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A transparent workflow for future EnergyPlus Weather (EPW) files for building energy simulation

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Abstract

Introduction: Building performance assessments frequently rely on historical weather files that do not represent future climatic conditions, introducing uncertainty and risk for long-lived buildings and low-carbon design decisions. This paper presents a transparent and replicable method to generate future EnergyPlus Weather (EPW) files by morphing a baseline EPW file, derived from typical meteorological year (TMY) datasets representative of recent historical climate conditions, using monthly climate anomalies derived from a Global Climate Model (GCM).

Materials and methods: The proposed workflow integrates an automated routine that extracts climate anomalies for any geographic location through inverse-distance weighting of the four nearest GCM grid points, followed by variable-specific shift and stretch transformations and psychrometric post-processing to preserve internal consistency among EPW parameters. The method is demonstrated for two climatically and geographically contrasting locations—Exeter (UK) and Bahía Blanca (Argentina)—using a 2080 time horizon (multi-decadal average centred on the 2080s), allowing evaluation across different hemispheres and climate regimes.

Results: Generated time series are benchmarked against available future weather datasets for the selected regions (PROMETHEUS, Meteonorm, and Future Weather Generator). For dry-bulb temperature, the proposed approach shows strong agreement in temporal behaviour with reference data, with Pearson correlation coefficients ranging from 0.744 to 0.799 ($p < 0.05$). For Exeter, the method reproduces the expected warming signal, with annual maximum dry-bulb temperatures increasing from approximately 27.0 °C to 31.6 °C and minimum dry-bulb temperatures shifting from −4.4 °C to −2.5 °C relative to the baseline.

Conclusions: The results demonstrate that morphing coupled with globally available climate projections can provide practical, location-agnostic future EPW files suitable for early-stage design and sensitivity analyses, while highlighting the importance of baseline weather data quality and climate-model resolution.

Keywords: *future weather files, EPW, morphing, climate projections, building energy modelling, climate adaptation*

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1. Introduction

1.1. Importance of future weather data in building performance simulation

Climate change is already altering ambient temperature regimes, solar radiation patterns, and the frequency and intensity of extreme weather events, with direct implications for the energy performance, thermal comfort, and resilience of buildings. Recent assessments by the Intergovernmental Panel on Climate Change (IPCC) indicate that global mean surface temperatures will continue to rise throughout the 21st century under all plausible emissions pathways, even under strong mitigation scenarios, increasing the likelihood of heatwaves and prolonged periods of thermal stress in many regions worldwide [1]. As buildings are typically designed for service lives extending several decades, reliance on historical or present-day climate data risks underestimating future energy demand, overheating risk, and system performance degradation.

Building Energy Modelling (BEM) is widely used to support low-carbon design, retrofit assessment, and policy development. However, most simulations continue to rely on historical typical meteorological year (TMY) datasets or equivalent reference weather files, which are constructed to represent past climatic conditions rather than plausible future ones [2, 3]. This limitation has been widely recognised in the literature, particularly in relation to overheating risk, growth in cooling demand, and the long-term robustness of passive and low-energy design strategies under climate change [4–6]. Consequently, the integration of future climate information into building performance simulation has become an increasingly active and policy-relevant area of research.

1.2. Existing approaches to future weather-file generation

Several approaches have been developed to generate Future Weather Data Files (FWDFs) suitable for building simulation. Among these, the morphing method has emerged as one of the most widely adopted techniques due to its conceptual simplicity and compatibility with established simulation workflows. Originally formalised by Belcher et al. [7], morphing modifies a

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baseline weather file by applying additive (shift) and multiplicative (stretch) transformations derived from climate-model projections, preserving the temporal structure and internal coherence of the original dataset. Subsequent studies demonstrated the applicability of morphing for long-term energy assessment, overheating analysis, and climate sensitivity studies across a wide range of building typologies and climatic contexts [8–10].

Beyond the original morphing framework, later research expanded both the generation and evaluation of future weather files. Jentsch et al. [4, 11] developed early workflows to transform existing weather datasets for worldwide locations and showed that predicted building performance is highly sensitive to the choice of baseline weather data, emissions scenario, and transformation method. This work underpinned the development of tools such as the Climate Change World Weather File Generator (CCWorldWeatherGen), which operationalised morphing for commonly used weather formats, including EnergyPlus Weather (EPW) files, and contributed to the wider uptake of future weather data in building performance practice [12, 13]. These studies highlighted the practical strengths of morphing-based approaches while also identifying recurring challenges related to transparency, reproducibility, and consistency between different generators.

A parallel strand of research has focused on stochastic weather generators and probabilistic climate projections. In the UK, work associated with UKCP09 and later datasets demonstrated methods for constructing future probabilistic design weather years, enabling risk-based assessment rather than reliance on a single representative year [14]. Comparative studies have shown that morphed observed weather and weather-generator-derived series can yield different representations of extremes, particularly heatwaves, with significant implications for overheating and resilience analysis [5, 15]. In professional practice, these developments are reflected in the use of Test Reference Years (TRYs) for annual energy assessment and Design Summer Years (DSYs) for overheating analysis, as formalised in CIBSE datasets and guidance, including TM49 and subsequent national releases [6, 16, 17]. While this ecosystem has helped embed future-weather thinking in design workflows, it also underscores the need for reproducible methods that clearly document assumptions when transitioning between baseline datasets, time horizons, and emissions pathways.

More recent studies have emphasised the need for transparent, reproducible, and up-to-date FWDF methodologies. Herrera et al. provided a comprehensive synthesis of requirements for future weather data in building simulation, highlighting gaps related to uncertainty, extremes, and model transparency [18]. Open-source and modular toolchains have since gained prominence, including the Future Weather Generator (FWG), which exposes morphing assumptions and supports reproducible workflows across global locations [19], and tools such as epwshiftr, which integrate openly available CMIP6-era climate projections into EPW transformation pipelines [20, 21]. In addition to widely used tools, dedicated datasets have been developed to support building energy simulation under future climate conditions, providing EPW-compatible files for multiple time horizons and scenarios across selected locations [22]. Applied studies continue to demonstrate that FWDF choice can materially affect predicted energy use and thermal risk, particularly when moving from single-year proxies to ensembles or multi-year representations of climatic variability [23].

In parallel, recent government-backed research has explored “improved” weather datasets that better capture inter-annual variability and enable percentile-based performance reporting, rather than pass/fail assessment against a single DSY [24]. Finally, emerging work on future-urban weather files shows that coupling regional climate projections with urban microclimate and urban heat island (UHI) models can significantly alter predicted overheating risk compared with background or rural weather assumptions [25].

Despite these advances, there remains a practical need for FWDF generation methods that are (1) transparent in their use of climate anomalies and transformation assumptions, (2) applicable to data-sparse as well as data-rich regions, and (3) suitable for benchmarking against established tools and datasets. This paper addresses these needs by presenting a transparent and replicable workflow to generate future EnergyPlus Weather (EPW) files through morphing, using monthly anomalies from a Global Climate Model (GCM) applied to a user-selected baseline EPW (commonly available or derived from representative datasets). The method explicitly documents the extraction, spatial interpolation, and application of climate anomalies and maintains internal consistency across meteorological variables through psychrometric post-processing. To assess robustness and transferability, the workflow is demonstrated for two climatically and geographically contrasting locations—Exeter (UK) and Bahía Blanca (Argentina)—and the resulting datasets are benchmarked against established future weather sources where available.

The methodology and results presented in this study rely on climate projections and future weather datasets derived from different modelling assumptions, scenarios, and temporal horizons. To support correct interpretation of the proposed workflow and subsequent comparisons, this section outlines the basis of Global Climate Models, future climate scenarios, and the characteristics of the future weather data sources employed.

1.3. Climate models, scenarios, and datasets

Future climate projections used in building performance simulation are derived from Global Climate Models (GCMs), which simulate the long-term response of the climate system to prescribed radiative forcing conditions rather than attempting to predict specific future weather events. GCM outputs are typically expressed as changes in the statistical properties of climatic variables over multi-decadal periods and are commonly provided as anomalies relative to a historical reference period for application in impact assessment and downscaling studies [26, 27]. In building simulation, these anomalies are frequently combined with observed weather data through morphing or other downscaling techniques to generate future weather files suitable for hourly energy modelling.

Future climate projections are framed using scenario families that define plausible trajectories of greenhouse gas concentrations. Earlier generations of building-focused studies commonly employed Special Report on Emissions Scenarios (SRES) pathways (e.g., A2 and A1B), which remain embedded in several established future weather generators and datasets [28]. More recent studies increasingly adopt Representative Concentration Pathways (RCPs), which specify radiative forcing levels by the end of the century (e.g., RCP4.5 and RCP8.5), and their successors, the Shared Socioeconomic Pathways (SSPs), introduced in the CMIP6 framework [29, 30]. Despite these advances, legacy

GCM–scenario combinations continue to be widely used in building simulation practice due to data availability, compatibility with established workflows, and the long development cycles associated with weather-file generation tools. Although many existing tools rely on earlier GCM–scenario combinations, the increasing availability of CMIP6 datasets highlights the need for flexible workflows that can accommodate updated climate projections.

Future weather files are typically generated for specific projection horizons, such as the 2030s, 2050s, or 2080s, representing multi-decade climatological averages centred on a target year rather than individual future years. These horizons are intended to support long-term design assessment, climate adaptation studies, and risk screening for long-lived buildings. Differences between future weather datasets therefore reflect not only methodological choices but also differences in climate-model selection, scenario framing, and projection period, and should be interpreted accordingly.

