

Article

Estimating Future Urban Heat Island Effect Based on Shared Socioeconomic Pathway Scenario: A Case Study of Busan City

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Abstract

Urban Heat Islands (UHIs) intensify extreme heat, raise energy demand, and risk citizen thermal comfort in densely built cities. However, spatially detailed, scenario-differentiated estimates of future UHI intensity are still limited for complex coastal mountainous cities. This study set out to forecast UHI intensity variations in Busan, South Korea, under SSP2-4.5 and SSP5-8.5 scenarios. Daily temperatures from 19 automatic weather stations (2010–2014) were spatially interpolated using Empirical Bayesian Kriging Regression (EBKR), which included elevation and coastline distance variables. Among the 16 CMIP6 Global Climate Models (GCMs) tested, CNRM-CM6-1 ($r = 0.902$, $RMSE = 4.937$ °C) was chosen and bias-corrected using Empirical Quantile Mapping (EQM). The results reveal that mean maximum UHI intensity rises gradually, with ΔUHI (compared with the 2010–2014 baseline of 0.90 °C) reaching $+7.03$ °C (SSP2-4.5) and $+9.60$ °C (SSP5-8.5) in the far future, roughly 1.43 times more under the high-emission scenario. Summer through autumn has a UHI intensity increase, whereas long-term warming concentrates in Busan's urban core. These findings inform targeted urban heat adaptation strategies, prioritizing green infrastructure, cool urban surfaces, and energy-resilient city planning to protect human well-being.

Keywords: urban heat island; climate change; heat stress; Shared Socioeconomic Pathways; Bayesian kriging

1. Introduction

Climate change has profound consequences for both humanity and the environment. From 2011 to 2020, the global surface temperature soared 1.09 times faster than between 1850 and 1900 [1], indicating a clear acceleration of global warming. The World Meteorological Organization (WMO) mentioned that the effects of climate change affect multiple sectors, although their magnitude and spatial distribution remain uncertain [2]. Increasing uncertainty in future climate conditions is expected to affect economic stability, social well-being, productivity, quality of life, and the achievement of national development goals [3]. In response to these challenges, climate scientists and international research communities have collaborated to develop the Coupled Model Intercomparison Project Phase 6 (CMIP6), which provides a coordinated framework for assessing past, present, and future climate conditions.

Within CMIP6, Global Climate Models (GCMs) simulate meteorological variables across different time periods and Shared Socioeconomic Pathways (SSPs), which represent alternative development trajectories up to 2100 under varying assumptions about mitigation and policy [4–7]. These include SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0, and



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SSP5-8.5, with SSP2-4.5 reflecting moderate mitigation and SSP5-8.5 representing a fossil fuel-intensive pathway [5]. Despite their value for global assessments, GCMs have limitations at local scales due to their coarse spatial resolution (100–250 km), which restricts their ability to capture fine-scale climatic processes and urban variability. Additionally, differences in model structure, parameterization, and resolution within the CMIP6 ensemble introduce uncertainties, particularly at local levels where projections are influenced not only by emission scenarios but also by model-specific characteristics and downscaling approaches [8].

In response, a number of studies used a range of downscaling techniques to narrow the spatial resolution gap between GCM and urban-scale evaluations [9–14]. For example, statistical downscaling provides a computationally efficient technique to solve higher spatial resolution by running statistical correlations between observation data and GCMs [10,11]. It introduces uncertainty by selecting a bias correction procedure and assuming that previous transfer functions will be valid under future climate conditions [15]. These cumulative uncertainties require a comprehensive multi-criteria GCM evaluation before applying any one model to local-scale urban climate projections on city systems [8]. The most popular method, known as Quantile Mapping (QM), corrects distributional biases in GCM outputs by modifying the Cumulative Distribution Function (CDF) of model outputs to match the observed data [12]. While some studies employ many methods, QM is frequently used by researchers in terms of confidence and reliability in every point, even in extreme values.

Through downscaling, GCM outputs can be made more suitable for assessing urban-scale climate phenomena, including the Urban Heat Island (UHI) effect, in which urban surfaces experience higher temperatures than surrounding rural areas [16,17]. Besides the complexity of a city system, the study of urban climates has evolved into a vast interdisciplinary subject field that traverses the social and physical sciences [16]. Estimating future UHI effects requires reliable projections of temperature differences between urban and rural areas [18]. Cities must adopt urban weather and climate services to give suitable information to city administrations and urban stakeholders [16,19]. For this purpose, several studies recommend taking the effect of UHI under extreme conditions and projecting how UHI intensity may change under future warming scenarios [20–26].

Recent studies have projected future UHI effects based on CMIP6 climate scenarios. For example, mitigation measures aimed at building energy consumption can significantly reduce urban warming under high-emission SSP pathways [27]. However, the majority of UHI projection studies concentrate on large inland cities, while coastal cities with complex topography have received comparatively limited attention. This gap is particularly important because coastal locations have been identified as a critical factor influencing UHI intensity in East Asian cities, making it directly relevant to Busan's location along the Korea Strait [28]. In coastal urban contexts, land–sea interactions and topographic complexity may reduce the coastal buffering effect and amplify UHI intensity beyond what inland calibrated models are able to predict [29].

South Korea provides a relevant context for examining coastal urban heat dynamics because it is a peninsula surrounded by the sea on three sides and experiences hot, prolonged summers, particularly in major coastal cities such as Busan [30]. As the country's second largest city, Busan has undergone intensive urban development and regeneration, which has increased population density and potentially heightened vulnerability to climate change impacts [31]. Recent studies further suggest that air temperature-based UHI patterns in South Korean coastal cities are strongly influenced by marine exposure and coastal urban morphology [8,32]. Although climate change projections exist for Korea, the assessment of UHI effects under SSP scenarios remains limited for coastal cities like Busan. Addressing this gap requires downscaled GCM projections that integrate scenario-based

climate data with topographic and coastal characteristics relevant to UHI formation. With a focus on the methodological issues above, this study assesses how well GCM data simulate urban–rural thermal performance, as well as the performance of GCMs and downscaling methods in simulating UHI as a climate impact.

This study has three primary objectives. First, we use Empirical Bayesian Kriging Regression (EBKR) with topography data and coastline distances to identify the effect of urbanization on Busan observations. Second, we compare the performance of CMIP6 GCMs with observations. Third, we analyze the impact of future UHI effects on Busan using the Empirical Quantile Mapping (EQM) technique. While the EBKR and EQM approaches are widely recognized in the climatic literature, this study makes an academic contribution by systematically integrating them into a unified spatial statistical workflow designed for coastal mountainous urban contexts. Specifically, this study contributes: (1) a demonstration that EBKR with topographic and coastline distance covariates significantly improves spatial temperature representation over limited AWS grids in topographically complex cities, (2) the first EQM-based downscaled UHI projection for Busan under CMIP6 SSP scenarios, and (3) scenario-based, spatially resolved UHI evidence directly applicable to UHI adaptation policy in South Korean coastal cities. Our findings may be utilized to make suggestions to policymakers.

2. Materials and Methods

2.1. Data

The main focus of our study is on observational and modeled data. Urban stations are defined as areas with more than 500 person/km² and rural stations as areas with below 300 person/km² [33]. We define the data collection from the Busan area, which is a high-density urban area. We chose Milyang and five nearby Gyeongsangnam-do stations as the rural reference area since their population densities are consistently less than 300 people per square kilometer. Milyang is also around 60 km from Busan's urban core, with no intervening big urban area and the region has the same climate as Busan, maintaining uniformity in the rural thermal baseline. This selection approach is consistent with previous research on Busan's climate risk [30,32]. For hourly temperature recordings from 2010 to 2014, we chose thirteen Automatic Weather Stations (AWSs) in the urban area of Busan, South Korea, and six stations distributed throughout the rural area of Gyeongsangnam-do province.

