Heat Exposure Information at Screen Level for an Impact-Based Forecasting and Warning Service for Heat-Wave Disasters

Chaeyeon Yi * and Hojin Yang

Research Center for Atmospheric Environment, Hankuk University of Foreign Studies, Yongin-si, Gyeonggi-do 17035, Korea; hobakzzz@nate.com
* Correspondence: prpr2222@hufs.ac.kr; Tel.: +82-31-8020-5589

Received: 12 July 2020; Accepted: 24 August 2020; Published: 28 August 2020

Abstract: The importance of impact-based forecasting services, which can support decision-making, is being emphasized to reduce the damage of meteorological disasters, centered around the World Meteorological Organization. The Korea Meteorological Administration (KMA) began developing impact-based forecasting technology and warning services in 2018. This paper proposes statistical downscaling and bias correction methods for acquiring high-resolution meteorological data for the heat-wave impact forecast system operated by KMA. Hence, digital forecast data from KMA, with 5 km spatial resolution, were downscaled and corrected to a spatial resolution of 1 km using statistical interpolation methods. Cross-validation indicated the superior performance of the Gaussian process regression model (GPRM) technique with low root mean square error and percent bias values and high CC value. The GPRM technology had the lowest forecast error, especially during the hottest period in Korea. In addition, temperatures for land-use areas with low elevations and high activity, such as the urban, road, and agricultural areas, were high. It is essential to provide accurate heat exposure information at the screen level with high human activity. Spatiotemporally accurate heat exposure information can be used more realistically for risk management in agriculture, livestock and fishery, and for adjusting the working hours of outdoor workers in construction and shipbuilding.

Keywords: heat-waves; meteorological data; statistical downscaling; health hazards; screen level; heat exposure map

1. Introduction

Recently, due to extreme weather phenomena such as heat-waves, the world has experienced setbacks in several sectors, including health, energy, agriculture, dairy, fishery, transportation and tourism [1–3]. A global coupled climate model has shown that there is a distinct geographic pattern to future changes in heat-waves. Model results for areas of Europe and North America, associated with the severe heat-waves in Chicago in 1995 and Paris in 2003, show that future heat-waves in these areas will become more intense, more frequent, and longer lasting in the second half of the 21st century. Further observations and modeling results also show that present-day heat-waves over Europe and North America coincide with a specific atmospheric circulation pattern that is intensified by ongoing increases in greenhouse gases, indicating that it will produce more severe heat-waves in those regions in the future [4]. Similar to the global and continental trends, regional temperatures in Central/Eastern Europe increased during the second half of the 20th century. Furthermore, the regional intensity and frequency of extreme precipitation events increased, while the total amount of precipitation decreased, and the mean climate became drier [5]. Changes in...
maximum temperature ($T_{\text{max}}$) and in heat-wave indices were also studied. Because of changes in both the mean temperature and the variability of $T_{\text{max}}$, heat-waves simulated for the future (2071–2100) across Europe are more frequent, more severe, and last longer. Their intensity and frequency are predicted to increase by at least a factor of 3, with highly differing patterns, depending on season and location. Thus, the increase in heat-wave days observed across large parts of Europe during the last 30 yr is expected to continue (winter) or even accelerate (summer) until the end of this century [6]. Since the introduction of the modern meteorological observation system in South Korea during the summer of 2018, several high temperature-related records have reached all-time highs, including the daily maximum temperature, daily minimum temperature, daily sunshine hours, heat-waves days, and tropical nights. In South Korea, 48 deaths were caused by heat-waves in 2018 (based on the heat-related illness monitoring system), which is twice the number of deaths in the past 3 years [7]. Based on the increasing fluctuations in summertime temperatures, the number of heat-wave days is expected to increase significantly in the future [8,9].

Since 2017, the Korea Meteorological Administration (KMA) has been releasing an “effective wet-bulb globe temperature index” from May to September every year, with the aim of reducing the health hazards caused by hot environments among different social classes and communities. The effective web-bulb globe temperature (WBGT) is based on the existing WBGT, which provides information regarding the heat hazard levels for various heat-vulnerable subjects and environments [10]. Moreover, efforts have been devoted towards minimizing the human casualties due to heat-waves through different heat-wave response policies. Since 2013, the number of heat-related illnesses have been monitored; and shelters, and break time policies for extremely hot weather have been implemented. In 2018, the government legislated heat-waves to be a form of natural disaster and began responding at the government level. However, as the damages caused by heat-waves manifest differently depending on age, occupation, type of household, and climate [11,12], the meteorological data within downscaled spaces and conditions in terms of the population, society, economy, and environment should be considered for forecasting and responding to the impacts of heat-waves [13–20].

Thus far, there has been a lack of comprehensive and quantitative evaluation results regarding the extent of damage and impact of heat-waves owing to the complex and diverse health hazards and socioeconomic impacts. In South Korea, a heat-wave is defined as a daily maximum temperature of 33 °C or higher lasting for two or more days; this definition is different from those in other countries such as the USA, Europe, Japan, and Australia. Due to the lack of a single standard for defining heat-waves, the definitions of a heat-waves may differ with respect to the region. This implies that, instead of restricting heat-waves as a weather phenomenon, the overall impacts and consequences of these heat-waves on human health, ecosystems, and socioeconomic systems need to be considered comprehensively [21].

In this regard, the KMA has been preparing a forecasting service for the impact of heat-waves; this service provides weather forecast data regarding temperature, humidity, wind speed, and solar radiation in order to reflect locally distinguished heat exposure information; provide heat-wave impact assessments in terms of the incidence of heat-related illnesses and death rates; establish class definitions of heat stress for assisting decision making; and enable systems for communicating relevant hazard information to the public, specific groups, or government units [22,23].

As a heat-wave response system, the heat–health behavioral guidelines include heat-wave information for the public with the aim of enhancing vigilance, providing customized information to interested parties, offering personal action tips for individuals to avoid and mitigate heat-wave damage, establishing strategic response plans with a diverse scope for local or national governments, and facilitating emergency management plans for social infrastructures. Additionally, these guidelines also include post-evaluations of crisis management, real-time health monitoring, integration of building and urban planning to reduce heat-related risks in the long term, and systems to continuously monitor the effects of active intervention for heat-waves management and assess efficiency and improvements. For such applications, the heat stress data during heat-waves should reflect the regional characteristics. Thus, high-resolution weather data are used in studies
related to the spatial distribution of weather conditions [24] and as the basis for forecasting heat-wave impacts within downscaled spaces.