Several tools and databases are currently used to generate future weather files for building energy simulation, and this study draws on a subset of these for comparison. PROMETHEUS was developed to support probabilistic assessment of climate change impacts on buildings in the UK and combines climate projections with stochastic weather generation, making it particularly relevant for overheating and resilience studies [14]. Meteonorm is a widely used global commercial database that provides historical and future weather data based on GCM projections processed through proprietary interpolation and transformation methods, prioritising geographic coverage and ease of use but offering limited transparency of internal algorithms [31]. The Future Weather Generator (FWG) is a more recent open-source tool designed specifically for building performance research, implementing a transparent morphing-based approach that allows explicit selection of climate models, scenarios, and projection horizons [19].

Although these tools all aim to provide future weather files suitable for building simulation, they differ in their underlying climate data, scenario assumptions, temporal resolution, and treatment of derived variables. Recent reviews highlight that current research on climate change impacts in buildings remains fragmented, with inconsistencies in data sources, modelling approaches, and geographical coverage [32]. Comparisons between future weather files should therefore be interpreted as comparisons between consistent but non-identical representations of future climate, rather than as validation against a single reference dataset. This distinction is essential for interpreting the results presented in Sections 3 and 4 and underpins the benchmarking approach adopted in this study.

1.4. Aim and scope of this study

Recent studies have demonstrated that the choice of weather data, particularly whether future climate conditions are considered, can significantly influence predicted building energy performance and thermal risk. Viganò et al. [33] showed that simulations based solely on historical weather data can substantially underestimate future cooling demand and overheating risk in UK residential buildings, even within a traditionally heating-dominated climate. More recently, Tootkaboni et al. [34] conducted a comparative analysis of different future weather datasets and demonstrated that the same building model can exhibit markedly different energy demand profiles and peak loads depending on the future weather data source adopted, highlighting the sensitivity of simulation outcomes to both climate projections and weather-file generation methods. At the same time, other researchers have highlighted that the inappropriate processing and utilisation of future weather data in building and energy modelling are more common than often assumed, reflecting inconsistencies in the use of climate models, scenarios, and downscaling approaches [35]. Additionally, typical meteorological year (TMY) datasets are widely used in building simulation; however, they may not capture extreme climatic conditions or future variability. Recent studies have highlighted the need for alternative weather datasets, including extreme or modified reference years, to better assess building performance under changing climate conditions [36]. These findings, together with earlier work by Jentsch et al. [4], underline the importance of robust and transparent approaches for generating and applying future weather files in building performance simulation.

The objectives of this study are therefore to:

1. Develop a location-agnostic and transparent morphing workflow for future EPW generation using globally available climate data;
2. Evaluate its consistency relative to widely used future weather datasets;
3. Discuss the implications of baseline weather data choice and climate-model resolution for building energy simulation under future climates.

2. Materials and methods

2.1. Overview of the workflow

The proposed methodology generates future EnergyPlus Weather (EPW) files by applying a morphing procedure to a baseline EPW using monthly climate anomalies derived from a Global Climate Model (GCM). The workflow is designed to be transparent, reproducible, and applicable to any geographic location for which baseline EPW data are available. Rather than providing a new climate model, the approach focuses on explicitly documenting each transformation step typically embedded within black-box tools.

The workflow shown in **Figure 1** consists of five main steps:

(1) Selection of a baseline EPW representing current climatic conditions;

(2) Extraction of monthly climate anomalies from a GCM for a specified future time horizon and emissions scenario;

(3) Spatial interpolation of GCM data to the target location;

(4) Application of variable-specific morphing transformations to hourly EPW data;

(5) Derivation of secondary meteorological variables to ensure internal physical consistency.

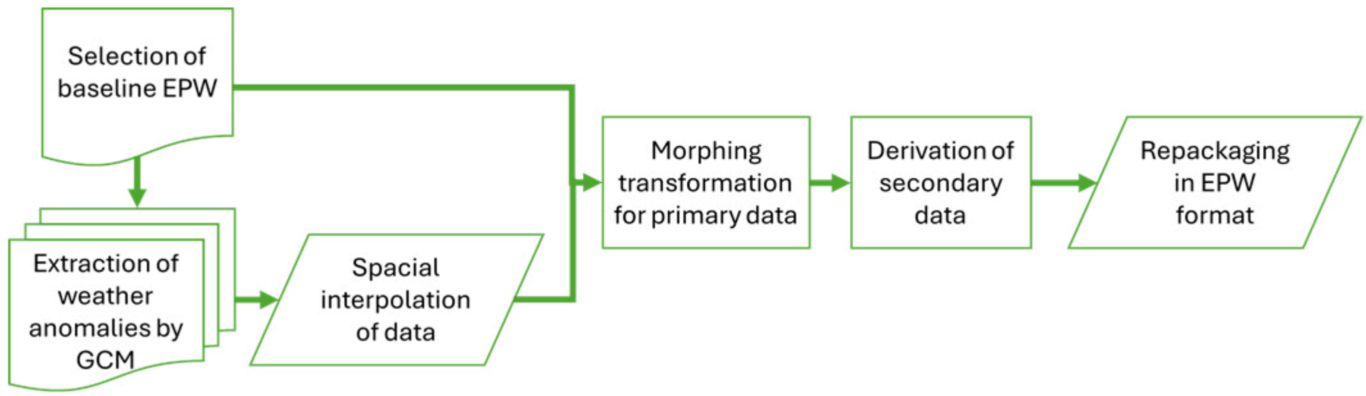


Figure 1 • Workflow schematic. EPW: EnergyPlus Weather Files; GCM: Global Climate Model; Green arrow: Data flow.

First, baseline weather data are obtained in an EnergyPlus Weather (EPW) format, which provides hourly values of key climatic variables such as dry-bulb temperature, solar radiation, wind conditions, and atmospheric pressure. This baseline file defines the temporal structure and site-specific characteristics of the dataset.

Second, climate-model data are extracted for the selected location and scenario. As Global Climate Model (GCM) outputs are typically available at coarse spatial resolution, spatial interpolation is applied to estimate climate variables at the specific site location. In this study, bilinear interpolation is used to derive site-specific monthly climate anomalies from gridded data.

Third, primary variables are identified and processed. These include variables directly influenced by climate-model outputs, such as temperature, solar radiation, and atmospheric pressure. These variables are modified using morphing techniques (shift, stretch, or combined transformations) [4, 7, 9] to incorporate projected changes while preserving the temporal structure of the baseline EPW. This step is further detailed in Section 2.5. Fourth, secondary variables are derived from the morphed primary variables to ensure internal consistency of the weather file. These include variables such as relative humidity, dew-point temperature, and other psychrometric properties, which are recalculated using standard thermodynamic relationships rather than directly morphed. The supplementary materials provide details related to all primary and secondary variables.

Finally, the morphed and derived variables are assembled into a new EPW file representing future climate conditions for the selected time horizon. This file retains the structure required for building performance simulation while reflecting projected climatic changes.

2.2. Baseline EPW selection

The workflow assumes the availability of a baseline EPW file, which provides the temporal structure and site-specific variability required for the morphing process. In practice, such files are widely available from sources including EnergyPlus Weather databases, Meteonorm, and national meteorological datasets. Where site-specific measured data are not available, typical meteorological year (TMY) or other representative datasets (e.g., IWEC) can be used as a suitable baseline. EPW files provide hourly meteorological data in a format widely adopted by building performance simulation tools, including EnergyPlus, and include dry-bulb temperature, humidity, pressure, solar radiation components, wind speed and direction, and cloud cover.

The choice of baseline EPW is a critical step, as morphing preserves the temporal structure and statistical characteristics of the original dataset. Differences in reference periods, station data quality, and typical year construction methods (e.g., TMY and TRY) can therefore influence absolute results. In this study, baseline EPWs were selected to reflect commonly used reference datasets for each case-study location, enabling direct comparison with future weather files generated by existing tools.

2.3. Climate-model data and future scenario

Future climatic changes are represented using monthly anomalies derived from a Global Climate Model (GCM). Anomalies describe deviations between a future projection period and a baseline reference period and are expressed either as absolute changes (e.g., temperature and pressure) or relative changes (e.g., radiation and humidity).

The future climate projections used in this study are based on the SRES A2 emissions scenario derived from the HadCM3 Global Climate Model. This scenario was selected to ensure consistency with widely used legacy datasets, including PROMETHEUS, and to enable a controlled comparison with existing tools. The projection horizon (e.g., the 2080s) is defined as a multi-decadal average centred on the target year. Although HadCM3 is no longer considered to be state of the art compared with CMIP6-era models, it remains suitable for methodological demonstration because its data structure, spatial coverage, and anomaly formulation are well documented and consistent with earlier morphing-based studies. HadCM3 was selected in this study to ensure consistency with widely used future weather datasets, including PROMETHEUS, which are based on comparable legacy GCM–scenario combinations. While more recent climate projections based on CMIP6 and Shared Socioeconomic Pathways (SSPs) are now available, the use of HadCM3 enables a controlled comparison with existing tools and datasets commonly used in building performance simulation. The implications of climate-model choice and resolution are explicitly discussed in Section 4.6. The objective of this work is to evaluate the proposed morphing workflow rather than the performance of specific climate models. For this reason, a single GCM and emissions scenario are adopted to isolate methodological effects and ensure comparability across datasets.