Figure 1 shows the locations of the data provided by KMA. For the GCM dataset, all of the variables were retrieved from WCRP CMIP6 servers (<https://esgf-metagrid.cloud.dkrz.de/search> (accessed on 24 June 2025)). We chose 16 GCMs members according to data availability from historical and future periods, with surface average temperature (*tas*), maximum temperature (*tasmax*), and minimum temperature (*tasmin*) variables. The retrieved data contain detailed information, such as daily temperatures over the historical period of 2010–2014 and future scenario GCMs (2015–2100,) which we extracted into periods of near (2031–2034), mid (2056–2060), and far (2091–2095) in SSP2-4.5 and SSP5-8.5. To analyze realistic city-level impacts, we needed to interpolate first, adding some parameters such as a Digital Elevation Model (DEM) as the topography map and distance to coastline to obtain a better realistic spatial resolution. Data were provided by V-World digital twin territory for South Korea (https://www.vworld.kr/v4po_main.do (accessed on 24 June 2025)). This will enrich observation data considered for high and mountainous areas that do not have any weather station nearby and rely on the interpolation method.

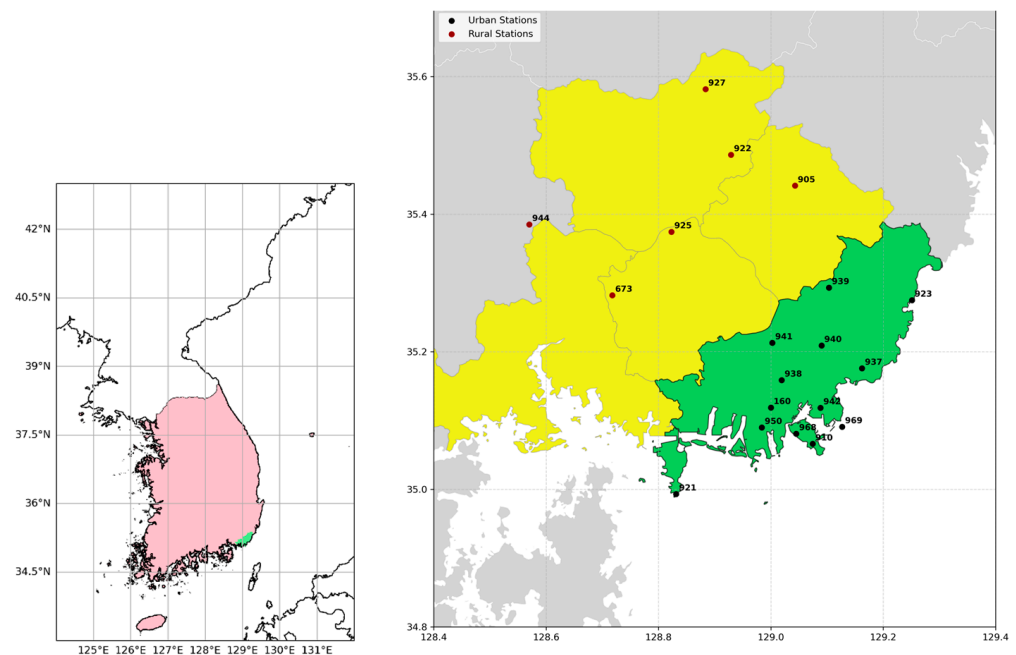


Figure 1. Map of South Korea (**left**) indicating national territory (pink) and specific location area (light green). The case study map (**right**) details for Busan as the urban area (green) and Gimhae, Yangsan, Changwon, and Milyang as rural areas (yellow). Points indicate locations of Automatic Weather Stations (AWSs) detailed on Table A1.

According to the Korea Meteorological Administration (KMA), the average temperature in Korea has risen 1.8 °C, which is higher than the global average. The average temperature in the past 30 years has risen nearly 1.4 °C, indicating a climate change problem in Korea. The government of South Korea implies that, compared with the 1912–1941 period, the 1988–2017 period had the longest trend of longer summers and shorter winters [34]. The long-term pattern of Siberian High and East Asian winter monsoons decreased during the early and mid-2000s as a result of highly frequent and intensified Korean marine heatwaves during the summers [29]. As the seventh largest emitter of CO₂, South Korea has put many efforts into implementing industrial green policies to support greenhouse gas mitigation [35].

2.2. Method

In our study, we categorized the method into three parts. First, to gain detailed coverage of the study case, observation data were interpolated using the EBKR method with raw observations, DEM as topography (m), and coastline distance (m) over the baseline period of 2010–2014. Second, after collecting interpolated observation data as our baseline, we evaluated 16 member GCMs to the baseline over the same time period to obtain the most correlated GCM, which will represent the future period, using a heatmap that includes four metric correlations: Pearson correlation, Root Mean Square Error (RMSE), mean bias error, and standard deviation. Finally, in both the historical and future periods, this GCM performs statistical downscaling by matching extreme values from the empirical CDF with the baseline using the EQM approach. To determine how Busan city performs in terms of UHI intensity in spatiotemporal resolution, the previous step's output is divided by the spatial mean maximum from urban and rural areas. This framework is illustrated in Figure 2.

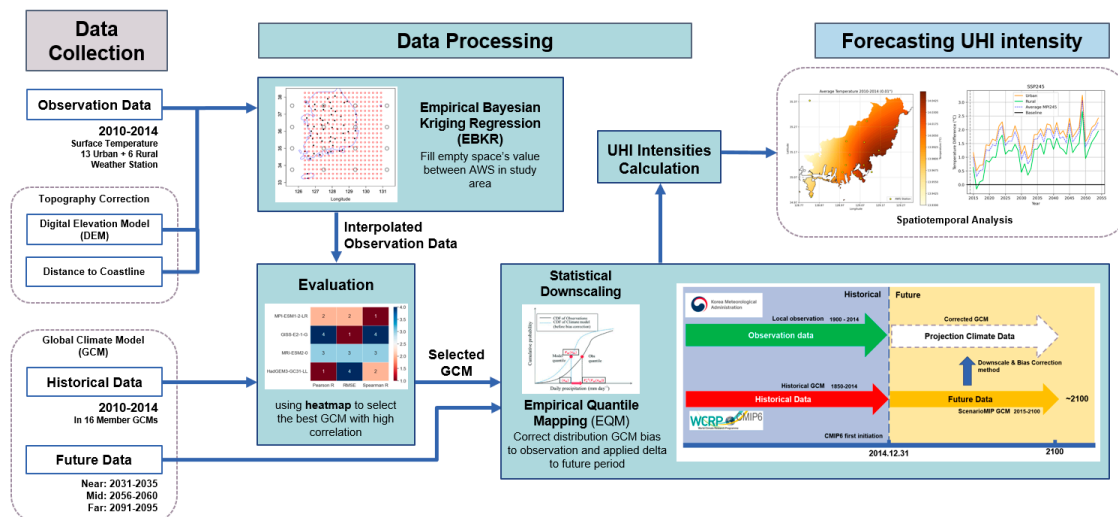


Figure 2. Methodology framework illustrating the operational steps and the statistical downscaling scheme.