Conducting studies to produce high-resolution meteorological data yields physically meaningful meteorological data; however, such studies require considerable computational resources and substantial calculation times. Statistical interpolation has emerged as an important methodology for producing high-resolution meteorological data, despite the limitations resulting from relatively limited computing power and analysis time.

There has been an increase in the number of studies focusing on statistical interpolation due to the growing number of weather observation stations [25–28]. Previously, methods such as inverse distance weight, kriging, natural neighbor, splines, and triangulated irregular network were used; these methods are solely based on the relationship between distances in the observed data [29]. However, as observation data suffer from limitations in reproducing spatial differences in the weather conditions varying with respect to terrains, approaches that employ additional terrain and spatial data have been suggested [30,31]. These approaches include co-kriging and parameter-elevation regressions on independent slopes model [32–41]. Refs. [42,43] proposed a method to parameterize downscaled spatial data, such as buildings in urban areas and land cover, to produce high-resolution meteorological data at an urban scale. Recently, methods such as machine learning and geographically weighted regression analyses have also been employed.

Thus far, studies focusing on statistical interpolation have been conducted as an approach to produce high-resolution weather distribution charts. Furthermore, national-scale research has primarily focused on producing data with a spatial resolution of 1 km, considering the density and simulation efficiency of weather observation networks in South Korea.

Weather forecasts should possess the same spatial resolution as previous weather data in order to forecast the impacts of heat-waves, especially the short-term effects. In several studies, researchers have compared and evaluated interpolation methods in order to identify the approaches suitable for particular factors such as the regions and type of interpolation [44–51]. However, very few studies have attempted to compare and evaluate interpolation methods for spatial downscaling in weather forecasting operations.

This paper proposes statistical interpolation methods for obtaining high-resolution weather forecast data in order to forecast the impacts of heat-waves within the downscaled spaces of the heat-wave impact forecast system currently operated by the KMA and to confirm whether the values for non-observation grids have been estimated appropriately. For this purpose, digital forecast data with a spatial resolution of 5 km, which were provided by the KMA, were downscaled to a spatial resolution of 1 km using various statistical interpolation methods; the results thus obtained were compared and evaluated. Additionally, the suitability of the information regarding areas where people are active with certain screen levels was determined by analyzing heat exposure characteristics based on the type of land use and urban areas in South Korea.

2. Materials and Methods

2.1. Research Area

For this study, the entire Korean Peninsula was considered as the research area, and the weather data were downscaled and corrected bias values for this region. Seven specific areas were selected for the downscaling analyses in the major cities (Figure 1): Incheon, Seoul, Daejeon, Daegu, Gwangju, Ulsan, and Busan. The characteristics of these areas are listed in Table 1. Geographic elevations and the land cover data for each city were acquired from the National Geographic Information Service and the Ministry of Environment, respectively.
Table 1. Climate, area, and observed temperatures for each research area (from June to August for 2010–2019; the maximum values are provided in parentheses).

| Name     | Climate  | Land Use    | Area (Ha) | Number of Observation Stations | Daily Average Temperature | Daily Maximum Temperature | Daily Minimum Temperature |
|----------|----------|-------------|-----------|--------------------------------|---------------------------|--------------------------|--------------------------|
| Incheon  | Oceanic  | Forests     | 6010      | 112                             | 24.3                      | 32.1                     | 17.7                     |
|          |          | * Urban area| 4523      |                                 | (28.1)                    | (36.0)                   | (21.6)                   |
| Seoul    | Continental | Agricultural area | 14,838   | 14,113                          | 25.4                      | 34.4                     | 17.8                     |
|          |          | Urban area   | 1858      | 108                             | (28.8)                    | (39.6)                   | (21.9)                   |
|          |          | Forests     | 34,280    |                                 |                           |                          |                          |
|          |          |             | 27,053    |                                 |                           |                          |                          |
| Daejeon  | Continental | Agricultural area | 7549      | 133                             | 25.5                      | 34.3                     | 17.1                     |
|          |          | Urban area   | 9973      |                                 | (29.0)                    | (39.4)                   | (22.3)                   |
|          |          | Forests     | 47,552    |                                 |                           |                          |                          |
| Daegu    | Continental | Agricultural area | 11,383    | 143                             | 25.9                      | 36.0                     | 17.3                     |
|          |          | Urban area   | 16,260    |                                 | (29.0)                    | (39.2)                   | (22.9)                   |
| Gwangju  | Continental | Agricultural area | 14,434    | 156                             | 25.6                      | 34.6                     | 18.0                     |
|          |          | Urban area   | 11,140    |                                 | (28.4)                    | (38.5)                   | (22.9)                   |
|          |          | Forests     | 66,073    |                                 |                           |                          |                          |
| Ulsan    | Oceanic  | Agricultural area | 12,603    | 152                             | 24.7                      | 34.3                     | 16.9                     |
|          |          | Urban area   | 11,482    |                                 | (29.0)                    | (38.8)                   | (22.4)                   |
|          |          | Forests     | 33,919    |                                 |                           |                          |                          |
| Busan    | Oceanic  | Agricultural area | 9001      | 159                             | 24.6                      | 32.1                     | 18.4                     |
|          |          | Urban area   | 18,155    |                                 | (28.0)                    | (37.3)                   | (24.0)                   |

* Urban areas include roads.

Figure 1. Location of the research areas in (a) South Korea, and land cover distributions in the capital and metropolitan areas. (b) Incheon (islands excluded); (c) Seoul; (d) Daejeon; (e) Daegu; (g) Ulsan; and (h) Busan. In the figures (b) to (h), the weather observation sites of the Korea telecom (KT) corporation network in the urban area have been indicated (gray dots).
2.2. Digital Forecast System of the KMA

The digital forecast system of the KMA is a service that provides weather forecasts every three hours in Eup-, Myeon-, and Dong-district units. There are 149 grids in the east–west direction and 253 grids in the north–south direction, resulting in a total of 37,697 grids (i.e., 4438 grids in the inland area). A forecast is announced eight times per day at 3 h intervals from +4 h to + 58–67 h. Temperatures (3 h, daily maximum, and daily minimum), wind direction, wind speed, sky conditions (clear, few clouds, many clouds, and cloudy), precipitation, probability of precipitation, amount of precipitation, snowfall, humidity, and waves are forecasted.

The initial data for digital forecasts are acquired from the KMA’s unified model, which covers the Korean Peninsula and its surrounding waters, with a spatial resolution of 40 km. These data are corrected through the gridded model output statistics technique and forecasters in order to produce gridded data for the Korean Peninsula, which has an area of 745 km × 1265 km, at 5 km intervals.