2.4. Spatial interpolation of climate anomalies

GCM outputs are provided on a coarse global grid and must be spatially mapped to the geographic location of the target EPW. Monthly climate anomalies are spatially interpolated from the four grid points surrounding the target location using a distance-weighted averaging scheme. This approach is equivalent to a bilinear interpolation on a regular latitude–longitude grid, while allowing explicit control over weighting as a function of distance. Similar interpolation strategies are widely used in climate data processing and downscaling of GCM outputs [27].

Weights are assigned inversely proportional to the square of the distance between each grid point and the target location, and monthly anomaly values are computed as weighted averages. This approach ensures continuity across geographic space while avoiding discontinuities that may arise from single-point selection, particularly near grid boundaries. The interpolation and morphing procedures were implemented in MATLAB; however, these methods are based on standard numerical techniques and can be readily implemented in other programming environments (e.g., Python or R).

2.5. Morphing of EPW variables

Hourly EPW variables are transformed using the morphing framework originally proposed by Belcher et al. [7], which applies one of three operations depending on the physical nature of the variable:

- Shift, applied when climate projections indicate absolute changes (e.g., dry-bulb temperature and atmospheric pressure);
- Stretch, applied when relative or percentage changes are appropriate (e.g., solar radiation and wind speed);
- Combined shift and stretch, applied when both mean and variability require adjustment.

Morphing is applied to a subset of primary meteorological variables, including dry-bulb temperature, relative humidity, atmospheric pressure, wind speed, and solar radiation components. Variables not directly morphed are either retained from the baseline EPW (e.g., wind direction) or derived from morphed variables using established psychrometric relationships, as discussed in Section 2.6. This approach maintains internal coherence between dependent variables while limiting unnecessary assumptions.

For clarity and reproducibility, the full set of equations, coefficients, and conditional constraints is provided in the supplementary materials. Table S1 provides a summary of all EPW variables, their category and the type of morphing applied. To illustrate the approach, this section presents a worked example for dry-bulb temperature, which is treated as a primary variable.

Dry-bulb temperature is morphed using a combined shift and stretch transformation to modify both the monthly mean temperature and the intra-monthly variability in line with climate-model projections. First, monthly mean temperature anomalies are computed from the GCM as the difference between future and baseline monthly means:

$$\Delta T_m = T_m^{GCM,f} - T_m^{GCM,a} \tag{1}$$

where

ΔT_m is the difference in the monthly average temperature (GCM).

$T_m^{GCM,f}$ is the monthly average temperature of the future projected time period (from the GCM).

$T_m^{GCM,a}$ is the monthly average temperature of the current time period (from the GCM).

To account for projected changes in temperature variability, a monthly scaling factor is derived from the ratio of future to baseline daily temperature ranges:

$$\alpha_m = \frac{\Delta T_{MAX,m} - \Delta T_{MINm}}{\langle T_{max}\rangle_{m,a} - \langle T_{min}\rangle_{m,a}} \tag{2}$$

where

$\Delta T_{MAX,m}$ is the monthly average of the daily maximum dry-bulb temperature variation for the month m (from GCM).

ΔT_{MINm} is the monthly average of the daily minimum dry-bulb temperature variation for the month m (from GCM).

$\langle T_{max}\rangle_{m,a}$ is the monthly average of the maximum daily dry-bulb temperature for month m, under current weather (a).

$\langle T_{min}\rangle_{m,a}$ is the monthly average of the minimum daily dry-bulb temperature for month m, under current weather (a).

The future hourly dry-bulb temperature (T_f) is then calculated as:

$$T_f = T_a + \Delta T_m + \alpha_m \cdot (T_a - \langle T_{m,a}\rangle) \tag{3}$$

where

T_a is the current hourly temperature.

$\langle T_{m,a}\rangle$ is the current monthly average temperature.

This formulation ensures that the future temperature series reflects both the projected change in monthly mean temperature and any change in temperature range, while preserving the diurnal and seasonal patterns embedded in the baseline EPW.

2.6. Derivation of secondary variables

Several EPW parameters, including dew-point temperature, water vapour pressure, and long-wave radiation components, are not directly available from GCM anomalies and are instead derived from morphed primary variables. These derivations follow standard psychrometric and radiative formulations [37, 38] widely used in building simulation practice and are further detailed in the supplementary materials.

Cloud-cover variables are retained from the baseline EPW due to the absence of reliable, location-specific future projections in the selected GCM dataset. The implications of this assumption are evaluated during validation and discussed as a limitation.

2.7. Case-study locations and validation strategy

The methodology is applied to two geographically and climatically distinct locations: Exeter (UK) and Bahía Blanca (Argentina). This selection enables assessment across different hemispheres, solar regimes, and climatic conditions, as well as comparison between data-rich and data-sparse contexts.

Validation is performed by benchmarking the generated future EPW files against established future weather datasets where available, including outputs from PROMETHEUS, Meteonorm, and the Future Weather Generator (FWG). Comparisons focus on both temporal behaviour and statistical consistency, using metrics such as mean, median, and Pearson correlation coefficients. The validation strategy is designed to assess whether the proposed workflow reproduces expected climate trends rather than to establish a single "correct" future dataset.

2.8. Scope and limitations

The proposed methodology is intended for early-stage design, research, and sensitivity analysis rather than regulatory compliance. While the use of a single GCM and emissions scenario allows clear methodological exposition, it does not capture the full range of future climate uncertainty. Similarly, the reliance on baseline EPW structure implies that extreme events not present in the historical record may be under-represented. As a result, the morphed EPW files generated using this approach are primarily intended for building energy performance assessment and sensitivity analysis, rather than for the explicit modelling of extreme events or detailed resilience analysis, for which specific extreme weather files should be used [36].

These limitations are common to morphing-based approaches and are discussed explicitly in Section 4.6, together with recommendations for extending the workflow using higher-resolution climate data, multiple scenarios, and ensemble-based approaches. The aim of the proposed workflow is not to replace existing future weather generation tools but to provide a transparent and reproducible alternative in which all methodological steps and assumptions are explicitly defined.

3. Results

3.1. Validation approach

The generated future EPW files are evaluated through comparison with established future weather datasets rather than against a presumed "true" future climate, which is inherently unobservable. Validation therefore focuses on consistency of temporal behaviour, statistical agreement, and plausibility of projected trends relative to widely used future weather generators. The comparison presented in this section is not intended to establish superiority over existing datasets, but to assess the consistency of the proposed workflow relative to widely used tools and to highlight the impact of methodological differences.

For the Exeter case study, results are compared against outputs from PROMETHEUS, Meteonorm, and the Future Weather Generator (FWG). For Bahía Blanca, where PROMETHEUS data are not available, comparisons are limited to Meteonorm. Validation metrics include visual comparison of time series, summary statistics (mean and median), and Pearson correlation coefficients to assess similarity in seasonal patterns.

For variables with high short-term variability, such as radiation and luminance, smoothed trendlines were added to the figures to improve readability and support comparison of seasonal behaviour across datasets.

3.2. Dry-bulb temperature: baseline versus future conditions

Figure 2 presents the comparison between the baseline dry-bulb temperature time series and the future series generated using the proposed morphing workflow for Exeter. The morphed series exhibits a systematic upward shift while preserving the temporal structure of the baseline EPW, consistent with the expected warming signal.

For Exeter, the annual maximum dry-bulb temperature increases from approximately 27.0 °C in the baseline dataset to 31.6 °C in the future scenario, while the annual minimum temperature increases from −4.4 °C to −2.5 °C. The warming effect is more pronounced during summer months, while winter temperatures show a smaller but consistent upward shift, also confirmed by the average increase in temperature over the year from 10.1 °C to 12.8 °C. These results indicate that the morphing process preserves the temporal structure of the baseline EPW (i.e., the timing of diurnal and seasonal patterns), while modifying the magnitude of the signal. The applied climate anomalies vary by month, which results in seasonally differentiated changes (e.g., more pronounced warming during summer), without altering the underlying sequence of hourly conditions.

Similarly, **Figure 3** below highlights the results shown for the morphing of dry-bulb temperature for Bahía Blanca. In line with the GCM used, a notable increase in temperatures can be seen, albeit less marked in its summer temperatures when compared to Exeter. Average temperature throughout the year rises from 15.7 °C to 18.3 °C, with an increase in maximum temperature and minimum temperature from 38 °C to 39.6 °C and from −6 °C to −3.0 °C, respectively.

3.3. Comparison with established future weather datasets

Figure 4 compares the future dry-bulb temperature series generated using the proposed workflow with outputs from Meteonorm (Met—scenario 4.5), Future Weather Generator (FWG—scenario 4.5) and PROMETHEUS (Prom—scenarios mid and high) for Exeter. The reference datasets used in this study are derived from climate projections with different spatial resolutions. The proposed workflow is based on HadCM3, which has a spatial resolution of approximately 300 km. PROMETHEUS uses UKCP09 projections with a finer spatial resolution of approximately 25 km. Meteonorm combines multiple data sources, including GCM outputs and satellite observations, resulting in a variable effective resolution ranging from approximately 2 km to 300 km depending on location and data availability. The Future Weather Generator (FWG) adopts the spatial resolution of the selected climate model; for CMIP6 datasets, this is typically in the order of 100 km. These differences in spatial resolution may contribute to variations observed between datasets.