2.2.1. Empirical Bayesian Kriging Regression (EBKR)

Observation data are only represented as one point. To fill the empty field between AWS station in study area, we need interpolation. EBKR is one method more suitable for interpolating continuous spatial variables like temperature [9,36–39]. It is partially mitigating this limitation but cannot fully compensate for missing sub-grid urban variables. Bayesian Kriging (BK) is a method to fill the uncertainty in the interpolation process and observed spatial patterns [39]. In this study, we integrated BK into external variables such as DEM and coastal distance by both regressions to capture the complex temperature distribution in the study area, unlike BK, which assumes a single fixed semi-variogram.

In EBKR, the relationship between daily temperature, elevation, and coastal distance are formulated as follows:

$$Z(s) = b_0 + b_1 \cdot \text{DEM}(s) + b_2 \cdot \text{Dist}_{\text{coast}}(s) + \epsilon(s) \quad (1)$$

where b_0 is the base temperature intercept (mean = 14.7003 °C); b_1 is the elevation coefficient (−0.0067 °C/m); b_2 is the distance to coast coefficient (mean = -2.5×10^{-5} °C/m), DEM and coastal distance to determine the rough surface temperature trend; ϵ represents the residual error of empirical BK. Negative values on both coefficients align with the standard atmospheric environmental lapse rate (6.77 °C per 1 km) for b_1 and captures the land–sea breeze thermal mitigation gradient across the coastal area for b_2 . The final result is the sum of the regression from topography and the residual kriging result producing a spatially detailed and physically accurate spatiotemporal temperature map. To ensure model reliability, we validated the EBKR gridded fields with local AWS datasets.

2.2.2. GCMs Evaluation

We compared the interpolated observation data with 16 GCM members by four metric correlations: Pearson correlation coefficient (r), Root Mean Square Error (RMSE), mean bias error (bias), and standard deviation (σ). These values are calculated using the formula below:

$$r = \frac{\sum_{i=1}^n (G_i - \bar{G})(O_i - \bar{O})}{\sqrt{\sum_{i=1}^n (G_i - \bar{G})^2 \sum_{i=1}^n (O_i - \bar{O})^2}} \quad (2)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (G_i - O_i)^2} \quad (3)$$

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n (G_i - O_i) \quad (4)$$

$$\sigma = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (5)$$

where G is the model simulations and O is observation. The value range of r is between -1 and $+1$; the closer the value to $+1$, the stronger the association. We ranked our models and chose one for each GCM that correlated well with the observations. Finally, GCMs that had high correlations were chosen for the next step.

2.2.3. Empirical Quantile Mapping (EQM) and Urban Heat Island (UHI)

The selected GCMs have resolutions mostly covering 80~250 km, which covers the entire Busan metropolitan area with single or few grid points. This large resolution cannot capture the urban-scale assessment. The EQM correction was applied pixel by pixel over the grid domain on a monthly basis, with 12 different transfer functions produced during the calibration period. This approach ensured that the quantile transfer functions captured the highly localized statistical distributions unique to each grid cell in the Busan metropolitan area. We downscaled our chosen GCM using statistical downscaling with EQM, unlike simple methods such as the delta method or linear scaling, which only correct the average values. EQM can correct the entire distribution of climate variables, including extreme values by empirical CDF to match observations [38–41]. For the baseline period, empirical CDFs were generated non-parametrically using ranked daily temperature readings for each calendar month, with observable (EBKR-interpolated) and GCM-simulated data treated independently. The equation is defined below:

$$T_{adj} = F_{obs}^{-1}(F_{mod,hist}(T_{mod,raw})) \quad (6)$$

where T_{adj} is the bias-corrected temperature, $F_{mod,hist}$ is the CDF of the GCM during the historical period (2010–2014), and F_{obs}^{-1} represents the inverse CDF (quantile function) of the observed data [41].

Regarding UHI intensities for the urban city, we calculated the differences between the daily observed temperatures at the urban (T_{urban}) and rural (T_{rural}) stations [18,32]. Our calculation uses the daily temperature maximum from the EQM bias correction to see the performance of daily maximum temperature on UHI intensity. The equation is represented below:

$$UHI_{Intensity} = T_{urban} - T_{rural} \quad (7)$$

We calculated UHI by the EQM output based on the urban and rural areas from the weather stations listed in Table A1. Stations located in rural areas are Jinyeong, Yangsang-Sangbuk, Danjang, Saengrim, Songbaek, and Gilgok, whereas the other stations are located in the urban area.

3. Results

3.1. Interpolation and GCM Evaluation

In Figure 3, the Probability Density Function (PDF) shows that temperature distribution during interpolation can be filled with data topography by the EBKR method. We found that the output of EBKR produces extreme values, capturing a wider range of temperatures and push peaks of the raw data's distribution, while keeping seasonal characteristics. This considers geographical conditions and gives logical specific temperatures from mountainous and coastal areas. The comparison between raw AWS observation data and the EBKR applied method reveals regional thermal profiles. By value $r = 0.977$, EBKR

shows significant spatial correction. The intercept value is -4.33 , meaning a result that implicates integrating topographic covariates. Therefore, PDF illustrates that the EBKR method successfully recovers the ‘hidden’ extreme values in the study area. The slope value is 1.20 , confirming that the inclusion of elevation and coastal distances allows interpolation to capture microclimate effects, which is good for representing spatial values in the UHI assessment.

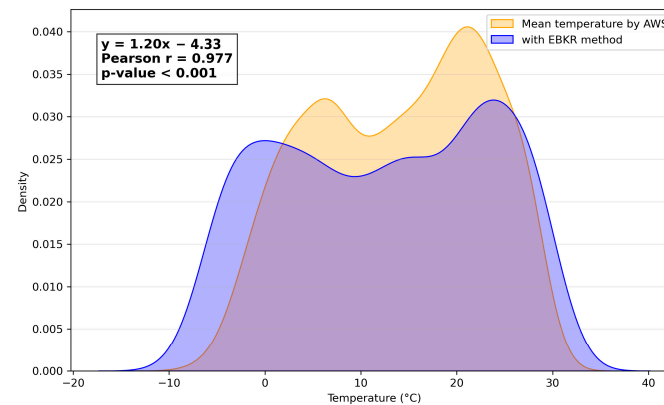


Figure 3. Probability Density Function (PDF) comparison between raw mean temperature observation data (yellow) and empirical Bayesian kriging regression (blue).

Figure 4 shows the selection process done by multi-criteria decision making that integrates Pearson (r) correlation, biases, and RMSE. The result shows that the CNRM-CM6-1 model has a high correlation with a value of 0.902 for observations during 2010–2014. The crucial point is that CNRM-CM6-1 is the only model that has an RMSE value below 5.0 . Also, we compare them with PDF between baseline and raw GCMs on Figure 5. At this point, we find that original South Korea GCMs like KACE-1-0-G and KIOST-ESM are not enough to be good representatives for the Busan area due to their correlation values below 0.9 . We expect that GCM produced by Korean institutes has to be detailed from their own national land. Furthermore, KIOST-ESM has a low correlation between GCMs, making it interesting for further investigation. Another finding is that KIOST-ESM is the only GCM that has a negative value on the bias score (-1.587) (refer to Table 1). We assume that the PDF distribution will move to the left, meaning the distribution temperature will underestimate the original, with many cooler areas but not enough to catch extreme cold temperatures. Therefore, this model took many parameters that decrease temperature, for example, albedo effects and aerosols, making the projections look cooler than other GCMs. For global warming and UHI assessments, it would be a misrepresentation for climate change because it will look cooler than the baseline.