Digital forecasts can be categorized based on the KMA’s digital analyzed data and the digital forecast data. Digital analyzed data are live data updated each hour from the standard time (t), using a total of 533 stations (i.e., 91 Automated Synoptic Observation System (ASOS) and 442 Automatic Weather System (AWS)). On the other hand, digital forecast data are based on the digital analyzed data and are forecasted 4 h after the standard time (t + 4–48). Gridded digital forecast data in the GRIdded Binary (GRIB) format, provided by the KMA, are converted to the GeoTiff format using geospatial data abstraction library in order to facilitate the process in GIS and stored and managed as Image Mosaic layers in GeoServer. In this study, data were collected during the summer of June–August 2018, starting at a standard time of 06:00. The daily maximum temperature (daily minimum temperature) data, collected several hours after the standard time, were used as the input data for interpolation.

2.3. Ground Observation Data

In this study, verification was performed by using observation data that had not been used for downscaling the 5 km resolution digital forecasts to a local scale with the resolution of 1 km. Since 2017, the Korea telecom (KT) mobile telecommunication company has been collecting high-density particulate matter and meteorological data (temperature and humidity) as part of the Air Map Korea Project involving 1500 locations built in seven cities: Seoul, Incheon, Daejeon, Daegu, Gwangju, Ulsan, and Busan. The measurement devices are installed on building rooftops (3–15 m above ground level) and on public telephone booths (2.5 m above ground level); only the data acquired at a height of 2.5 m from the ground level were used for verification.

The hourly data for the period between June and August 2018 were used. For each city, 20 observation points with a distance of more than 1 km between each other were selected; these points are represented by the gray dots in Figure 1. A majority of the meteorological data collected by KT were from urban areas and telephone booths located along pedestrian streets; thus, they reflected the weather conditions of locations and elevations with residential areas. Point verifications of the results from downscaling KT’s meteorological observation data from June to August 2018 were conducted using the support vector machine (SVM), random forest (RF), and Gaussian process regression model (GPRM) techniques. The verification indices included root mean square error (RMSE), correlation coefficient (CC), and percent bias (PBIAS).

Additionally, ASOS data were used to analyze the extent to which the surface data affected the observation points, including the daily maximum temperature, average temperature, and minimum temperature data from 88 points during the summer from 2003 to 2017. These ASOS data were also used to analyze the correlations among different areas with residential sectors (cities, roads, and farms).

2.4. Surface Data

In this study, surface data associated with the spatial distribution of temperatures were used as the independent variables for interpolation, in addition to the daily maximum temperature, which was used as a dependent variable for spatial interpolation. The independent variables used in this
study are the elevation above sea level, slope angle, distance from the shoreline, land cover, hollow depth, north–south azimuth, east–west azimuth, and slope aspect (Figure 2). The topographic data for the independent variables were calculated with a resolution of 1 km using the analysis algorithm in GIS [25]. The initial data for calculating surface data included the sub-divided land cover map from the Ministry of Environment and the digital map from the National Geographic Information Service. All the data used were in UTM-K coordinates. The independent variables were chosen to account for factors such as the temperature reduction rate, difference in heat emissions based on terrain, and duration of the sun’s influence (Table 2).

Table 2. Surface data of the ground surface analysis model.

| Data                | Label                  | Description                                                                 | Units |
|---------------------|------------------------|-----------------------------------------------------------------------------|-------|
| lon, lat            | Location               | Location                                                                    | -     |
| Elevation           | Temperature reduction  | Temperature reduction rate due to elevation                                 | m     |
| Slope               | Heat emissions from    | Heat emissions from the ground surface due to the angle of incidence of the  | deg   |
| Aspect              | Heat emissions from    | Heat emissions from the ground surface due to the direction of incidence of  | deg   |
| Surface             | dzdx                   | Time and intensity of the sun’s influence                                   | m/m   |
| data                | dzdy                   | Duration and intensity of the sun’s influence                               | m/m   |
| Hollow depth        | Heat-trapping phenomenon | Heat-trapping phenomenon                                                    | m     |
| distance from       | Distance affected by   | Distance affected by the ocean                                              | m     |
| shoreline           | the ocean              |                                                                             |       |
| Land cover          | Heat absorption and    | Heat absorption and emission due to land cover                             | -     |

![Figure 2. Surface data used in this study at a resolution of 1 km: (a) elevation, (b) slope, (c) aspect, (d) dzdx, (e) dzdy, (f) hollow depth, (g) distance from shoreline, and (h) land cover. The figure of [1] was referenced.](image)
2.5. Statistical Model and Evaluation Method

Modeling was performed using real-time temperature analysis data of the KMA (5 km grid that has already been assimilated with observation data) and spatially matching surface data (elevation, slope, aspect, etc.) as learning data. In this modeling approach, the relationship between temperature and surface data is learned, and the unknown temperature value is then predicted for each new 1 km grid. Statistical methods were used for the modeling and prediction processes.

The GPRM technique is a regression analysis method that employs Gaussian probability; it is a type of Bayesian nonparametric algorithm. It predicts the label of data in terms of probability distributions of the mean and variance; it also achieves a higher predictive performance than other regression models, despite the increased complexity. Various approximation methods have been used to handle the difficulties in computation when dealing with large-scale data. The Gaussian process can be defined based on the mean and covariance, where covariance is specified as a hyper-parameter. During the learning process, an initial value is assigned to the hyper-parameter, and iterative calculations are conducted to determine the optimal hyper-parameter, while minimizing the log marginal likelihood [52–54].

The RF technique is a model involving numerous decision trees, whereby various training data are created in a single dataset in order to generate several decision trees and combine the results. In a random forest, trees are generated by selecting m divided by 3 variables in each partition, where m is the number of variables. The predicted value of each tree is non-correlated because a random forest is composed of slightly different trees due to the sampling data and variables; this improves its performance in generalization [55].

The SVM technique is a machine learning approach that involves a map-learning model for pattern recognition and data analyses. It is mainly used for classification and regression analyses. For a given dataset, a non-probabilistic binary-linear classification model is generated to determine how new data are classified. While the generated model is expressed as boundaries of a space where the data exist, the SVM algorithm identifies the broadest boundary among them [42,56,57].

In this study, statistical downscaling was employed along with these methods, and the terrain elevation, slope angle, distance from the shoreline, land cover, hollow depth, south–north azimuth, east–west azimuth, and slope aspect were used as independent variables.

