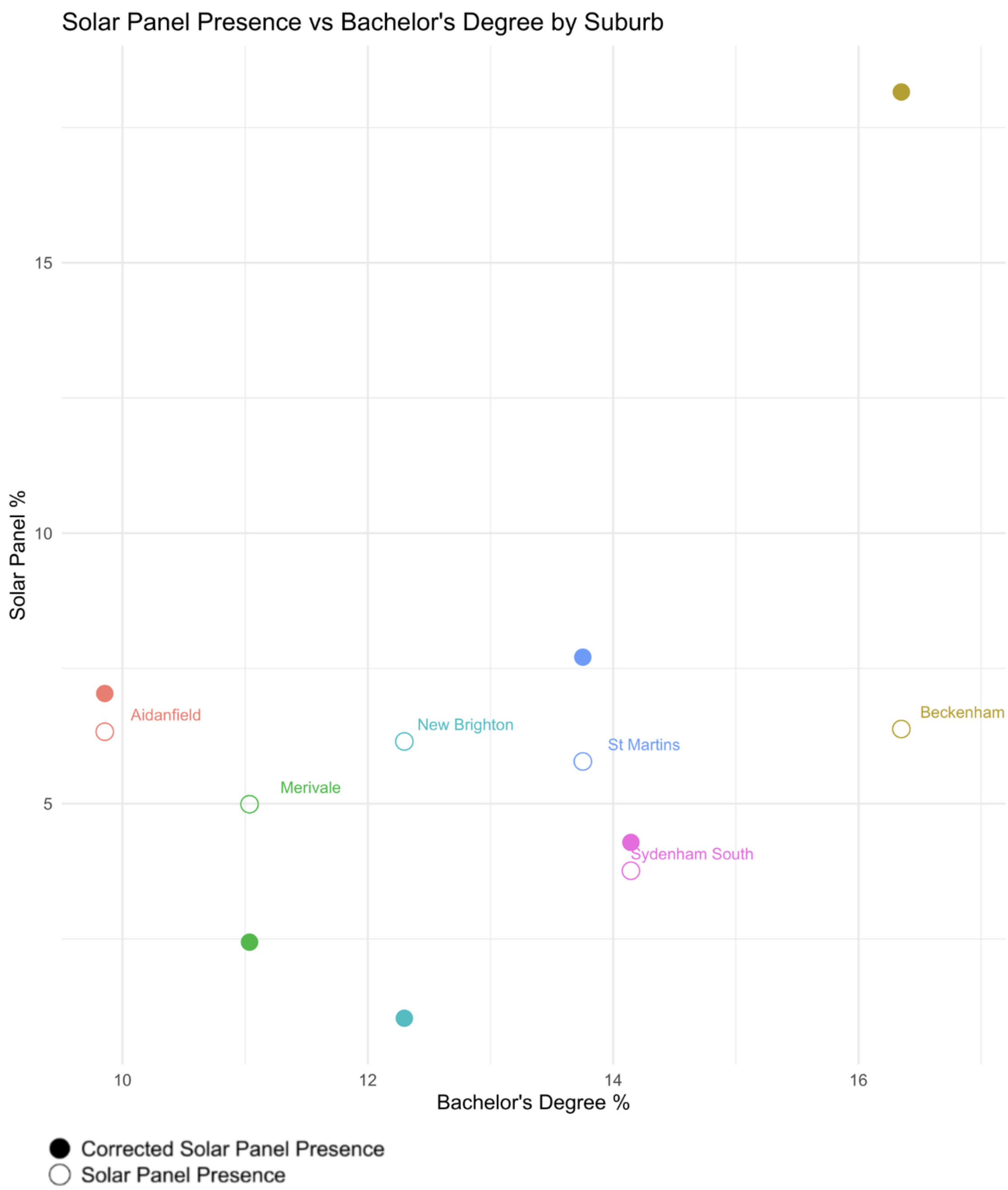


Figure 4b. *Scatterplot illustrating the relationship between solar panel presence and the proportion of residents holding a bachelor's degree or Level 7 qualification across Christchurch suburbs.*

The corrected data produced a larger range of solar panel presence percentages, from 1.01% to 18.17% (Table 2). Beckenham's 18.17% was over double that of the next closest suburb, reinforcing Dave Kelly's observation that Beckenham displays high solar panel presence. Contrastingly, New Brighton dropped to 1.01%, aligning with the expectations for its socio-economic profile as an area with higher deprivation.

These adjusted results shifted the interpretation of solar panel uptake; while the initial results indicated financial opportunity and structural feasibility as primary implementation drivers, the corrected results moved towards social and behavioural variables driving adoption. Drawing upon Dave Kelly's hypothesis, this sees motivation—rather than opportunity—driving solar panel implementation in our analysed suburbs.

Overall, the findings indicate that both social-environmental awareness and economic opportunity influence solar panel uptake across Christchurch. Beckenham represents the intersection of all these variables, with high proportions of every main variable—property ownership, single dwelling structure, education level, and bicycle commuting—alongside the highest actual proportion of solar panel implementation.