To ensure the dependability of the downscaled climate forecasts across the Busan metropolitan area, a comprehensive historical validation (2010–2014) was carried out, comparing the seasonal climatology of the raw CNRM-CM6-1 GCM and the EQM bias-corrected outputs with the localized observation baseline. Figure 6 shows that the raw GCM output persistently underestimates local temperatures throughout the annual cycle, resulting in a strong cold bias. This underestimation is mostly due to the coarse topographic smoothing inherent in global models, which fails to describe the complicated coastal mountainous thermal dynamics of southeastern South Korea. Also in Figure 6, a summary of statistical metrics on the right, the raw GCM’s significant cold bias (mean bias = -7.70 °C) is fully neutralized to baseline after evaluation. The climatological root-mean-square error is reduced from 11.72 °C to 3.70 °C in the EQM output.

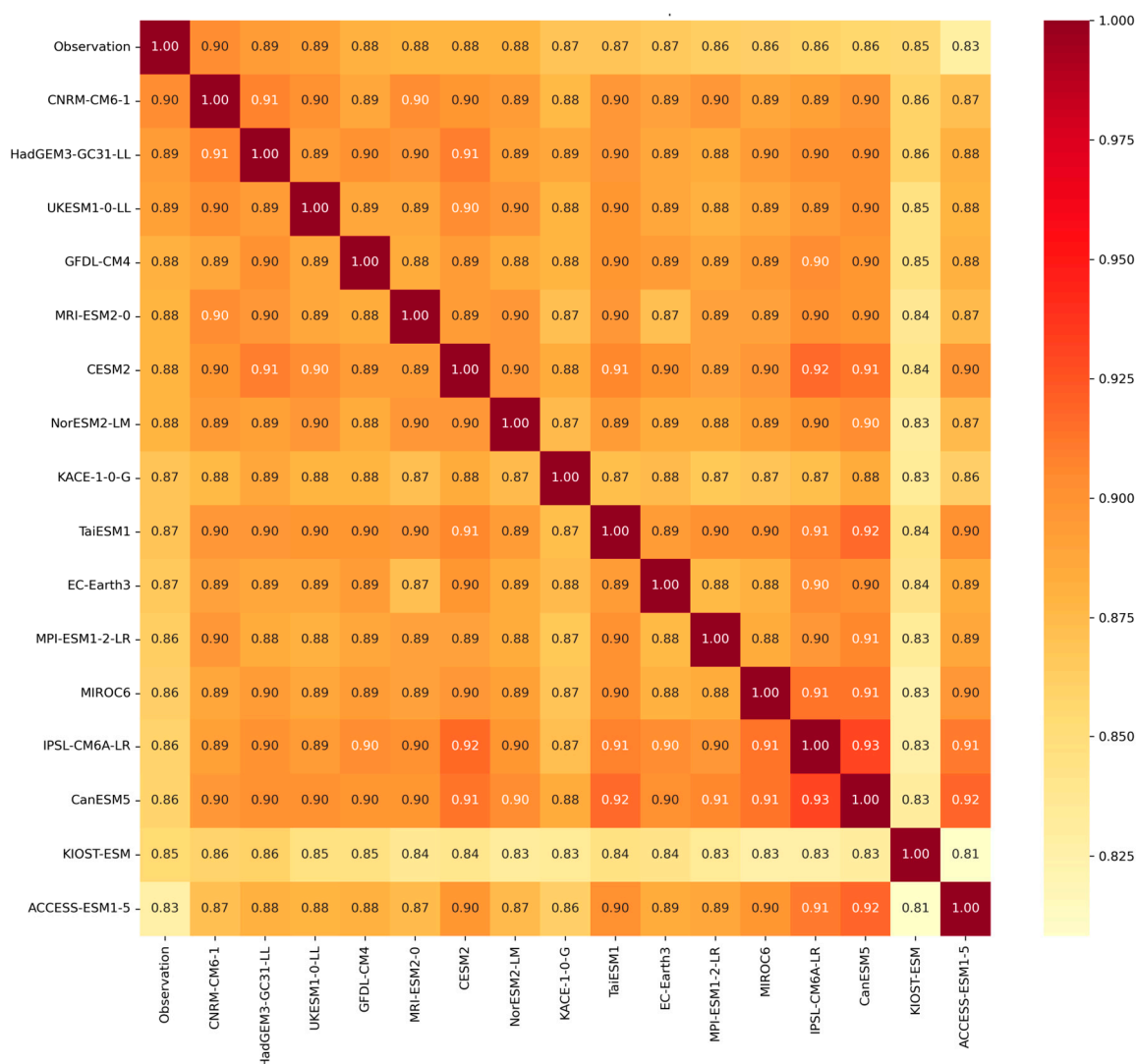


Figure 4. Correlation heatmap between observed UHI intensities in Busan and 16 GCMs during historical baseline period (2010–2014).

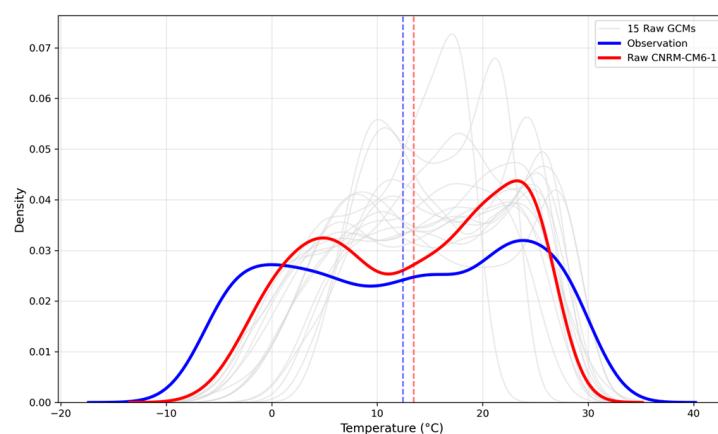
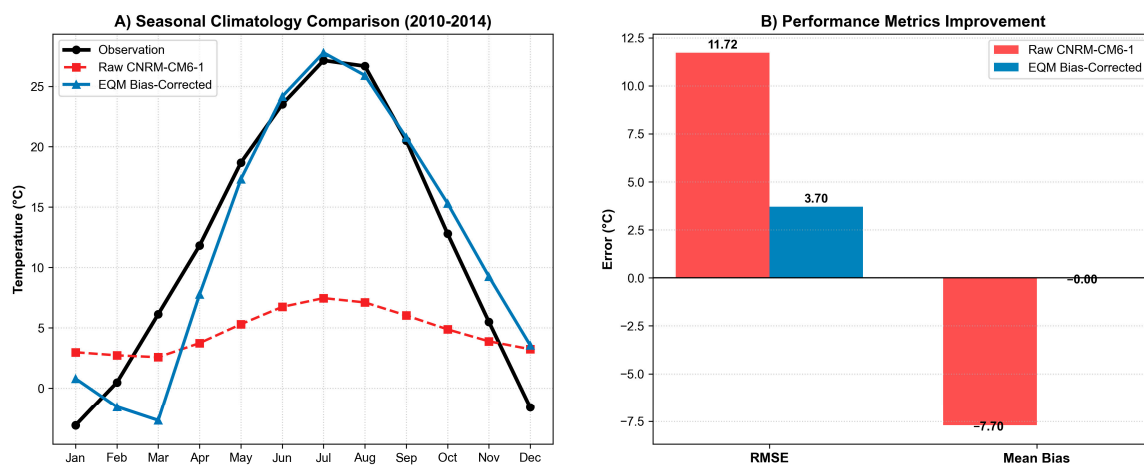


Figure 5. Comparison of PDF between interpolated observations and 16 GCM members for the average surface temperature variable from interpolated observations (blue), the CNRM-CM6-1 model (red), and other GCMs (gray).