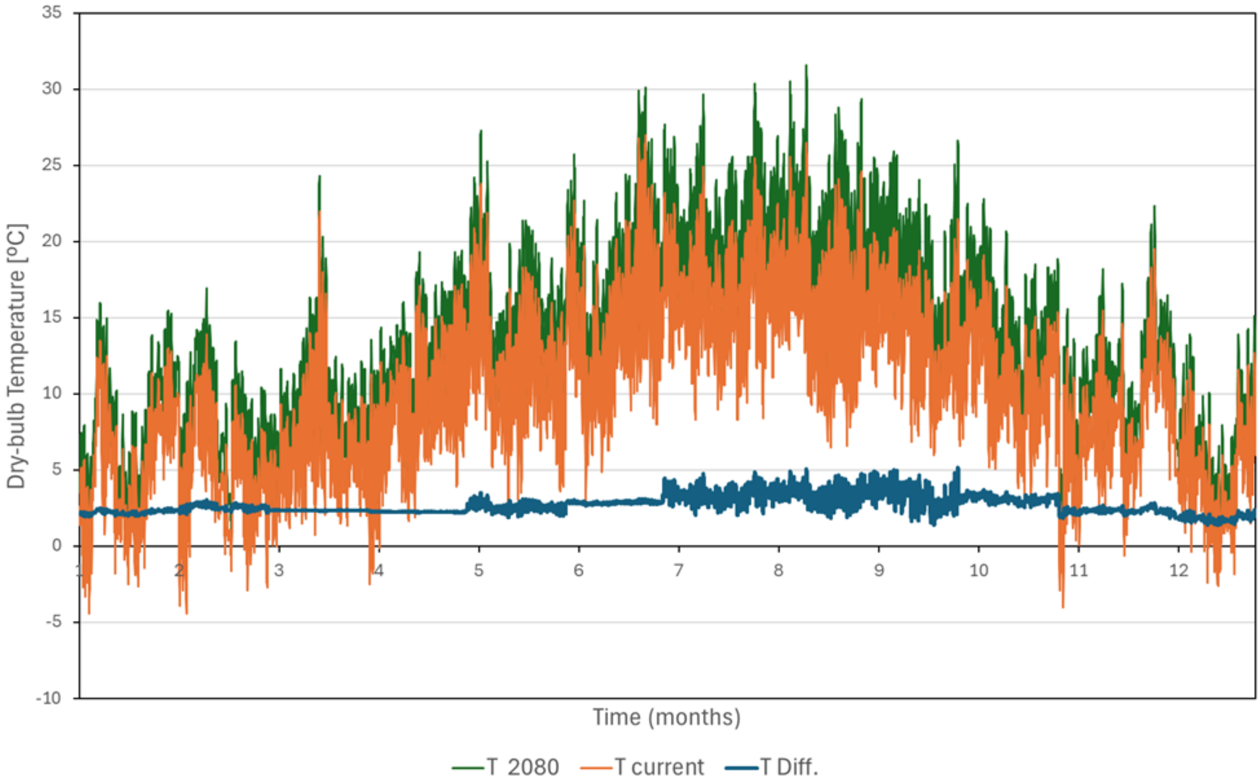


Figure 2 • Dry-bulb temperature comparison between current weather and future weather obtained through morphing for Exeter; hourly temperature difference between the morphed 2080 EPW and the baseline EPW highlighted in blue. EPW: EnergyPlus Weather; T 2080: Dry bulb temperature projections for year 2080; T current: Dry bulb temperature from current EPW file; T Diff.: Difference between the two temperature time series on an hourly step.

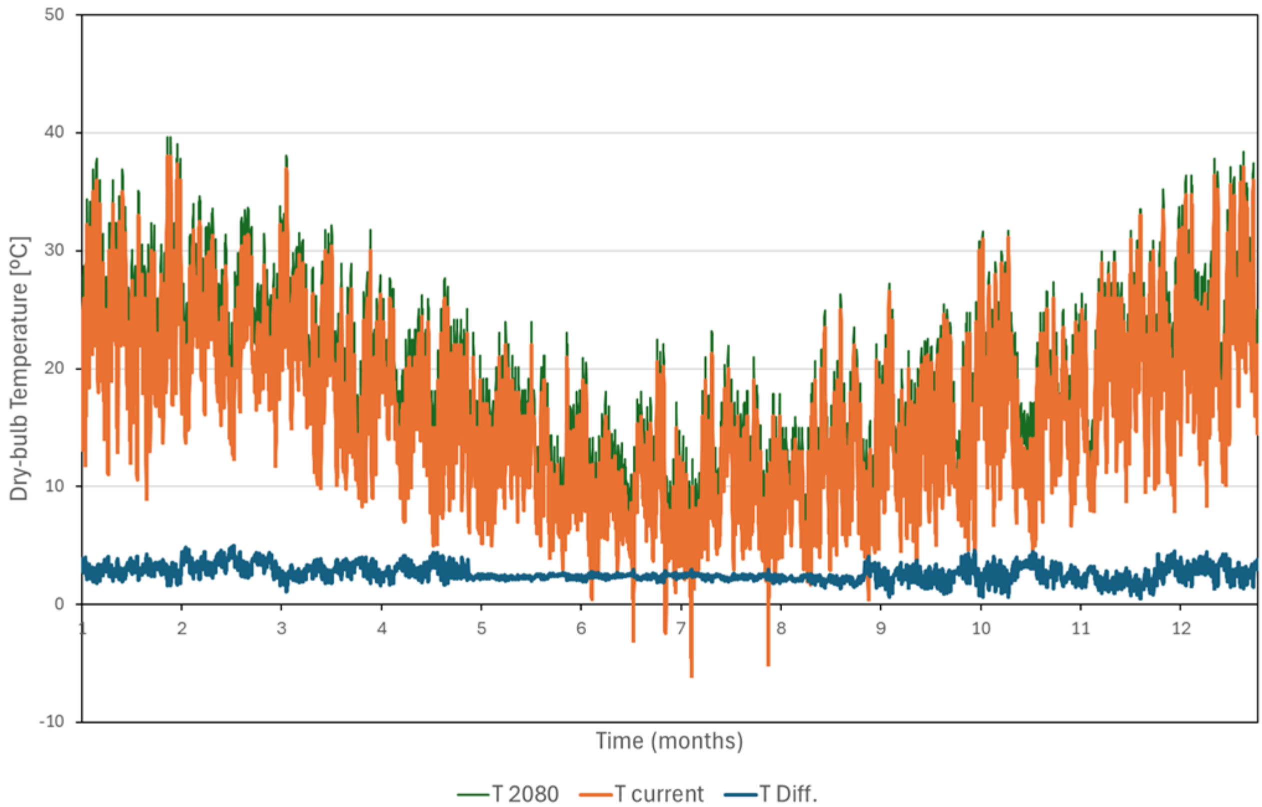
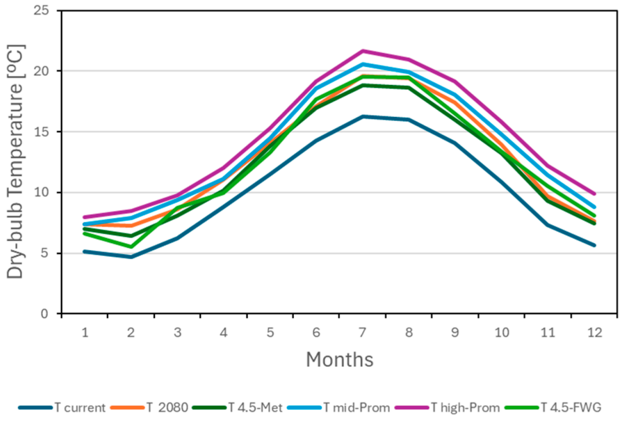
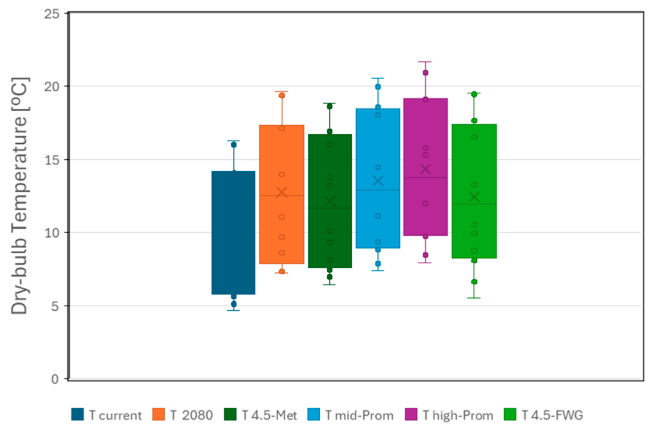


Figure 3 • Dry-bulb temperature comparison between current weather and future weather obtained through morphing for Bahía Blanca; hourly temperature difference between the morphed 2080 EPW and the baseline EPW highlighted in blue. EPW: EnergyPlus Weather; T 2080: Dry bulb temperature projections for year 2080; T current: Dry bulb temperature from current EPW file; T Diff.: Difference between the two temperature time series on an hourly step.



(**a**)



(**b**)

Figure 4 • Exeter dry-bulb temperature comparison for future weather projections from morphing, FWG and PROMETHEUS. (**a**) Monthly average plot; (**b**) yearly boxplot. FWG: Future Weather Generator; T current: Dry bulb temperature from current EPW file; T 2080: Dry bulb temperature projections for year 2080; T 4.5-Met: Dry bulb temperature projections obtained from Meteonorm 4.5 scenario; T mid-Prom: Dry bulb temperature projections obtained from Prometheus medium emissions scenario; T high-Prom: Dry bulb temperature projections obtained from Prometheus High emissions scenario; T 4.5-FWG: Dry bulb temperature projections obtained from FWG 4.5 scenario.