Two types of verifications were performed on the downscaled daily maximum and minimum temperature results. The first is a statistical technique whereby the KMA’s digital analyzed data with a resolution of 5 km were downscaled to digital analyzed data with a resolution of 1 km through spatial interpolation in order to cross-validate downscaled spatial grids. Cross-validation was conducted by modeling the data into a validation set (10% of the total data) and learning set (90% of the total data); thereafter, the statistical values were calculated, including RMSE, CC, and PBIAS. This process is iterated by varying the verification and learning sets in order to calculate the verification indices. For each technique, the verification and learning sets were randomly divided with a ratio of 1:9 into five separate folds for the verification.

The second verification involved verifying the KMA’s digital forecast data with a resolution of 1 km downscaled using the selected statistical method. For this purpose, two types of data were used: assimilated live digital analyzed data for verifying the digital forecast data; and a portion of KT’s meteorological observation data that was not used in the training set to verify the digital forecast data with a resolution of 1 km. RMSE, CC, and PBIAS were used as the verification indices. The flow diagram of this research in presented in Figure 3.
3. Results

3.1. Digital Analyzed Data Downscaled to a 1 km Resolution for Daily Maximum and Minimum Temperatures

The recent heat-wave events that occurred during the summer of 2016 to 2018 were selected, and the corresponding daily maximum and minimum temperature variables were downscaled to a resolution of 1 km (Figures 4 and 5). K-fold cross-validation was conducted on these downscaled daily maximum and minimum temperatures, which indicated that the GPRM technique yielded superior results in terms of the RMSE, CC, and PBIAS (Tables 3 and 4).
In a majority of the events, the RMSE prediction error was found to be the highest when using the SVM technique and the lowest when using the GPRM technique. The GPRM technique exhibited an improvement of 0.35–0.59 °C as compared to the SVM technique; this indicates its superiority in spatial predicting when downscaling the 5 km resolution grids to 1-km resolution grids. The value of CC was high (0.92 or greater) when using the GPRM technique; this also reflects the superiority of this technique. For a majority of the events, the PBIAS values, representing differences between the predicted and the actual values within a space in terms of numerical percentages, were found to be underestimated and calculated as negative values when using the SVM technique. PBIAS values of −0.12 (2016), −0.19 (2017), and −0.13 (2018) were regarded as biased and underestimated by 12%, 19%, and 13%, respectively. Furthermore, the GPRM and RF techniques did not appear to be particularly biased as they resulted in values near 0.
The CC and PBIAS values were similar to those of the daily maximum temperatures, indicating that the downscaling of daily minimum temperatures was more accurate. The RMSE values of the daily minimum temperature were higher than those of the daily maximum temperature, indicating that the downscaling of daily minimum temperatures was more accurate. The CC and PBIAS values were similar to those of the daily maximum temperatures, whereas the RMSE value was approximately 0.25 °C lower. This is believed to be a result of the more significant influence of surface data.

**Table 3. Cross-validation results via spatial prediction techniques applied to daily maximum temperatures.**

| Date       | RMSE [°C]  | CC  | PBIAS [%] |
|------------|------------|-----|------------|
|            | GPRM | RF | SVM | GPRM | RF | SVM | GPRM | RF | SVM |
| 2016-08-07 | 0.41 | 0.83 | 1.01 | 0.97 | 0.86 | 0.78 | 0.00 | -0.04 | -0.10 |
| 2016-08-08 | 0.46 | 0.84 | 1.03 | 0.96 | 0.87 | 0.78 | 0.02 | -0.02 | -0.06 |
| 2016-08-09 | 0.48 | 0.93 | 1.15 | 0.97 | 0.90 | 0.83 | -0.04 | -0.16 | -0.28 |
| 2016-08-10 | 0.45 | 0.87 | 1.13 | 0.98 | 0.93 | 0.86 | -0.02 | -0.06 | -0.14 |
| 2016-08-11 | 0.44 | 0.82 | 0.97 | 0.96 | 0.87 | 0.81 | -0.02 | 0.00 | -0.06 |
| 2016-08-12 | 0.48 | 0.83 | 1.01 | 0.96 | 0.89 | 0.82 | -0.02 | -0.04 | -0.12 |
| 2016-08-13 | 0.47 | 0.82 | 1.03 | 0.96 | 0.89 | 0.81 | 0.02 | 0.06 | -0.10 |
| Average    | 0.46 | 0.85 | 1.05 | 0.97 | 0.89 | 0.81 | -0.01 | -0.04 | -0.12 |
| 2017-08-01 | 0.64 | 0.89 | 1.15 | 0.97 | 0.93 | 0.89 | 0.04 | 0.06 | -0.06 |
| 2017-08-02 | 0.74 | 1.07 | 1.34 | 0.95 | 0.90 | 0.84 | 0.04 | 0.06 | -0.16 |
| 2017-08-03 | 0.74 | 1.08 | 1.29 | 0.94 | 0.86 | 0.80 | 0.00 | -0.06 | -0.24 |
| 2017-08-04 | 0.71 | 1.03 | 1.32 | 0.95 | 0.88 | 0.79 | 0.02 | 0.02 | -0.24 |
| 2017-08-05 | 0.74 | 1.16 | 1.37 | 0.93 | 0.84 | 0.75 | -0.02 | -0.02 | -0.30 |
| 2017-08-06 | 0.79 | 1.19 | 1.44 | 0.94 | 0.85 | 0.76 | 0.00 | 0.02 | -0.14 |
| 2017-08-07 | 0.80 | 1.13 | 1.42 | 0.95 | 0.90 | 0.84 | 0.06 | -0.06 | -0.16 |
| Average    | 0.74 | 1.08 | 1.33 | 0.95 | 0.88 | 0.81 | 0.02 | 0.02 | -0.19 |
| 2018-08-10 | 1.02 | 1.17 | 1.36 | 0.92 | 0.90 | 0.85 | 0.00 | 0.02 | -0.18 |
| 2018-08-11 | 1.08 | 1.18 | 1.41 | 0.95 | 0.95 | 0.92 | -0.08 | -0.08 | -0.20 |
| 2018-08-12 | 1.01 | 1.15 | 1.35 | 0.94 | 0.92 | 0.89 | 0.06 | 0.04 | -0.08 |
| 2018-08-13 | 1.11 | 1.23 | 1.38 | 0.89 | 0.86 | 0.82 | -0.02 | -0.06 | -0.22 |
| 2018-08-14 | 1.05 | 1.17 | 1.34 | 0.88 | 0.85 | 0.79 | 0.02 | 0.02 | 0.04 |
| 2018-08-15 | 1.08 | 1.21 | 1.42 | 0.88 | 0.85 | 0.78 | 0.02 | 0.02 | -0.18 |
| 2018-08-16 | 1.07 | 1.21 | 1.45 | 0.92 | 0.89 | 0.84 | 0.00 | -0.02 | -0.22 |
| 2018-08-17 | 1.12 | 1.23 | 1.43 | 0.96 | 0.95 | 0.93 | 0.02 | 0.06 | -0.02 |
| Average    | 1.07 | 1.19 | 1.39 | 0.92 | 0.90 | 0.85 | 0.00 | 0.00 | -0.13 |