Limitations & Future Directions

While this study generated meaningful insights into solar panel distribution, there were several limitations that shaped the scope and depth of the analysis. Recognising these limitations highlights clear directions for future research and improvement.

A primary limitation was the scale of our study. Focusing on six suburbs enabled close engagement with the data but limited the representativeness of the findings for Christchurch city. Expanding the analysis to include additional suburbs—or applying the same approach across the wider Canterbury region and nationally, would provide a clearer picture of solar uptake patterns and enhance the robustness of any conclusions.

Data availability further constrained the analysis. For each property, only the presence or absence of solar panels could be recorded, without detail on system size or capacity. This meant all installations were treated equally, despite substantial variation in investment and output. Future work could incorporate data from installation records or energy suppliers to capture system scale, allowing a gauge of socioeconomic influences, household energy goals, and the impact of incentive schemes.

Temporal limitations were also present. The aerial imagery used was captured in 2023 (LINZ, 2023), and as solar adoption has increased since, recent installations are highly likely underrepresented, especially in areas with accelerating uptake. Updating the dataset would enable the tracking of temporal change more accurately.

Data accuracy also posed additional challenges. Some corrected outputs did not fully align with manual verification, particularly in Beckenham, where outliers appeared in scatterplots. Future studies could benefit from more refined classification methods, larger training datasets, or the integration of machine learning approaches to improve detection reliability. Further, the use of 10% samplings has limited the representativeness of the data, reducing the likelihood of capturing outliers and unique patterns.

Another interpretive limitation was the reliance on proxy variables such as education level and cycling rates to represent environmental awareness. Variables used to represent environmental preferences, such as cycling commute and education level, are indirect indicators. While higher education often correlates with pro-environmental attitudes (Meyer, 2015), the relation is not causal, and cycling may reflect drivers beyond environmental motivation (Ibrahim & Marzuki, 2025). These proxies offer useful signals but cannot comprehensively capture the attitudes driving solar adoption. Combining quantitative GIS analysis with qualitative data through surveys, interviews, or focus groups, would help bridge this gap, revealing the social and behavioural dimensions driving renewable energy decisions.

Finally, while this study was grounded in spatial and statistical analysis, future iterations could more actively link these findings to policy design. Identifying variables associated with low uptake could inform targeted interventions such as subsidies, community outreach, or streamlined consent processes. Suburbs with high solar potential but limited adoption could be prioritised for education and incentive programmes.

Overall, these limitations point toward opportunities for growth. By expanding analysis area, refining the data collection, integrating qualitative perspectives, and connecting findings to policy applications, this project could evolve into a study of solar adoption across Christchurch and beyond. Such research would contribute not only to academic understanding but also to practical efforts supporting New Zealand’s renewable energy transition.

6. Conclusion

This research investigated which Christchurch suburbs have the highest prevalence of solar panels and the factors influencing their distribution. Using deep-learning detection, census data, and statistical analysis, the study found that both opportunity and motivation contribute to patterns of solar adoption. Suburbs with higher levels of home ownership, single-dwelling properties, residents cycling to work, and education displayed greater uptake.

When correction methods were applied to account for detection inaccuracies, behavioural and social variables–such as higher education levels and sustainable commuting—became more influential. This shift suggests that while financial capacity and property characteristics allow the ability to install residential solar, environmental awareness and lifestyle choices are key in driving adoption.

Although this project was limited by scale, data accuracy, and the absence of qualitative perspectives, there is a lesson learned in the value of combining spatial analysis with data to understand renewable energy behaviour at a local level. Expanding the scope to include more suburbs or incorporating surveys would provide more depth and reliability in future research.

Ultimately, this report shows that increasing solar adoption in Christchurch and across New Zealand requires more than financial incentives alone. It calls for community engagement, education, and policy frameworks that make solar energy both accessible and desirable. Combining opportunity with motivation, Christchurch can continue to lead by example in the transition toward a low-carbon, community-driven energy future.

7. Acknowledgements

We would like to acknowledge and thank Vanessa Bastos for her guidance throughout the research and analysis process. We also extend our gratitude to Dave Kelly and his role as the community partner from the Beckenham Neighbourhood Association for providing valuable direction and advice. Their time, expertise, and support were instrumental in helping us achieve our objectives and deepen our understanding of the research process. Finally, we would like to thank Course Coordinators, Simon Kingham and Sophie Horton, along with the rest of the GEOG309 team, for their support and for making this project possible.