Table 1. Evaluation ranking by correlation of the GCMs to interpolated EBKR observation data.

Model-ID	Pearson	RMSE	Bias	Std. Dev
CNRM-CM6-1	0.902	4.937	1.027	9.084
HadGEM3-GC31-LL	0.893	5.236	1.313	8.766
UKESM1-0-LL	0.891	5.470	1.854	8.605
GFDL-CM4	0.880	5.500	0.085	7.991
MRI-ESM2-0	0.879	5.906	2.374	8.397
CESM2	0.879	6.337	3.230	8.249
NorESM2-LM	0.878	7.513	4.944	7.632
KACE-1-0-G	0.870	5.621	0.832	8.442
TaiESM1	0.869	6.312	2.523	7.652
EC-Earth3	0.867	5.846	1.577	8.341
MPI-ESM1-2-LR	0.863	7.403	3.934	6.639
MIROC6	0.861	7.176	3.843	7.189
IPSL-CM6A-LR	0.859	6.377	2.878	8.713
CanESM5	0.858	7.535	4.241	6.872
KIOST-ESM	0.853	6.652	−1.587	6.453
ACCESS-ESM1-5	0.827	7.544	2.479	5.591

**Figure 6.** Validation between observation, raw CNRM-CM6-1, and results from EQM bias-corrected outputs during historical period (2010–2014) with monthly mean comparison (A) and correlation metrics (B).

3.2. UHI Analysis

Figure 7 shows the spatial distribution of mean UHI intensity across the Busan metropolitan area for the observation baseline (2010–2014) and several future periods under the SSP2-4.5 and SSP5-8.5 scenarios, as calculated using the CNRM-CM6-1 model with EQM bias correction.

The observation period mean UHI intensity (2010–2014) is confirmed at 0.90 °C, which is comparable to previous findings for South Korean coastal cities [30,32]. The estimated mean UHI gradually increases from +4.66 °C in the near future (2031–2035) to +5.69 °C in the mid future (2056–2060), eventually reaching +7.03 °C in the far-future period (2091–2095). Similar with extreme SSP5-8.5 scenarios, heating continues from +4.62 °C to +9.60 °C, representing approximately double the warning magnitude compared with SSP2-4.5 by the end of the century.

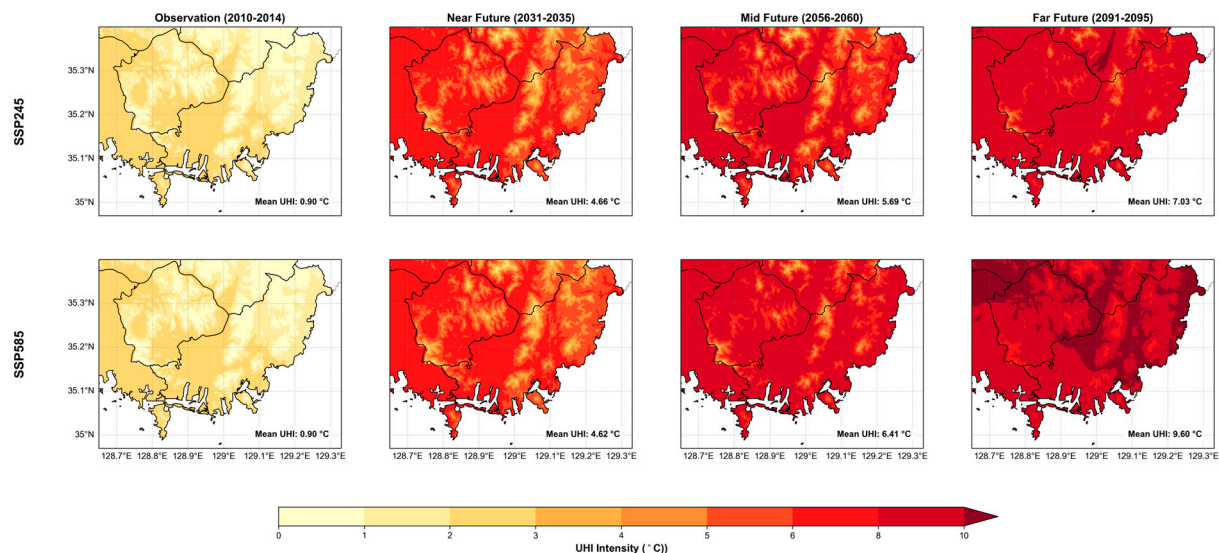


Figure 7. Spatial distribution of mean UHI intensity (°C), computed as the difference between mean daily maximum temperature for the observation and future projection periods.

As a result, these UHI hotspots are centered in crowded coastal and commercial areas, including Seomyeon, Sasang, Haeundae, and Gwangalli, where the UHI intensities are increased by high-density infrastructure in the far-future period. Spatially, UHI intensification spreads evenly across the study area [42], with relatively uniform warming gradients expected in the near future under both scenarios. However, the far future has significant warming concentrates across Busan's urban core, consistent with the compounding effect of greater anthropogenic heat emissions and reduced heat loss capacity under higher greenhouse gas forcing. Coastal and topographically elevated zones have somewhat lower UHI intensification, implying that sea breeze dynamics and terrain-driven circulation help reduce urban warming in these places [28]. However, this buffering effect decreases significantly for SSP5-8.5's far-future conditions. With SSP5-8.5 creating UHI intensities roughly 1.43 times larger than SSP2-4.5 in the far future, these results show that the choice of emission pathway has a modest near-term impact on UHI trajectories but becomes crucial after the mid-century. This result highlights the importance of taking early mitigation efforts to avoid a lock-in of high-warming trajectories.

Figure 8 shows the spatial distribution of projected Δ UHI (future and observation) for all eras and scenarios. Several major findings arise from this investigation. Under SSP2-4.5, the near-future Δ UHI of +3.24 °C is regionally homogenous, indicating a moderate and uniform response to near-term warming under a sustainability-oriented approach. The mid-future timeframe indicates a Δ UHI of +4.23 °C, with significantly stronger increases concentrated in the Busan metropolitan core and surrounding lowland areas. By the far future, Δ UHI reaches +5.56 °C, with a more significant spatial gradient. This suggests that long-term urban warming is not uniform but increases in existing heat-stressed zones. Under SSP5-8.5, the near-future Δ UHI (+3.18 °C) is comparable to SSP2-4.5, indicating that both scenarios have similar forcing trends until around 2040. However, from the mid-century forward, SSP5-8.5 diverges substantially, with Δ UHI reaching +4.94 °C in the mid future and an excessive +8.12 °C in the far future.

The combination of near-future Δ UHI values for scenarios demonstrates that committed warming in the climate system will lead to comparable short-term UHI rises regardless of emission pathway. To avert the catastrophic end-of-century warming projected by SSP5-8.5, policy interventions must target both near-term adaptation (cooling infrastructure, green roofs, urban albedo management) and long-term mitigation effectively [30].