The selection of comparison datasets is influenced by both availability and underlying scenario frameworks. PROMETHEUS datasets are based on SRESs, while Meteonorm and FWG rely on RCP-based projections, and direct alignment between these frameworks is not possible. For Exeter, Meteonorm RCP4.5 was considered sufficient given the observed agreement with the proposed HadCM3–A2 projection, while the PROMETHEUS high-emission scenario provided an additional high-emission reference included as an upper-bound reference within the SRES-based framework. Its role is therefore to contextualise the range of projected conditions rather than to provide a directly comparable scenario. For Bahía Blanca, where PROMETHEUS data are not available, both Meteonorm RCP4.5 and RCP8.5 were included to provide a broader range of comparison scenarios.

The series display similar seasonal profiles, with peaks and troughs occurring at comparable times of the year. Differences in absolute values reflect variations in emissions scenarios, baseline EPW selection, and climate-model inputs adopted by each generator. Nonetheless, it is possible to appreciate how, despite the different data, each 2080 projection result is comparable, and particularly, the manually generated projection through the proposed method aligns well with all other projections. Boxplot data also show a clear difference from the current weather (T current) and all other projections, again with all projections having comparable results. Notably, the PROMETHEUS projection under the "high" scenario results in consistently higher temperatures compared to other projections. This is to be expected as the "high" scenario is more aligned with an 8.5 scenario rather than a 4.5 scenario used by other projections. While projection horizons have been aligned as closely as possible, exact equivalence between SRES and RCP scenarios is not always achievable. The comparison should therefore be interpreted as an evaluation of methodological consistency rather than a strict scenario-matched validation.

Statistical agreement between datasets is summarised in **Table 1**. Pearson correlation coefficients between the proposed method and reference datasets range from 0.748 to 0.799, with *p*-values below 0.05, indicating statistically significant similarity in temporal behaviour. Mean and median temperatures obtained using the proposed workflow lie between those of moderate and higher-emission reference scenarios, reflecting both the selected future pathway and the characteristics of the baseline EPW.

Table 1 • Statistical comparison between different future weather projections for Exeter.

Projection	**T 2080**	**T 4.5-Met**	**T mid-Prom**	**T high-Prom**	**T 4.5-FWG**
Correlation	-	0.764	0.795	0.799	0.748
p-value	-	<0.05	<0.05	<0.05	<0.05
Average	12.78	12.17	13.54	14.36	12.45
Median	12.23	12.2	13.1	13.9	11.9
Maximum	31.6	28.5	31	31.2	31.3
Minimum	−2.5	−4.1	−4.6	−1.4	−4

T 2080: Dry bulb temperature projections for year 2080; T 4.5-Met: Dry bulb temperature projections obtained from Meteonorm 4.5 scenario; T mid-Prom: Dry bulb temperature projections obtained from Prometheus medium emissions scenario; T high-Prom: Dry bulb temperature projections obtained from Prometheus High emissions scenario; T 4.5-FWG: Dry bulb temperature projections obtained from FWG 4.5 scenario.

Looking at the second assessed location, Bahía Blanca, the temperature projections behave in a similar manner, albeit with a mirrored pattern throughout the year, since the location is located in the southern hemisphere. **Figure 5** shows a summary for monthly average temperatures (a) and a corresponding boxplot. Like for Exeter, the projections obtained through morphing show a similar pattern to the ones obtained from existing sources (in this case, both scenario 4.5 and 8.5 from Meteonorm), showing good alignment with both, but particularly with scenario 8.5. Similarly, the boxplot shows a tangible difference in distribution between the current weather and all three projections, with the 2080 morphed data being comparable and again aligning with the 8.5 scenario from Meteonorm.

Table 2, below, provides a summary of key statistical data for Bahía Blanca, showing similar behaviour to Exeter. Pearson correlation coefficients between the proposed method and reference datasets range from 0.744 to 0.767, with p-values below 0.05, indicating statistically significant similarity in temporal behaviour, albeit slightly lower than in a data-rich location such as Exeter. Mean and median temperatures obtained using the proposed workflow lie slightly higher than those of moderate and higher-emission reference scenarios for Meteonorm, reflecting the characteristics of the baseline EPW.

Most of the other variables included in the EPW (defined in Sections 2.5 and 2.6, and detailed in the supplementary materials) follow similar patterns to the dry-bulb temperature, and comparisons among different projections give similar results, indicating similarity in temporal behaviour among different projections and confirming the morphed variables through the proposed procedure to be comparable with the ones available from existing sources. Below, we will focus on the few that provide data for interesting considerations. Similar divergence between future weather datasets has been reported in previous studies [18, 34].

3.4. Solar radiation and long-wave radiation sensitivity

Radiation-related variables exhibit greater variability than temperature-based variables, as shown in **Figure 6**, which compares horizontal infrared radiation (HIR) from the sky obtained using different cloud-cover assumptions. When baseline cloud-cover values are retained, the resulting series shows higher mean values (359.73 Wh/m²) than when cloud-cover projections derived from FWG are applied (347.66 Wh/m²).

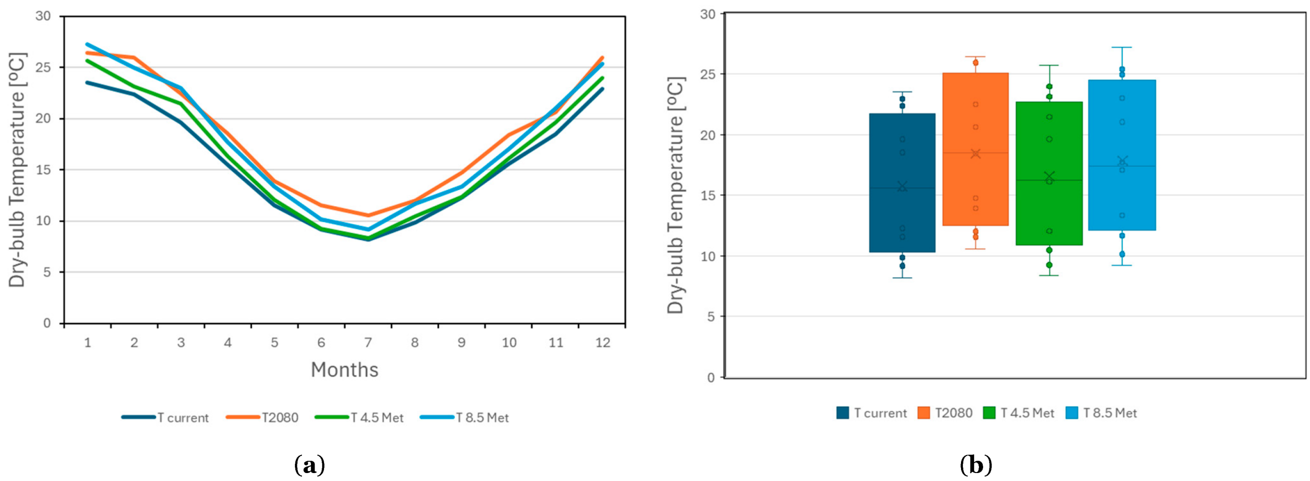


Figure 5 • Bahía Blanca dry-bulb temperature comparison for future weather projections from morphing, and Meteonorm. (**a**) Monthly average plot; (**b**) yearly boxplot. T current: Dry bulb temperature from current EPW file; T 2080: Dry bulb temperature projections for year 2080; T 4.5-Met: Dry bulb temperature projections obtained from Meteonorm 4.5 scenario; T 8.5-Met: Dry bulb temperature projections obtained from Meteonorm 8.5 scenario.

Table 2 • Statistical comparison between different future weather projections for Bahía Blanca.

Projection	**T 2080**	**T 4.5-Met**	**T 8.5-Met**
Correlation	-	0.744	0.767
p-value	-	<0.05	<0.05
Average	18.3	16.5	17.8
Median	17.9	16.0	17.3
Maximum	39.6	40.9	42.8
Minimum	−3.0	−4.2	−3.2

T 2080: Dry bulb temperature projections for year 2080; T 4.5-Met: Dry bulb temperature projections obtained from Meteonorm 4.5 scenario; T 8.5-Met: Dry bulb temperature projections obtained from Meteonorm 8.5 scenario.