**Table 4. Cross-validation results via spatial prediction techniques applied to daily minimum temperatures.**

| Date       | RMSE [°C]  | CC  | PBIAS [%] |
|------------|------------|-----|------------|
|            | GPRM | RF | SVM | GPRM | RF | SVM | GPRM | RF | SVM |
| 2016-08-07 | 0.38 | 0.65 | 0.77 | 0.97 | 0.90 | 0.85 | -0.02 | 0.02 | -0.04 |
| 2016-08-08 | 0.37 | 0.69 | 0.87 | 0.97 | 0.88 | 0.79 | -0.04 | -0.10 | -0.18 |
| 2016-08-09 | 0.36 | 0.69 | 0.85 | 0.98 | 0.92 | 0.86 | -0.02 | -0.04 | -0.02 |
| 2016-08-10 | 0.34 | 0.62 | 0.81 | 0.98 | 0.94 | 0.89 | -0.04 | -0.06 | -0.12 |
| 2016-08-11 | 0.36 | 0.68 | 0.87 | 0.97 | 0.91 | 0.83 | 0.00 | 0.02 | -0.02 |
| 2016-08-12 | 0.37 | 0.68 | 0.87 | 0.97 | 0.91 | 0.85 | 0.02 | -0.02 | -0.04 |
| 2016-08-13 | 0.39 | 0.77 | 0.94 | 0.97 | 0.89 | 0.82 | -0.04 | 0.02 | 0.06 |
| Average    | 0.37 | 0.68 | 0.85 | 0.97 | 0.91 | 0.84 | -0.02 | -0.02 | -0.05 |
| 2017-08-01 | 0.46 | 0.66 | 0.76 | 0.96 | 0.91 | 0.88 | 0.02 | 0.08 | -0.06 |
| 2017-08-02 | 0.49 | 0.72 | 0.86 | 0.96 | 0.92 | 0.88 | 0.04 | 0.08 | -0.06 |
| 2017-08-03 | 0.54 | 0.80 | 0.97 | 0.98 | 0.95 | 0.92 | -0.12 | -0.10 | -0.22 |
| 2017-08-04 | 0.50 | 0.77 | 0.94 | 0.97 | 0.93 | 0.88 | 0.00 | -0.04 | -0.12 |
| 2017-08-05 | 0.49 | 0.79 | 0.95 | 0.96 | 0.91 | 0.86 | 0.02 | 0.02 | -0.08 |
| 2017-08-06 | 0.50 | 0.79 | 0.89 | 0.97 | 0.93 | 0.90 | 0.08 | 0.10 | 0.02 |
| 2017-08-07 | 0.52 | 0.79 | 0.97 | 0.95 | 0.89 | 0.83 | 0.06 | 0.16 | -0.04 |
3.2. Daily Maximum and Minimum Temperatures Downscaled to 1 km Resolution Digital Analyzed Data Using Different Techniques

The performance of predicting high temperatures was compared for the techniques based on the daily maximum and minimum temperature frequencies. It was found that the predicted distributions of the temperature range varied even within the same area. In a majority of the areas, the range of temperature distributions was relatively wider when using the GPRM technique, as compared to those when using the RF and SVM techniques (Figures 6 and 7).

For the daily maximum temperatures, the SVM and RF techniques predicted a low frequency of high temperatures and even no frequency in certain areas. In particular, for Seoul, the GPRM technique yielded a prediction in the range of 39.5–41.0 °C, even when there were no predicts by the SVM and RF techniques. The SVM and RF techniques tend to result in distributions within certain temperature ranges. However, the GPRM technique exhibited a relatively wider temperature distribution range without leaning toward a particular range, thereby resulting in higher and lower temperature distributions as compared to the other techniques.

The SVM and RF are representative machine learning models for making predictions. Shmueli 2010 [58] distinguished statistical models into explanatory predictive models. Machine learning aids scientific interpretations, but has some limitations. Statistical models created via machine learning belong to predictive models that cannot be explanatory model because of their complexity. However, GPRM is a spatial linear model, in which the covariance matrix and spatial correlation generally follow the Gaussian process. This process serves to increase the correlation between the actual values of an area with similar geographical characteristics. For this reason, the range of temperature distribution predicted spatially is broadened and the performance is considered excellent.

The GPRM technique (red colored line, Figures 6 and 7) indicated a high frequency of high-temperature occurrences, especially in the inland cities such as Seoul, Daejeon, Daegu, and Gwangju. This is because the GPRM technique appears to be more sensitive towards surface data, which affects the calculation of daily maximum temperatures.

The distribution of the daily minimum temperature was similar for the RF and GPRM techniques; both these approaches exhibited better prediction performance for the higher temperatures in all the areas, as compared to the SVM technique.
Figure 6. Comparison of daily maximum temperature distributions (on 1 August 2018) with respect to the techniques for a downscaled 1 km resolution. (b) Incheon; (c) Seoul; (d) Daejeon; (e) Daegu; (f) Gwangju; (g) Ulsan; (h) Busan. (b–h) are the analysis areas shown in Figure 1.
Figure 7. Comparison of daily minimum temperature distributions (on 2 August 2018) with respect to the techniques for a downscaled 1 km resolution. (b) Incheon; (c) Seoul; (d) Daejeon; (e) Daegu; (f) Gwangju; (g) Ulsan; (h) Busan. (b–h) are the analysis areas shown in Figure 1.
3.3. Verification of KMA’s Digital Forecast Data Downscaled to a 1 km Resolution

Point verification was performed on the downscaled digital forecast data using the SVM, RF, and GPRM techniques on KT’s meteorological observation data collected during the summer of June to August 2018. RMSE, CC, and PBIAS were used as the verification indices in order to verify the downscaled digital forecast data using KT’s meteorological observation data. The RMSE values were found to be 2.8, 2.9, and 3.0 °C when using the SVM, RF, and GPRM techniques, respectively; on average, the CC value was 0.9 or greater, as compared with all the three techniques. The PBIAS values, ranging from −7.5 to +7.8%, were slightly underestimated (negative values). The three techniques exhibited a similar tendency in June, whereas the accuracy of the GPRM technique was relatively higher (low RMSE, high CC, and low PBIAS) than that of the other two techniques when the heat-waves intensity increased during July and August (Figure 8).