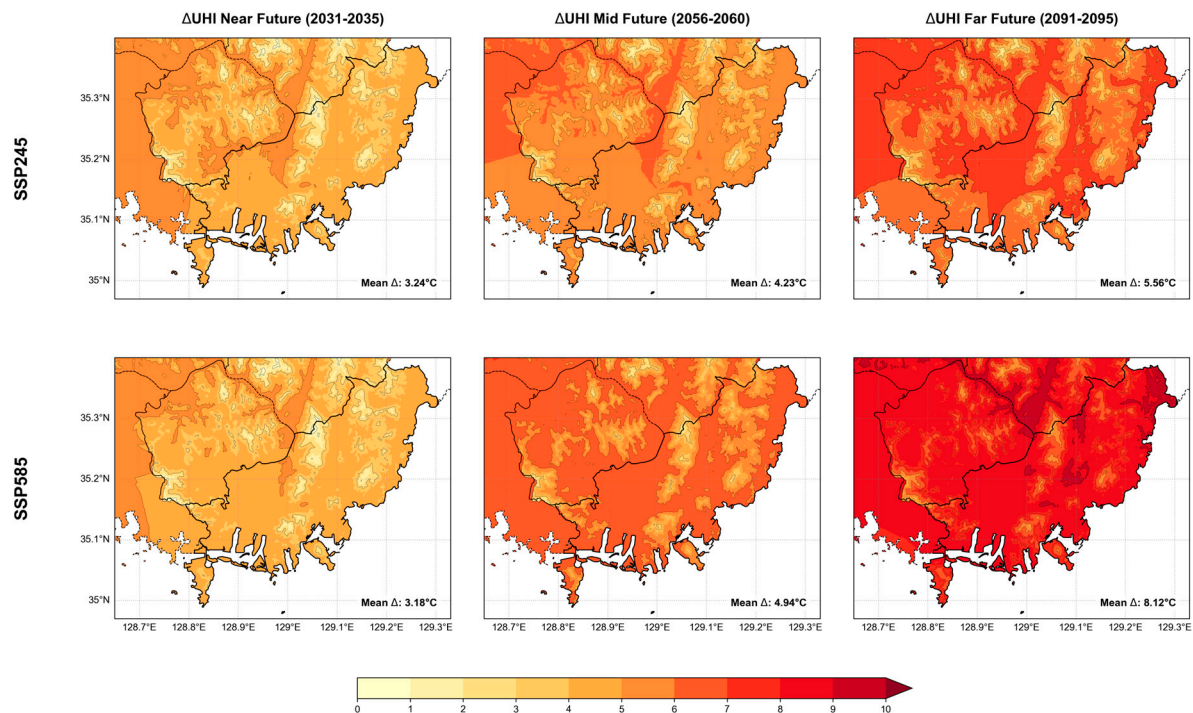


Figure 8. Projected changes in Δ UHI intensity (future and observation) across all multi-temporal horizons and emission scenarios.

Figure 9 shows the seasonal distribution of UHI intensity (spring, summer, autumn, and winter) over the observation baseline and three future periods for both scenarios. The results indicate a strong and constant seasonality in UHIs, which has significant implications for urban heat management. All times and situations show that summer through autumn has the highest UHI intensity, with median values significantly higher than those of other seasons [30,43]. This is consistent with the main role of solar radiation loads, lower wind speed, and increased human heat release in generating urban–rural thermal variations. Autumn UHI intensity approaches extreme positive values under SSP5-8.5 in the far future, with the mean UHI intensities around $+10\text{ }^{\circ}\text{C}$, indicating a major amplification of heat stress in urban areas. From the figure, this effect explains why rural areas experience lower temperatures while summer heat spots maintain their temperatures into the following season. This pattern has been observed in several East Asian coastal cities and is explained by a combination of reduced solar heating, greater urban longwave radiation loss, and coastal thermal regulation effects from the Korea Strait [30]. Historically, the Siberian air mass has brought cold temperatures during the winter, giving the city a seasonal break or natural thermal buffer. However, the consistent above-baseline behavior of far-future SSP5-8.5 projections indicates that year-round UHI intensity will greatly counter this historical Siberian cooling effect.

Figure 10 shows the monthly UHI intensity profiles for the observation period and all future projections under SSP2-4.5 and SSP5-8.5. The charts show a strong unimodal seasonal cycle throughout all time periods, increasing during August–October and falling in December–March, which is consistent with the Korean climate. Under SSP2-4.5, projections for the future show a slow upward shift in the monthly UHI curve, with the far future (2091–2095) constantly exceeding the observation baseline throughout the year. From July to October show the highest absolute departures, with far-future UHI intensity reaching a maximum of $+13\text{ }^{\circ}\text{C}$. The near-future and mid-future curves mainly align with the observation, particularly during the winter months, indicating a limited near-term signal. Under SSP5-8.5, the temporal progression becomes more evident. While near-future

estimates stay close to the observation baseline, particularly in winter, the mid-future curve begins to show a noticeable positive shift from July to November. By the far future, the entire seasonal cycle will be increased, with October reaching around +15 °C and even winter months displaying upward movements in comparison with observations. As the severe scenario increases, the uncertainty lines in both panels widen, reflecting increased model spread and internal climatic variability across longer projection horizons.

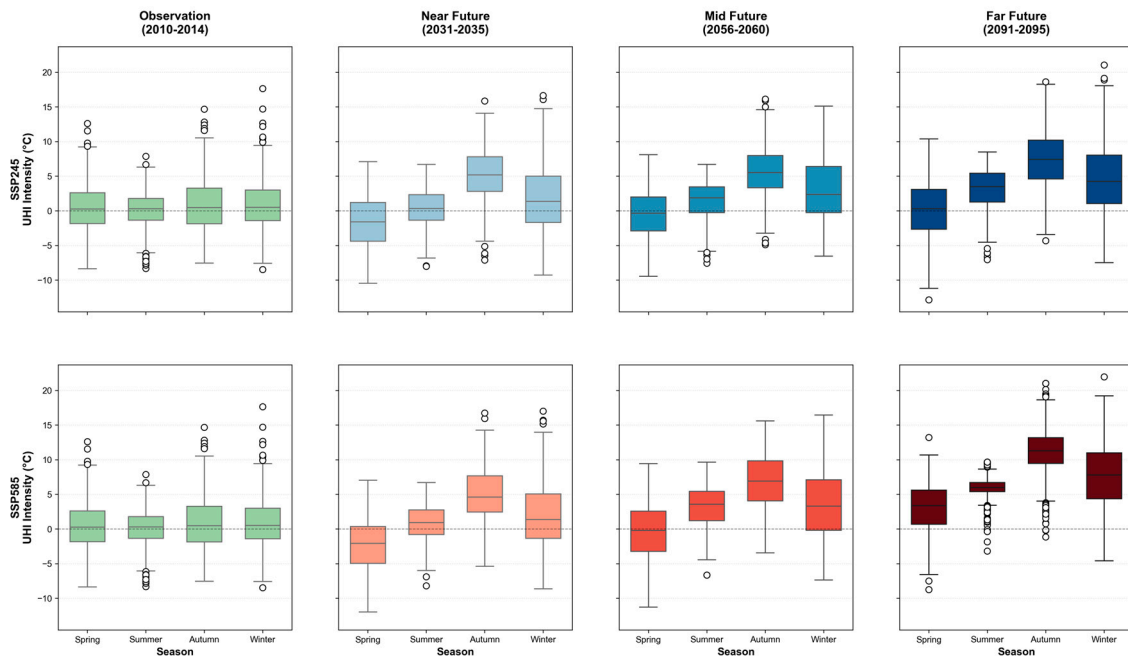


Figure 9. Seasonal distribution of UHI intensities during the baseline observation and future horizons.