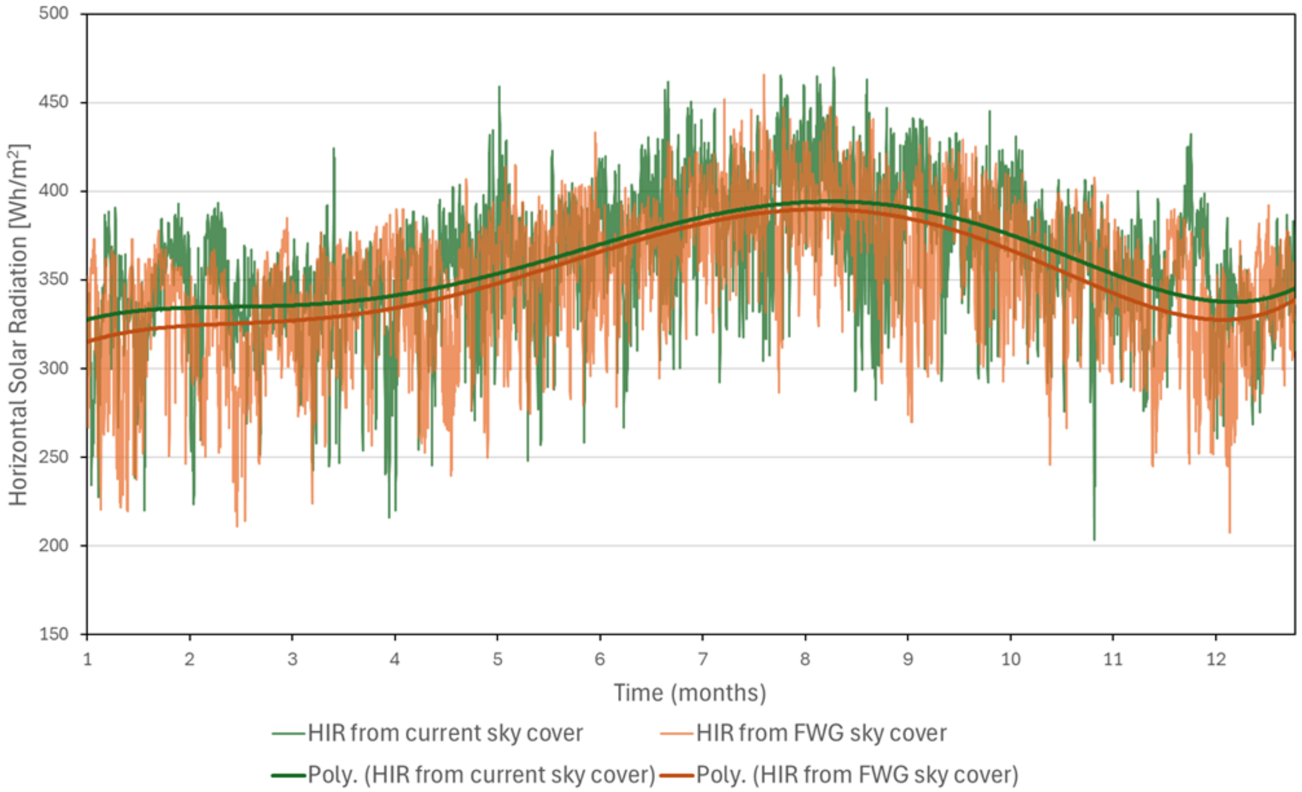


Figure 6 • Horizontal infrared radiation (HIR) comparison based on different sky-cover assumptions (Exeter). FWG: Future Weather Generator.

Although overall seasonal trends remain similar, differences in magnitude highlight the sensitivity of long-wave radiation components to cloud-cover assumptions. This result demonstrates that while morphing preserves temporal coherence, assumptions regarding variables not directly available from GCM projections can materially influence derived radiation outputs. Nonetheless, the resulting output remains comparable, confirming the initial assumption that using current sky cover in the absence of more refined data is acceptable. The polynomial trendlines included in **Figure 6** help highlight this by underlining the similar trend between the two time series, while the hourly values are broadly different and highly variable depending on the sky-cover assumptions made.

3.5. Luminance and illuminance variables

Derived luminance and illuminance variables display smooth and physically consistent temporal profiles following morphing and post-processing. **Figure 7** illustrates the comparison between future zenith luminance for Exeter generated by the proposed procedure and that obtained by Future Weather Generator, showing increased peak values and a modest redistribution across the year. The temporal shape of the curve remains consistent with solar geometry, indicating that the derivation process maintains physical plausibility and both projections are consistent for the location. The 168-period (1-week) moving average further reinforces the similar distribution of solar luminance throughout the year.

Comparisons with FWG outputs for a data-sparse region such as Bahía Blanca, visible in **Figure 8**, show similar seasonal behaviour; although differences in absolute values are observed due to differences in baseline datasets and scenario assumptions, the significantly reduced values of zenith luminance can be compared with the values included in the original weather file in **Figure 9**, where the reduced data quality is clear. Nonetheless, for both Exeter and Bahía Blanca, the proposed method generates coherent luminance and illuminance series (**Figure 10**) despite the potential absence of complete reference datasets, demonstrating the applicability of the workflow to both data-rich and data-sparse regions, albeit with diminishing quality in results. On an interesting note, the Meteonorm file does not contain usable data for zenith luminance, as the value is not reported and therefore unusable for comparison.

The larger divergence observed in **Figure 10b** should be interpreted with caution, as diffuse horizontal illuminance is a derived variable and is sensitive to the radiation and sky-condition assumptions adopted by each dataset.

3.6. Summary of validation outcomes

Across both case-study locations, the proposed workflow generates future EPW files that are temporally and statistically consistent with established future weather datasets. Strong agreement is observed for primary variables such as dry-bulb temperature (**Figures 2–4**; **Tables 1** and **2**), while greater divergence is observed for radiation-related variables where assumptions regarding cloud cover and atmospheric conditions differ between generators (**Figure 6**).

These results confirm that the proposed method reproduces expected climate signals while preserving the local climatic characteristics embedded in the baseline EPW. The validation supports its use for building energy simulation, sensitivity analysis, and early-stage assessment of climate resilience, while acknowledging that differences between tools reflect methodological choices rather than error.

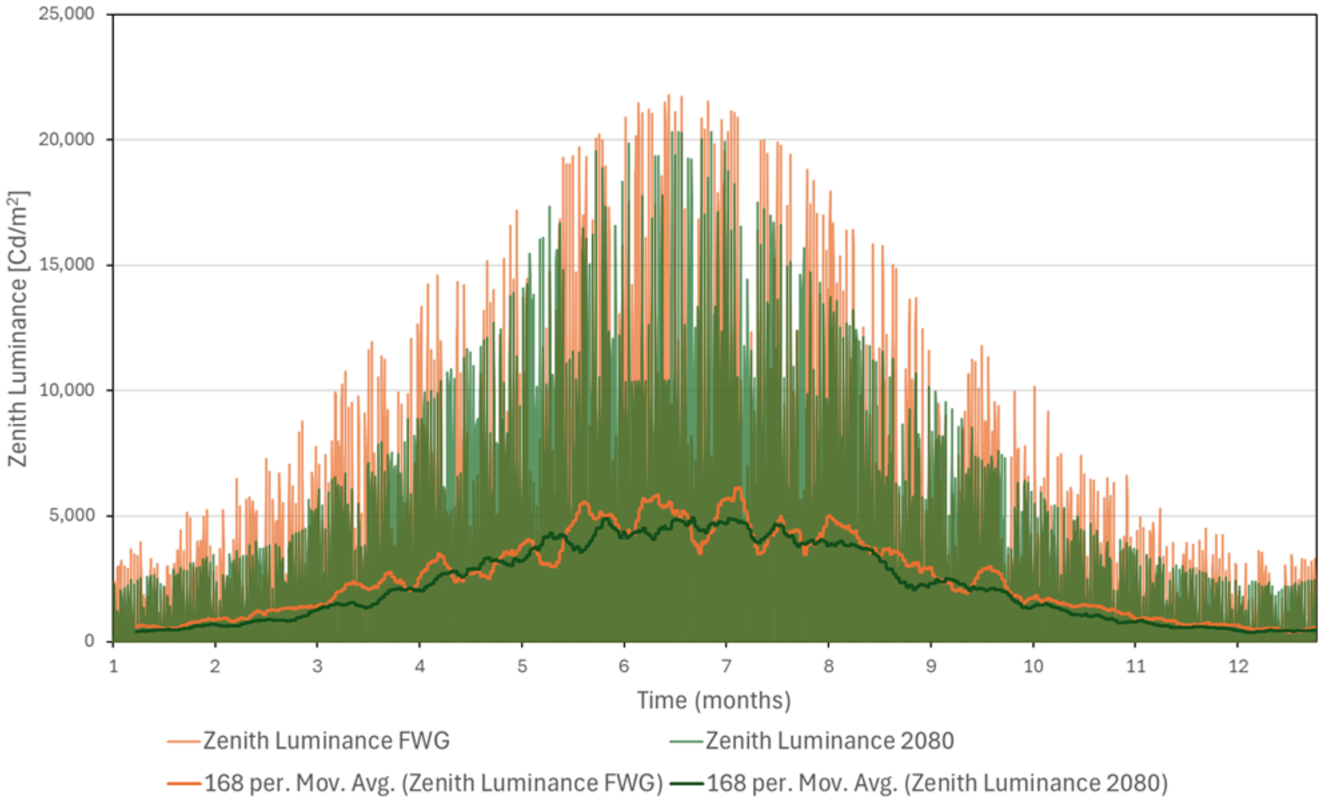


Figure 7 • Zenith luminance comparison for Exeter. FWG: Future Weather Generator.