Figure 8. Verification results of daily maximum temperature prediction data with a 1 km resolution using observation data for the urban areas. The bright orange shading is the hottest time of summer in Korea.
3.4. Analysis of Spatial Characteristics of Major Cities

The downscaled data for the seven major cities were analyzed using the GPRM technique, which demonstrated relatively superior verification indices than the other techniques. The daily maximum and minimum temperatures were extracted by dividing each major city into road, water, grass and bare soil, forest, agricultural, and urban areas.

Seoul, Daejeon, Daegu, and Gwangju are the inland cities investigated, and the daily maximum temperature during the daytime in these cities varies little (interquartile range (IQR) is small), being 38 to 39 °C on average. In Incheon, Ulsan, and Busan, which are coastal cities, the temperature variability is large (IQR is large), even during daytime, with average values of 33 to 35 °C. Based on these data, the inland cities exhibit higher temperatures than the coastal cities during daytime.

With regard to the daily maximum temperature, a range of 37–39 °C was predicted for the inland cities of Daejeon, Daegu, and Gwangju; a range of 37–41 °C was predicted for Seoul; a range of 30–36 °C was predicted for the coastal cities of Ulsan and Busan; and a range of 33–39 °C was predicted for Incheon. Temperature variation ranges of 3 °C and 7 °C were observed for the inland and coastal cities. Incheon did not exhibit a similar temperature range as Busan and Ulsan, despite being a marine city. This was attributed to the heat sources within the infrastructure of Incheon and its relative location with respect to the sea. A significant proportion of land cover in Incheon has been urbanized; contrarily, forests account for a major proportion of the land cover in Busan and Ulsan (Table 1).

The temperature range in Seoul is different from that in the other inland cities, such as Daejeon, Daegu, and Gwangju, because of its high urban area ratio. Incheon and Seoul are located in the capital region of South Korea; feature the highest density of buildings, population, and traffic; and experience intensive land use. These factors could possibly affect the prediction results [59–61].

Considering the various land-use types, the highest daily maximum temperature values were observed in the urbanized areas of Incheon, Seoul, Daejeon, and Gwangju, in terms of both mean and maximum values (Figure 9b,c,d,f). In Ulsan and Busan, the mean value of agricultural and road areas was higher than that of urban areas (Figure 9g,h). The daily minimum temperatures of Seoul and Daejeon were higher in the urban areas, as compared to that in the other land areas (Figure 10c,d). Moreover, the daily minimum temperatures of Daegu and Gwangju were higher for the road areas, as compared to the urban areas. Since most of the urban areas are located on the coast of Busan and Ulsan, it was assumed that the heat absorption and emission processes in the three-dimensional structure of the city will be affected by wind blowing from the sea.

In the IQR of the daily minimum temperature distribution by land cover (Figure 10), high temperature trends were predicted for roads and urban areas in most regions, while agricultural areas in Busan were on average 0.3 °C warmer than roads and urban areas. In Seoul, agricultural areas were cooler than urban areas and warmer than roads, which was thought to be due to the fact that agricultural areas in Busan or Seoul occupy a smaller land proportion than in other areas. Given this small contribution of the agricultural areas (3.6% in Seoul and 14.5% in Busan), the 1-km resolution seemed to insufficiently reflect these patterns.

The correlations between surface and meteorological observation parameters (last 15 summers, 2003–2017), indicated that the correlations were stronger in August than in July. In addition, the daily minimum temperature, daily average temperature, and daily maximum temperature had a clear order (Table 5). The coefficient of determination was particularly high for the correlation between the surface data and the daily minimum temperature, which indicates that synoptic weather conditions are dominant factors during the day, while surface conditions have a greater effect at night. The correlation between the surface data and the daily minimum temperature was high and indicated that high temperatures appeared in low-altitude urban areas, while the high correlation to the daily maximum temperature indicated that high temperatures appeared in low-altitude agricultural areas.
Table 5. Correlations among meteorological elements and surface data.

| Meteorological Elements | July 2003–2017 | August 2003–2017 |
|-------------------------|----------------|-------------------|
| Daily average temperature | Surface data: hollow depth, urbanization area, agriculture area, elevation | R²: 0.61 | Surface data: elevation, urbanization area | R²: 0.71 |
| Daily maximum temperature | Surface data: distance from the shoreline, elevation, agriculture area | R²: 0.48 | Surface data: elevation, distance from the shoreline | R²: 0.55 |
| Daily minimum temperature | Surface data: urbanization area, elevation | R²: 0.68 | Surface data: urbanization area, elevation, distance from the shoreline | R²: 0.73 |

Figure 9. Daily maximum temperature distribution on 1 August 2018 with respect to the land use in each city. (b) Incheon; (c) Seoul; (d) Daejeon; (e) Daegu; (f) Gwangju; (g) Ulsan; (h) Busan. (b–h) are the analysis areas shown in Figure 1.
Figure 10. Daily minimum temperature distribution on 2 August 2018 with respect to the land use in each city. (b) Incheon; (c) Seoul; (d) Daejeon; (e) Daegu; (f) Gwangju; (g) Ulsan; (h) Busan. (b)–(h) are the analysis areas shown in Figure 1.
3.5. Correlation between Screen Level (Activity Height of People) and Observation Data

The purpose of generating detailed weather information as part of the heat-waves forecasts is to predict the risk of exposure to weather elements at a specific elevation where people are active. A common tendency observed in each city is the higher temperatures for urban, agricultural, and road areas, as compared to the other land cover areas. To analyze the explanatory power of the applicable land cover data, the overall grids in each city (mountains, streams, urban, and agricultural areas included; I, Figure 11b) and the urban and agricultural grids where people reside (mountains and streams excluded; II, Figure 11c) were separated, and their correlations with the observed daily maximum and minimum temperature data were analyzed (Figure 11).