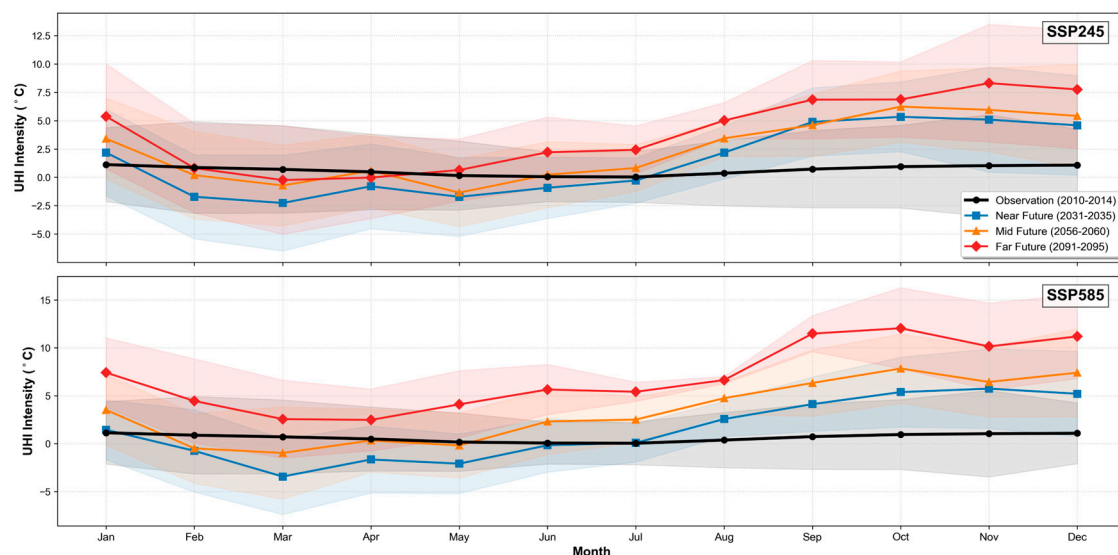


Figure 10. Monthly UHI intensity projection by surface maximum temperature variable for every period under SSP2-4.5 (**top**) and SSP5-5.5 (**bottom**) scenarios. The solid lines indicate the monthly mean UHI intensity for Observation (black), near (blue), mid (orange), and far future (red). The corresponding shaded areas represent the range between the maximum and minimum UHI intensity for each respective period.

The constant above-baseline behavior of far-future SSP5-8.5 forecasts over the last twelve months suggests that, under high-emission conditions, Busan will experience year-round UHI increases, removing the currently observed seasonal reprieve during the winter

months. This has significant consequences for urban energy demand, including increased cooling loads in the summer and the loss of a seasonal thermal buffering capacity.

4. Discussion

This study evaluates the capacity of GCMs and downscaling methods to simulate urban–rural thermal differences and assess future UHI impacts in Busan under different climate scenarios, including SSP2-4.5 and SSP5-8.5 scenarios, which indicate intermediate and extremely high greenhouse gas emission paths, respectively. According to SSP5-8.5, UHIs are anticipated to rise by an average of 4.4 °C by 2081–2100, while SSP2-4.5 predicts an average of 2.7 °C worldwide [44,45]. With the same scenario in far-future projections, we discover that Busan may suffer UHI intensities reaching averages of +7.03 °C (SSP2-4.5) and +9.60 °C (SSP5-8.5) during the far-future period, which is consistent with global projections but notably higher due to Busan’s coastal effects. These results corroborate historical observations in East Asian coastal metropolises, where sea breeze suppression and high impervious surface fractions systematically elevate urban temperatures above inland baselines [44–47]. By integrating EBKR with topographic and coastal covariates alongside EQM bias correction, this framework yields a more spatially realistic and physically grounded projection than legacy frameworks relying strictly on raw GCM outputs or uncorrected point records. Korea’s unique climate extremes increase the significance of these findings. The proposed method successfully illustrates how topographically driven sea breeze dynamics interact not only with the excessive heat and humidity of East Asian summers but also with the severe cold baselines dictated by Siberian winter monsoons. Consequently, these severe trajectories introduce profound risks for municipal energy resilience, public health, and urban ecological functions.

Busan’s coastal mountainous geography influences its UHI dynamics. First, the Korea Strait shoreline generates a constant sea breeze circulation, bringing marine air into coastal metropolitan areas and somewhat balancing anthropogenic heat accumulation [28]. This explains why the coastline and topographically elevated zones in our spatial analysis had lower UHI intensities than the inland urban core. However, when greenhouse gas forcing increases under SSP5-8.5, the regional land–sea temperature gradient is predicted to diminish, reducing the sea breeze’s buffering impact [29]. Second, Busan’s complicated geography provides orographic barriers that limit midnight cold air drainage from mountainous sub-districts, trapping warm air in valley bottom urban areas and exacerbating nocturnal UHI severity. These aspects collectively highlight the importance of the topographic factors introduced into the EBKR architecture.

The downscaled projection in the future period indicates a significant increase in UHI intensities by the far future, with a potential UHI intensity maximum reaching a typical 10–13 °C and a spatially average maximum UHI intensity of +9.60 °C in urban areas. From the results, these UHI hotspots are centered in crowded coastal and commercial areas such as Seomyeon, Sasang, Haeundae, and Gwangalli area, which has crucial implications for citizens’ outdoor comfort, heat-related health risks, and season-dependent urban activities. Furthermore, these areas require more attention for mitigation in future urban heat dissipation. From an urban science view, these projections highlight the critical need for evidence-based climate adaptation strategies in Busan. Specifically, the findings of this study suggest that policymakers should: (1) prioritize urban greening strategies such as expanding tree canopy coverage and green roofs in the identified high-intensity urban core zones in the Busan metropolitan area to reduce surface heat retention and improve residents’ thermal well-being; (2) revise urban design codes to mandate higher albedo building materials in future developments, particularly in the Busan metropolitan core, where far-future SSP5-8.5 concentrations are the most severe; and (3) build district-level

heat sensitivity maps with reference to Δ UHI warming in mid-century to guide cooling infrastructure investment, safeguarding the most heat-exposed and socially disadvantaged communities. Between 2012 and 2016, Busan emphasized industrial planning over climate change monitoring and predictions in national budget planning, resulting in a unique scenario for the city as a future adaptation priority [48]. According to a study, office building energy consumption in Korea is predicted to rise by 27% for cooling and fall by 10% for heating over the next two decades [49]. This increased energy demand directly impacts urban energy resilience, emphasizing the significance of including UHI projections in the city's long-term energy infrastructure design. Policies concentrating on green building implementation, cool urban surfaces, and renewable energy adoption are critical for reducing GHG emissions while moderating UHI intensity, maintaining Busan's livability and resilience for its residents [50].