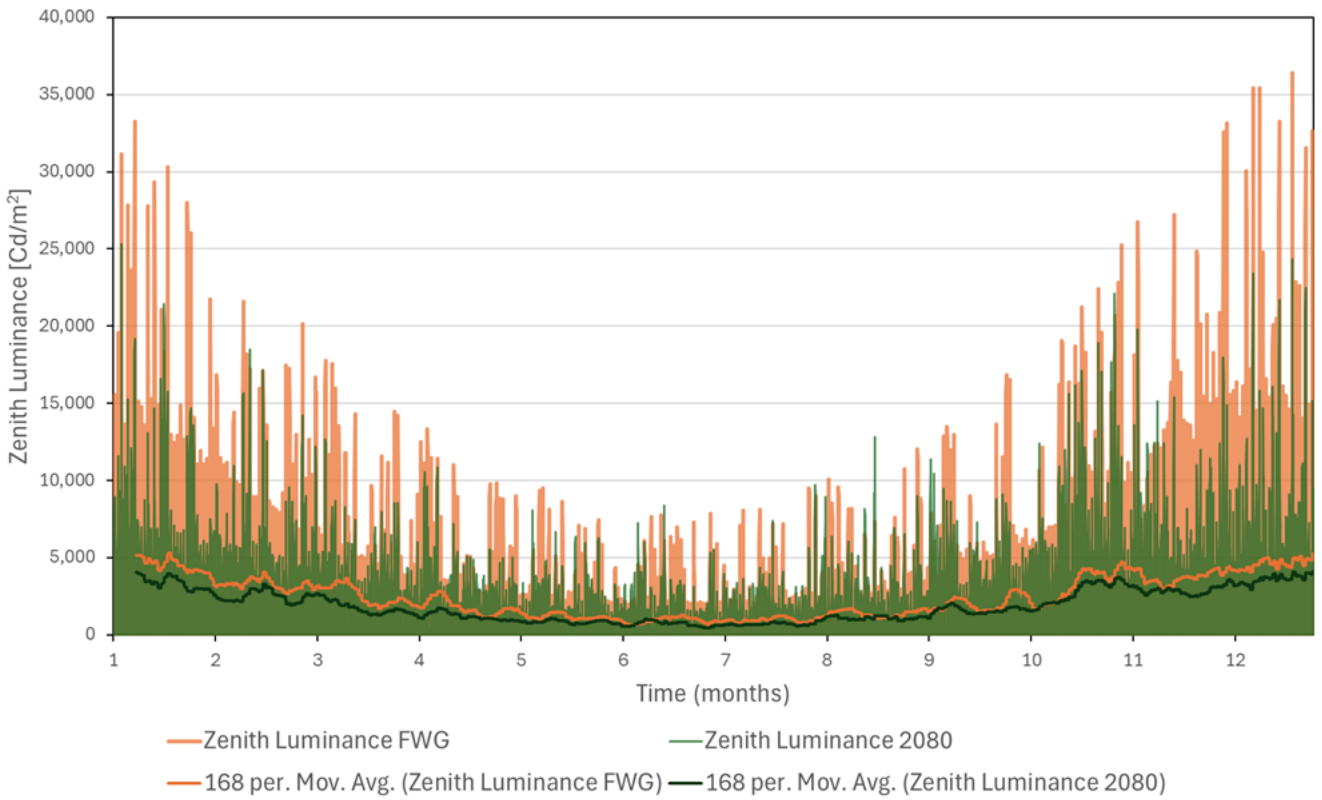


Figure 8 • Zenith luminance comparison for Bahía Blanca for 2080. FWG: Future Weather Generator.

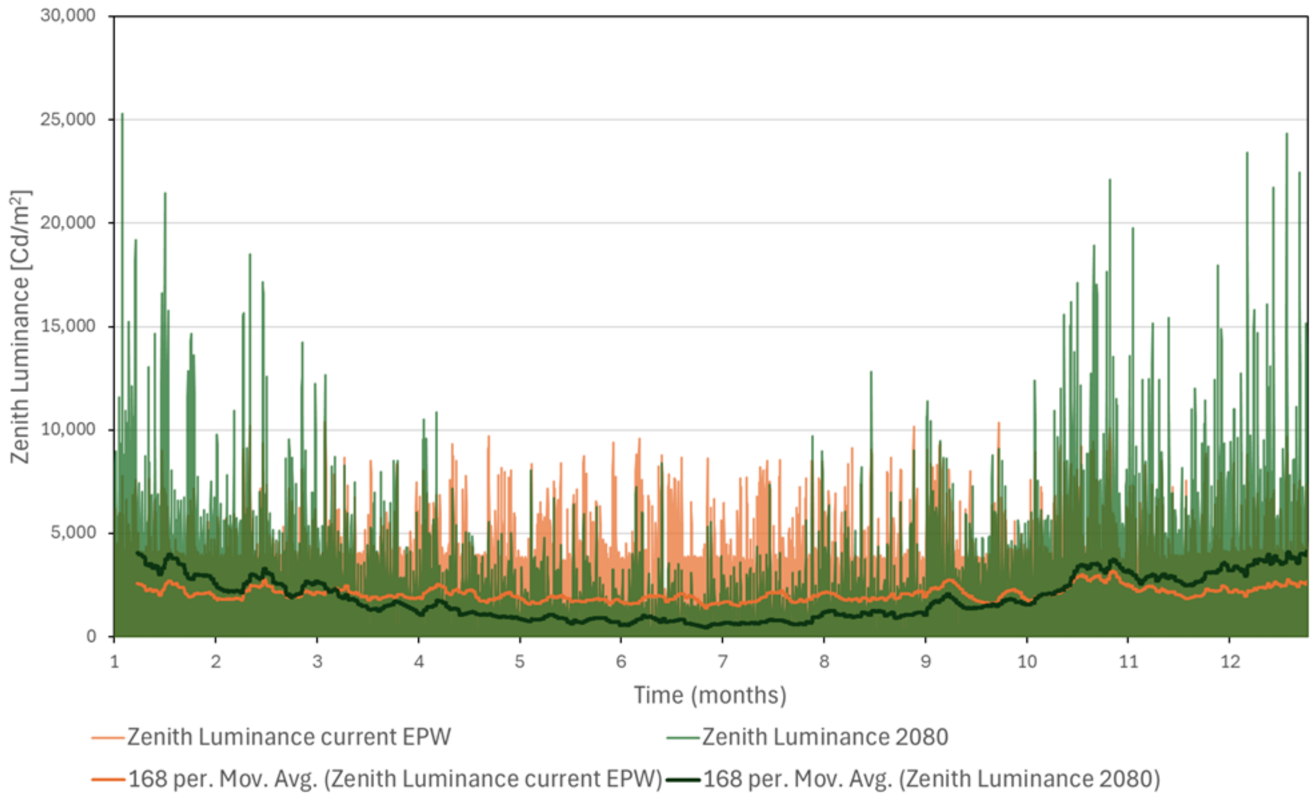


Figure 9 • Zenith luminance comparison for Bahía Blanca between current weather and 2080 projection. EPW: EnergyPlus Weather.

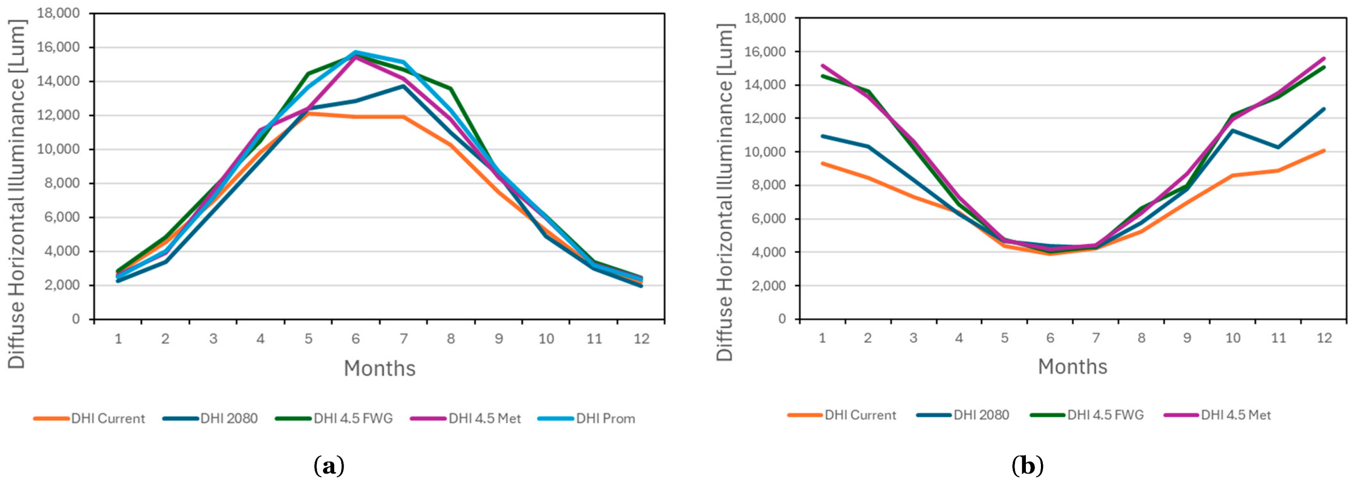


Figure 10 • Diffuse horizontal illuminance projections for Exeter (**a**) and Bahía Blanca (**b**). DHI current: Diffuse horizontal illuminance from current weather file; DHI 2080: Diffuse horizontal illuminance projections for year 2080; DHI 4.5 FWG: Diffuse horizontal illuminance projections from FWG; DHI 4.5 Met: Diffuse horizontal illuminance projections from Meteonorm.

4. Discussion

4.1. Interpretation of temperature projections and validation outcomes

The strong agreement observed between the proposed workflow and established future weather datasets for dry-bulb temperature indicates that the morphing-based approach successfully reproduces expected seasonal warming signals while preserving the temporal structure of the baseline EPW. The magnitude of warming observed for Exeter, particularly the increase in annual maximum temperatures, falls within the range reported by other generators despite differences in emissions scenarios and climate-model inputs. This supports the suitability of the workflow for representing future temperature conditions in building energy simulations where relative changes and seasonal behaviour are more critical than exact absolute values. Part of the divergence between datasets may also reflect differences in the spatial resolution of the underlying climate data, which influence the representation of local climatic conditions.