The overall grids (I) of the digital analyzed data with a resolution of 1 km and the extracted urban and agricultural area data (II) were compared by subtracting (I) from (II), whereby a positive value would indicate a higher temperature for the extracted data in the urban and agricultural areas. From June to August for 2016–2018, the daily maximum temperature was 85% and the daily minimum temperature was 92% for the cases where the extracted data for urban and agricultural areas were high with respect to the city, county, and district. In August 2018, the daily maximum and minimum temperatures exhibited a difference of 0.5–1.5 °C in the forest areas, with a more significant difference between (I) and (II) along the East Coast for the daily minimum temperature.

When the overall grid data (I) and the extracted data for urban and agricultural areas (II) were compared with the data from 88 ASOS observation points across the country, the observed daily maximum and minimum temperatures and the values of (II) exhibited a higher coefficient of determination and explanatory power (over 70%) for the analysis of average daily maximum and minimum temperatures during July and August of 2018 (Figure 12).

As observed in the temperature distributions at a downscaled resolution of 1 km, the higher correlation of temperature in urban and agricultural areas, which is associated with people’s activity, with the actual observation data representative of these areas implies that downscaling meteorological elements is suitable for spatial heat exposure analyses and predictions. It is also believed that the temperature information applicable to urban and agricultural areas should be included in the detailed meteorological information as a part of the impact forecasts.

Figure 11. (a) Two types of land used for analyzing the temperature correlations at the screen level; (b) daily minimum temperature distribution of 167 administrative boundary units, based on all the grids (average of August 2018); and (c) daily minimum temperature distribution of 167 administrative boundary units based on urban and agricultural grids (average of August 2018). The black dots in (b) and (c) represent the 88 ASOS observation points.
4. Discussion

The detailed heat exposure information calculated in this study was used to forecast the effects of heat-waves. The daily change in the rate of mortality at a given temperature per average summer mortality (MCR) was analyzed as a result of the damage effect of the heat-waves. Age, occupation, household type, chronic disease, and regional temperature distribution were considered. As a result, it was confirmed that MCR depends on socio-economic factors and the regional temperature distribution [16]. It was found that the MCR of the elderly, outdoor workers, chronically ill, and single-person households were relatively high compared to other groups. However, current warnings and policies on heat-waves do not appear effective for the elderly and outdoor workers. In particular, the regional temperature distribution was found to be one of the key factors to consider when determining the effects of heat-waves. The regional temperature distribution should be taken into account when establishing heat alert levels and practical and effective policies. To establish a heat-wave policy at the regional level, it is suggested that the heat stress risk assessment in cities should be carried out separately for vulnerable areas and vulnerable groups via a heat stress impact assessment to quantify vulnerability. For example, high-risk areas can focus on reducing heat loads, such as by greening and shadowing, while vulnerable people can be protected, e.g., by providing shelters for people who are economically vulnerable to heat stress, or through special care for the elderly, i.e., groups can be focused on [23]. Through this heat stress impact assessment, the heat stress map and high temperature early warning system by the National Institute of Meteorological Science were used to develop a prototype of an event-based heat-related risk assessment model. The highest daily temperature for predicting the summer excess mortality rate for six major cities in Korea, the daily maximum air temperature (T\text{max}), the daily maximum perceived temperature (PT\text{max}), and the daily maximum wetbulb globe temperature (WBGT\text{max}) were compared to assess the risks associated with heat. In this study, it was found that the highest PT\text{max} during the day showed the best performance in expressing the thermal stress for Koreans. To use PT\text{max}, the necessity of collecting temperature, dew point temperature, relative humidity, wind speed, cloud amount, and geographical information data was presented [11]. However, at present, spatially detailed data are not available for all areas of Korea. The detailed weather information

![Figure 12. Correlations among daily maximum temperature, overall grids (I), and urban and agricultural areas (II). The first row pertains to the daily maximum temperature, whereas the second row pertains to the daily minimum temperature. (a) Average daily maximum air temperature in July; (b) Average daily maximum air temperature in August; (c) Average daily minimum air temperature in July; (d) Average daily minimum air temperature in August. (a–d) are the average daily temperature in summer.](image-url)
system we developed calculates temperature, humidity, insolation (opposite cloudiness), and wind speed forecasts for every hour as well as daily maximum and minimum temperatures associated with heat exposure information. This information can be used for early warning by connecting detailed weather information to forecast PT\textsubscript{max} during summer in Korea.

5. Conclusions

This paper proposes statistical interpolation methods for acquiring high-resolution meteorological data for the heat-wave impact forecast system currently operated by the KMA. For this purpose, digital forecast data with a spatial resolution of 5 km, provided by the KMA, were downscaled and corrected to a spatial resolution of 1 km using various statistical interpolation methods; the results thus obtained were compared and evaluated. The statistical interpolation methods used included the SVM, RF, and GPRM techniques. Surface data with a resolution of 1 km and the digital analyzed data were used as the learning data for modeling. The values estimated via downscaling to a resolution of 1 km were cross-validated, indicating the superior performance of the GPRM technique with low RMSE and PBIAS values and a high CC value. This is because the GPRM technique involves an iterative estimation process to determine a solution that is closest to the actual value, while accounting for surface data, in order to build a model. The widest range of estimated daily maximum temperature distributions was obtained using the GPRM technique; however, the SVM and RF techniques were more focused on certain temperature ranges. As it is essential for heat-wave impact forecasts to predict high-temperature occurrences when people are more exposed during the day (i.e., the daily maximum temperature) and at night (i.e., the daily minimum temperature), the GPRM technique is considered to be an optimal solution. Based on the verification for urban areas, which was performed using a portion of KT’s meteorological data (from 132 locations in major cities) that had not been used as learning data, the GPRM technique demonstrated superior performance and resulted in the lowest prediction errors from mid-July to mid-August, which is the duration of the highest summer temperatures in South Korea.

On analyzing the daily maximum temperature in terms of the land-use type, the highest values were observed in the urban areas of Incheon, Seoul, Daejeon, and Gwangju. Moreover, the mean values were high for the agricultural and road areas in Ulsan and Busan. The daily minimum temperature in the urban areas was higher than that in the other land-use areas of Seoul and Daejeon. Alternatively, it was higher in the road areas than in the urban areas of Daegu and Gwangju. The temperatures for land-use areas with low elevations and high activity of people, such as the urban, road, and agricultural areas, were high; these surface variables were highly correlated with the meteorological observation data. The correlation between urban, road and agricultural areas with the observed meteorological data for these areas was analyzed. As a result, of analyzing the correlation, it should not be down-leveled due to low grid values in areas with mountains or rivers in the phase of providing weather information of the heat-waves forecast system. Currently, it is provided on an administrative boundary basis, and is calculated on average with urban, road, and agricultural areas with high heat exposure, along with mountains or rivers with low heat exposure. It is essential to provide accurate heat exposure information in areas with high human activity. The more detailed spatially and temporally accurate heat exposure prediction information can be used more realistically for the health of people engaged in agriculture, livestock and fisheries, and outdoor workers such as construction and shipbuilding.