While offering a downscaling approach to estimate future UHI intensity, several limitations to this study should be addressed. First, UHI estimates are based on a single best-performing GCM (CNRM-CM6-1), which may not capture the full range of inter-model uncertainty seen in CMIP6 ensembles. In our examination, CNRM-CM6-1 fulfilled both the $r > 0.90$ and $RMSE < 5.0$ °C criteria. However, adopting a model based solely on historical skill does not ensure the lowest projected uncertainty. Future studies should utilize a formally weighted multi-model ensemble approach, integrating at least the top three GCMs (CNRM-CM6-1, HadGEM3-GC31-LL, UKESM1-0-LL), to offer probabilistic UHI projections and better quantify the inter-model spread for Busan. Second, the statistical downscaling approach (EQM) corrects distributional biases but does not account for changes in atmospheric dynamics or urban land use caused by future development trends. Third, while the AWS network represents Busan's urban–rural gradient, it has low spatial density in hilly sub-districts, implying that EBKR interpolation in such zones is more questionable. Fourth, this study only considers near-surface air temperature. Physical factors influencing UHI intensity include wind speed, atmospheric humidity, and surface characteristics. Future studies should include CMIP6 variables like surface wind speed and near-surface relative humidity, as well as land use change forecasts, to better understand urban thermal stress and its implications on citizen comfort and health. In order to increase the spatial specificity of UHI forecasting, it should also incorporate urban land use change projections, multi-model ensemble approaches, and higher resolution dynamical downscaling. Additionally, researching nighttime versus daytime UHI asymmetry and sub-daily UHI dynamics would yield important information for evaluating energy use and public health effects.

5. Conclusions

This work estimates UHI intensities in SSP2-4.5 and SSP5-8.5 scenarios for Busan City, South Korea, using complicated GCM assessments. Several datasets have been included for defining the baseline, including daily temperatures from 19 AWS stations (2010–2014), coastal distance variables, and DEM elevation data, which will be used by EBKR for interpolation. Following GCM evaluation, CNRM-CM6-1 was identified as the highest correlated GCM to the baseline ($r = 0.902$, $RMSE = 4.937$ °C) representing the future climate. This study used EQM for bias-correction statistical downscaling between baseline and CNRM-CM6-1, which was used after GCM evaluation, to offer UHI intensity projections for the near (2031–2035), middle (2056–2060), and far future (2091–2095). The main findings of this study are the following.

First, Busan's average annual UHI intensity is anticipated to increase significantly under both scenarios, with far-future warming reaching +7.03 °C (SSP2-4.5) and +9.60 °C (SSP5-8.5) relative to the observation baseline, approximately 1.43 times higher under a high-

emission pathway. Second, summer through autumn consistently demonstrates the largest UHI intensification across all periods during the far-future SSP5-8.5. Third, spatial analysis shows that, while near-future UHI changes are uniform across the Busan metropolitan area, far-future growth, particularly under SSP5-8.5, becomes increasingly concentrated in the urban core such as crowded coastal and commercial areas such as Seomyeon, Sasang, Haeundae, and Gwangalli, with rural buffer zones in Gimhae, Yangsan, Milyang, and Changwon losing their relative thermal advantage under extreme forcing conditions.

Collectively, these findings provide identifiable, scenario-specific evidence of increasing UHI risk in Busan, as well as actionable information for urban planners and decision makers. In the short term, adaptation techniques like urban sustainability, cool pavement implementation, coastal wind corridor protection, and district-level heat early warning systems are strongly encouraged. In the long run, aggressive emissions reductions aligned with SSP2-4.5 or lower pathways are required to avoid the severe end-of-century UHI intensification projected by SSP5-8.5, which would make large portions of the Busan urban environment dangerously unpleasant during the summer months.

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Abbreviations

The following abbreviations are used in this manuscript:

UHI	Urban Heat Island
SSP	Shared Socioeconomic Pathways Scenario
GCM	Global Climate Model
EBKR	Empirical Bayesian Kriging Regression
EQM	Empirical Quantile Mapping
AWS	Automatic Weather Station
DEM	Digital Elevation Model
CMIP6	The Coupled Model Intercomparison Project 6
RMSE	Root Mean Square Error
PDF	Probability Distribution Function

KMA	Korean Meteorological Administration
CDF	Cumulative Distribution Function
IPCC	Intergovernmental Panel on Climate Change
AR6 IPCC	The Sixth Assessment Report of Intergovernmental Panel on Climate Change

Appendix A

Table A1. Weather stations selected for this study.

Code	Name	Latitude	Longitude	Code	Name	Latitude	Longitude
<i>Urban</i>				910	Yongdo	35.0661	129.0742
160	Busan-Re	35.1188	129.0000	937	Heundae	35.1761	129.1624
921	Gadeokdo Island	34.9931	128.8314	923	Gijang	35.2751	129.2511
939	Geumjeong-gu	35.2932	129.1035	<i>Rural</i>			
968	South Port	35.0810	129.0450	673	Jinyeong	35.2822	128.7175
940	Dongrae	35.2091	129.0901	905	Yangsang-Sangbuk	35.4414	129.0429
942	Busan Nam-gu	35.1186	129.0884	922	Danjang	35.4865	128.9291
938	Busan-Jin	35.1589	129.0193	925	Saengrim	35.3744	128.8230
941	Buk-gu	35.2130	129.0026	927	Songbaek	35.5820	128.8837
969	North Port	35.0910	129.1270	944	Gilgok	35.3852	128.5701
950	Saha	35.0900	128.9839				

Table A2. Global Climate Models (GCMs) from CMIP6 used in this study.

No.	Model-ID	Institution	Country	Label	Resolution
1	GFDL-CM4	NOAA Geophysical Fluid Dynamics Laboratory	USA	r1i1p1f1	1.2° × 0.9° (~100 km)
2	MRI-ESM2-0	Meteorological Research Institute	Japan	r1i1p1f1	1.1° × 1.1° (~100 km)
3	HadGEM-GC31-LL	Met Office Hadley Centre	UK	r1i1p1f3	1.9° × 1.2° (~135 km)
4	MPI-ESM1-2-LR	Max Planck Institute for Meteorology	Germany	r10i1p1f1	1.9° × 1.9° (~250 km)
5	ACCESS-ESM1-5	CSIRO	Australia	r3i1p1f1	1.9° × 1.2° (~250 km)
6	CanESM5	Canadian Centre for Climate Modelling	Canada	r10i1p1f1	2.8° × 2.8° (~250 km)
7	CESM2	National Center for Atmospheric Research	USA	r4i1p1f1	1.2° × 0.9° (~100 km)
8	CNRM-CM6-1	CNRM/Cerfacs	France	r1i1p1f2	1.4° × 1.4° (~150 km)
9	EC-Earth3	EC-Earth Consortium	Europe	r10i1p1f1	0.7° × 0.7° (~80 km)
10	KACE-1-0-G	Korea Meteorological Administration	South Korea	r1i1p1f1	1.9° × 1.2° (~135 km)
11	KIOST-ESM	Korea Institute of Ocean Science & Tech	South Korea	r1i1p1f1	1.9° × 1.9° (~250 km)
12	NorESM2-LM	Norwegian Climate Centre	Norway	r1i1p1f1	2.5° × 1.9° (~250 km)
13	TaiESM1	Academia Sinica	Taiwan	r1i1p1f1	1.2° × 0.9° (~100 km)
14	UKESM1-0-LL	Met Office Hadley Centre	UK	r10i1p1f2	1.9° × 1.2° (~135 km)
15	IPSL-CM6A-LR	Institut Pierre-Simon Laplace	France	r10i1p1f1	2.5° × 1.3° (~150 km)
16	MIROC6	JAMSTEC/University of Tokyo	Japan	r3i1p1f1	1.4° × 1.4° (~150 km)

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