The correlation-based validation highlights that differences between datasets are primarily attributable to methodological choices rather than inconsistencies in the proposed approach. Variations in baseline EPW construction, reference periods, and scenario assumptions are reflected in mean and median values, reinforcing findings from previous studies that no single future weather file can be considered definitive [18]. Instead, the results emphasise the importance of transparency and reproducibility when generating and applying FWDFs. Part of the observed differences between datasets may be attributed to variations in underlying emissions scenarios (e.g., SRES A2 versus RCP-based projections), in addition to differences in weather-file generation methodologies. These differences also reflect the inherent uncertainty associated with future climate projections, which arises from variations in emissions pathways, climate-model structure, and internal climate variability. As highlighted by the IPCC [1], the use of multiple scenarios and models is essential to capture the range of plausible future climate outcomes and associated impacts.

4.2. Sensitivity to baseline EPW structure

The preservation of the baseline EPW's temporal characteristics is both a strength and a limitation of morphing-based approaches. As shown in Section 3, the proposed workflow maintains diurnal and seasonal patterns embedded in the historical dataset, enabling consistent comparison between current and future simulations. However, this also implies that any biases or smoothing inherent in the baseline EPW such as the under-representation of extreme events will persist in the morphed future file.

This dependence is particularly evident for radiation and illuminance variables, where baseline data quality and construction methods (e.g., TMY selection criteria) can influence the shape and variability of derived series. The results therefore reinforce the need for careful baseline EPW selection and for sensitivity analysis when future weather files are used to inform design decisions with long-term implications.

4.3. Radiation-related divergence and cloud-cover assumptions

Greater divergence is observed for radiation-related variables than for temperature-based variables (**Figure 6**), reflecting the compounded uncertainty associated with cloud cover, atmospheric composition, and radiative transfer. In the present workflow, cloud-cover parameters are retained from the baseline EPW due to the absence of reliable, location-specific future projections in the selected climate dataset. The comparison with FWG-based cloud-cover projections illustrates how alternative assumptions can materially affect long-wave radiation outputs without fundamentally altering seasonal trends.

This finding highlights a broader challenge in FWDF generation: while temperature anomalies are relatively robust across climate models, radiation variables are more sensitive to secondary assumptions. The explicit treatment of these assumptions in the proposed workflow allows users to understand and, where necessary, modify them, an advantage over black-box generators where such choices may be implicit or undocumented.

The divergence observed for diffuse horizontal illuminance/radiation in **Figure 10b** may also reflect differences in radiation decomposition models, cloud-cover representation, atmospheric turbidity assumptions, and source-data processing between datasets. While FWG provides greater visibility of some assumptions, Meteonorm combines climate-model outputs, satellite data, ground-station observations, and proprietary interpolation routines. Consequently, the specific cause of the discrepancy cannot be isolated from the available data. The results should therefore not be interpreted as showing that one dataset is inherently more accurate than another, but rather as evidence that derived radiation and illuminance variables are particularly sensitive to the assumptions embedded in each weather-file generation method. Differences observed between datasets in this study are aligned with findings that projections vary significantly depending on the choice of climate data, modelling approach, and geographical context [32, 35].

4.4. Transferability across climatic contexts

Application of the workflow to both Exeter and Bahía Blanca demonstrates its transferability across hemispheres and climatic regimes. While results for Exeter closely align with those from other tools, differences observed for Bahía Blanca underscore the influence of baseline data availability and quality in data-sparse regions. The ability of the workflow to generate coherent future EPW files in such contexts suggests particular value for global or comparative studies, where access to region-specific future weather datasets may be limited.

However, the results also indicate that caution is required when interpreting derived variables in regions with less robust baseline data, reinforcing the importance of context-aware application and validation.

4.5. Implications for building energy simulation and design practice

The reliability of simulation results is closely linked to the quality and assumptions of the underlying weather data, which are often themselves processed or modelled datasets [39]. The results support the use of the proposed workflow for early-stage design, research, and sensitivity analysis, where understanding relative changes in performance under future climates is more important than predicting exact future conditions. By maintaining compatibility with standard EPW-based simulation tools and making transformation steps explicit, the method enables practitioners and researchers to explore climate-resilience questions while retaining control over key assumptions. Recent initiatives have also focused on developing location-specific future weather datasets for building simulation and climate resilience assessment, highlighting the growing demand for accessible and standardised future weather inputs [22].

At the same time, the findings reaffirm limitations common to morphing-based approaches, including the potential under-representation of extreme events and the dependence on historical variability. These limitations suggest that FWDFs generated using morphing should be complemented by other approaches such as probabilistic weather years or ensemble-based analyses when assessing risks associated with extremes or regulatory compliance.

4.6. Policy relevance and alignment with international frameworks

The findings of this study have implications beyond methodological development, particularly in the context of climate adaptation and mitigation strategies in the built environment. The generation of transparent and reproducible future weather data supports the design and assessment of buildings under changing climatic conditions, contributing to improved resilience and energy performance. In this context, the proposed workflow aligns with broader international policy frameworks, including the United Nations Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). Reliable future weather data enable more accurate assessment of building energy demand and overheating risk, supporting both energy efficiency and climate adaptation objectives.

Furthermore, the use of future-oriented weather data in building simulation is consistent with the direction of international climate policy, including the outcomes of the United Nations Climate Change Conferences (COP), which emphasise the need for climate-resilient infrastructure and evidence-based adaptation planning. By improving transparency in the generation of future weather files, the proposed approach contributes to more robust and reproducible analyses that can inform design decisions, policy development, and long-term planning in the built environment.

While the present study focuses on building performance simulation, the methodological principles may also support broader sectoral applications where climate projections are required, reinforcing the importance of consistent and transparent data processing in climate-related decision-making.

4.7. Limitations and future developments

The proposed workflow relies on the availability of a baseline EPW file, which may introduce limitations in data-sparse regions. However, the use of representative weather datasets (e.g., TMY or IWEC) provides a practical workaround and maintains the applicability of the method [39].

A key limitation of the present study is the reliance on a legacy GCM (HadCM3) and a single emissions scenario. While the use of a single GCM and emissions scenario facilitates methodological clarity, it does not capture the full range of future climate uncertainty. Recent advances in climate modelling, including higher-resolution CMIP6 datasets and Shared Socioeconomic Pathways, offer opportunities to extend the workflow presented here. Integrating multiple climate models and scenarios would enable ensemble-based future EPW generation, supporting probabilistic assessment rather than reliance on a single projection. Future work should extend the workflow to incorporate CMIP6-based projections and ensemble approaches to better capture climate uncertainty.

Another limitation of the present study is the lack of full consistency in scenario comparisons across locations, driven by the availability of reference datasets and differences between SRES- and RCP-based frameworks. As a result, comparisons are intended to provide contextual benchmarking rather than strict scenario equivalence. This reflects broader challenges in the field, where the selection and processing of future weather data remain a key source of uncertainty in building performance simulation [35].

Further development will focus on automation and user accessibility, reducing the manual effort required to generate future weather files and enabling broader uptake. In this context, future work will also aim to develop a user-friendly implementation of the workflow and make it publicly available (e.g., via a Git-based repository) to further support reproducibility and adoption. Additionally, coupling the workflow with urban climate models could improve the representation of urban heat island effects, particularly for dense urban contexts where local microclimates significantly influence building performance.

5. Conclusions

This study presented a transparent and reproducible workflow for generating future EnergyPlus Weather (EPW) files using a morphing-based approach driven by Global Climate Model projections. The workflow explicitly documents each step of the process, from climate data selection and spatial interpolation to variable-specific transformations and derivation of secondary variables, addressing a lack of transparency in many existing tools.

Application to two climatically distinct locations demonstrated that the proposed approach produces results consistent with widely used future weather datasets, while highlighting how differences in underlying assumptions, scenario frameworks, and data processing methods influence simulation outcomes. The findings emphasise that comparisons between future weather files should be interpreted as contextual benchmarking rather than strict validation against a single reference dataset.

The results confirm that morphing-based future weather generation remains a practical and effective approach for early-stage building design, research, and sensitivity analysis, particularly where relative performance trends under future climates are of primary interest. By explicitly documenting each transformation step and making assumptions transparent, the proposed workflow enables informed interpretation of simulation results and facilitates comparison across tools and scenarios.

Overall, the proposed workflow contributes a transparent, flexible, and globally applicable method for future EPW generation, supporting more robust assessment of building energy performance and climate resilience in a warming world. However, the method should be applied with caution for analyses focused on extreme events, as the underlying baseline EPW structure may not fully capture future extreme climatic conditions. When investigating extreme weather data, appropriate baseline EPW and climate models must first be identified.

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Author contributions

Conceptualization, M.P. and M.M.; methodology, M.P.; software, M.P.; validation, M.P., M.R. and M.M.; formal analysis, M.R.; investigation, M.R.; resources, M.P.; data curation, M.R.; writing—original draft preparation, M.P.; writing—review and editing, M.M.; visualization, M.P.; supervision, M.M.; project administration, M.P. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare that they have no competing interests.

Data availability statement

The data supporting the findings of this publication can be made available upon request.

Supplementary materials

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