8. Appendix

Appendix 1. *Cohen's Kappa Index Calculation.*

P_0 = Agree / Total

$P_0 = 888/935 = 0.95$

$K = (P_0 - P_e) / (1 - P_e)$

$P_e = (63/935) * (44/935) + (872/935) * (891/935)) = 0.89$

$K = (0.95-0.89) / (1-0.89) = 0.54$

Kappa > 0.4 = Moderate

Appendix 2. *Adjusted Apparent Prevalence Method.*

Worked Example in Beckenham

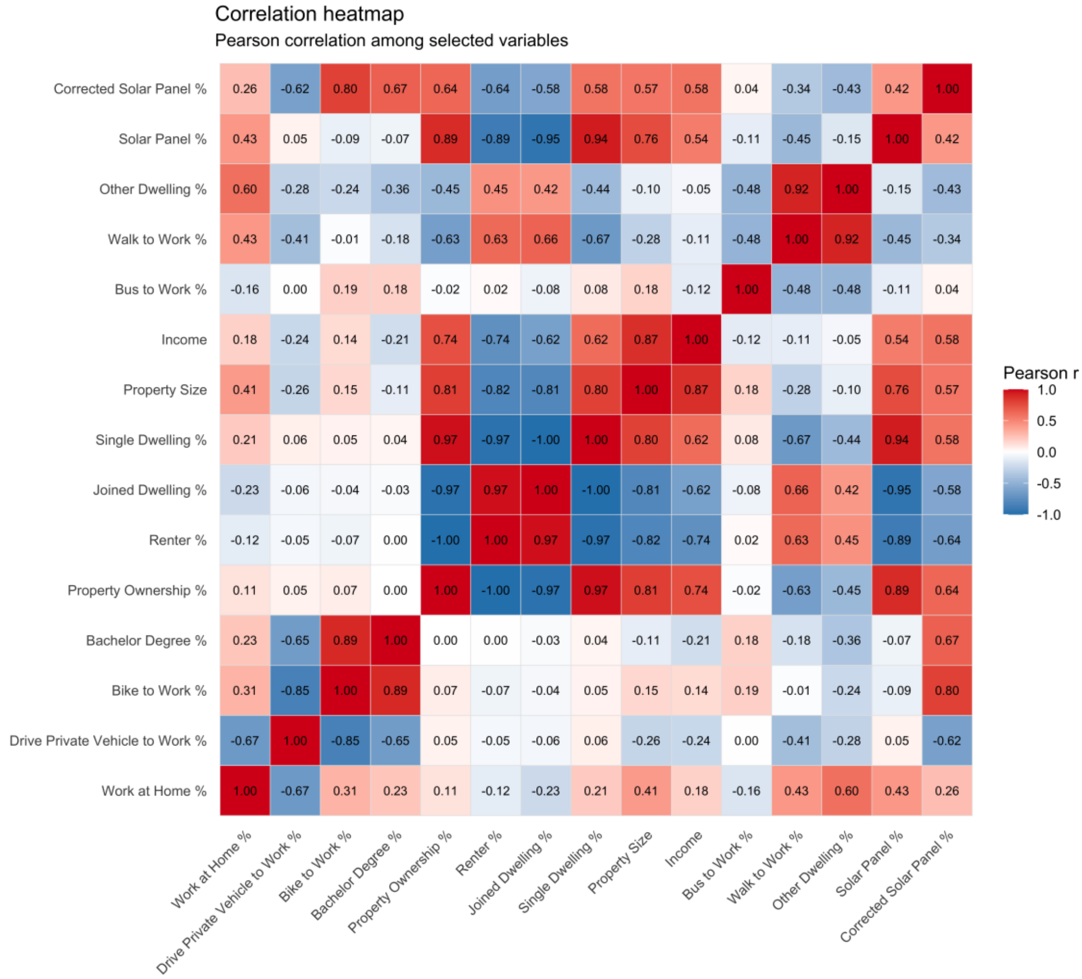
Apparent prevalence	*0.06*
Sensitivity	*0.25*
Specificity	*0.98*
Total houses	*831*

True Prevalence = (0.06 + 0.98 − 1) / (0.25 + 0.98 − 1) = 0.18

Corrected Count = 0.18 x 831 = 151 Houses

Appendix 3. *Corrected numbers of solar panel detections based on a 10% manual sample from each suburb.*

Suburbs	Beckenham	Aidanfield	Merivale	St Martins	Sydenham South	New Brighton
Total House Count	831	1279	1122	1107	797	1479
Total Detected	53	81	56	64	30	91
Sample Size	93	128	180	122	120	180
True Positive Count	1	9	4	3	1	6
False Negative Count	3	1	2	1	1	0
True Negative Count	87	118	168	118	116	165
False Positive Count	2	0	6	0	2	9
Sensitivity	0.25	0.9	0.67	0.75	0.5	1
Specifity	0.98	1	0.97	1	0.98	0.95
Sensitivity + Specificity ≥ 1	1.23	1.9	1.63	1.75	1.48	1.95
Apparent Prevalence	0.06	0.06	0.05	0.06	0.04	0.06
True Prevalence	0.18	0.07	0.02	0.08	0.04	0.01
Corrected Count	150.86	90	27.38	85.33	34.14	15.29
Corrected Solar Panel Presence	18.15	7.04	2.44	7.71	4.28	1.03



Appendix 4. *Correlation heat map generated in RStudio illustrating the relationships between all predictor variables and the percentage of residential solar panel installations across suburbs. The figure includes both the original and corrected datasets, highlighting how variable correlations have changed after data correction.*

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