Author Contributions: C.Y. conceived and designed the experiments; C.Y. and H.Y. performed the experiments and analyzed the data; H.Y. contributed to data collection and analysis tools; C.Y. wrote the paper; Anonymous reviewers and editors gave scientific comments. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Korea Meteorological Administration grant number KMI2018-01410.

Acknowledgments: This research was funded by the Korea Meteorological Administration Research and Development Program grant number KMI (KMI2018-01410).
Conflicts of Interest: The authors declare no conflict of interest. The funding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

References

1. Yang, H.J.; Yi, C.; Chae, Y.; Park, J. Comparison of statistical interpolation methods for downscaling of summer temperature data from the Korea Meteorological administration’s digital forecasts. Assoc. Korean Photo-Geogr. 2019, 29, 19–32.
2. Lee, J.J.; Sung, N.M.; Park, B.J.; Lee, J.S.; Kang, K.W. Transportation strategies under adverse weather conditions for climate change adaptation. Korea Transp. Inst. 2011, 21, 1–159.
3. Gómez-Martín, M.B.; Martínez-Ibarra, E. The Spanish tourist sector facing extreme climate events: A case study of domestic tourism in the heat-waves of 2003. Int. J. Biometeorol. 2014, 58, 781–797.
4. Meehl, G.A.; Tebaldi, C. More intense, more frequent, and longer lasting heat-waves in the 21st century. Science 2004, 305, 994–997.
5. Pongrácz, R.; Bartholy, J. Tendency analysis of extreme climate indices with special emphasis on agricultural impacts. In Bioclimatology and Water in the Land; Lapin, M., Matejka, F., Eds.; FMFI Comenius University: Slovakia, Czech Republic, 2006.
6. Koffi, B.; Koffi, E. Heat-waves across Europe by the end of the 21st century: Multiregional climate simulations. Clim. Res. 2008, 36, 153–168.
7. UNWMO. Meeting of the Joint CCI/CLIVAR Task Group on Climate Indices. World Climate Data and Monitoring Programme, WCDMP No. 37, -WMO-TD No. 930; WMO: Bracknell, UK, 1999.
8. Korea Environment Institute. Evidence-Based Climate Change Risk Management Framework for Customized Adaptation; Korea Environment Institute: Sejong, Korea, 2018; pp. 1–231.
9. Kim, D.W.; Chung, J.H.; Lee, J.S.; Lee, J.S. Characteristics of heat-waves mortality in Korea. Atmosphere 2014, 24, 225–234.
10. Kim, H.M.; Min, K.R.; Kim, I.G.; Lim, B.H.; Youn, M.J.; Kim, S.B. Paradigm shift to impact-based forecasting and warning services for natural hazard response. Korea Soc. Innov. 2017, 12, 161–178.
11. Kang, M.; Kim, K.R.; Shin, J.Y. Event-Based Heat-Related Risk Assessment Model for South Korea Using Maximum Perceived Temperature, Wet-Bulb Globe Temperature, and Air Temperature Data. Int. J. Environ. Res. Public Health 2020, 17, 2631.
12. Jeong, D.; Lem, S.H.; Kim, D.W.; Lee, W.S. The effects of climate elements on heat-related illness in South Korea. J. Clin. Chang. Res. 2016, 7, 205–215.
13. Kang, Y.; Shin, J.; Park, C.S. Assessing climate change risk and adaptation policy improvements through text-mining. Urban Des. 2016, 17, 69–84.
14. Anderson, B.G.; Bell, M.L. Weather-related mortality: How heat, cold, and heat-waves affect mortality in the United States. Epidemiology (Camb. Mass.) 2009, 20, 205.
15. Heo, S.; Lee, E.; Kwon, B.Y.; Lee, S.; Jo, K.H.; Kim, J. Long-term changes in the heat-mortality relationship according to heterogeneous regional climate: A time-series study in South Korea. BMJ Open 2016, 6, e011786, doi:10.1136/bmjopen-2016-011786.
16. Park, J.; Chae, Y.; Choi, S.H. Analysis of Mortality Change Rate from Temperature in Summer by Age, Occupation, Household Type, and Chronic Diseases in 229 Korean Municipalities from 2007–2016. Int. J. Environ. Res. Public Health 2019, 16, 1561, doi:10.3390/ijerph16091561.
17. Son, J.-Y.; Lee, J.-T.; Anderson, G.B.; Bell, M.L. The impact of heat-waves on mortality in seven major cities in Korea. Environ. Health Perspect. 2012, 120, 566–571.
18. Son, J.-Y.; Bell, M.L.; Lee, J.-T. The impact of heat, cold, and heat-waves on hospital admissions in eight cities in Korea. Int. J. Biometeorol. 2014, 58, 1893–1903.
19. Lim, Y.-H.; Lee, K.-S.; Bae, H.-J.; Kim, D.; Yoo, H.; Park, S.; Hong, Y.-C. Estimation of heat-related deaths during heat-waves episodes in South Korea (2006–2017). Int. J. Biometeorol. 2019, 63, 1621–1629.
20. Heo, S.; Bell, M.L.; Lee, J.-T. Comparison of health risks by heat-waves definition: Applicability of wet-bulb globe temperature for heat-waves criteria. Environ. Res. 2019, 168, 158–170.
21. Dieter, S.; Ute, F.; Tobia, L.; Steen, L.; Fred, M.; Christian, S. Quantification of heat-stress related mortality hazard, vulnerability and risk in Berlin, Germany. Die Erde 2014, 144, 238–259.
22. Korea Meteorological Administration. Meteorological Technology & Policy; Korea Meteorological Administration: Seoul, Korea, 2018; Volume 11, pp. 1–97.

23. Jänicke, B.; Holtmann, A.; Kim, K.R.; Kang, M.; Fehrenbach, U.; Scherer, D. Quantification and evaluation of intra-urban heat stress variability in Seoul, Korea. Int. J. Biometeorol. 2019, 63, 1–12.

24. Kim, K.R.; Yi, C.; Lee, J.S.; Meier, F.; Jänicke, B.; Fehrenbach, U.; Scherer, D. Biometeorological Climate Impact Assessment System for building-scale impact assessment of heat-stress related mortality. Die Erde J. Geogr. Soc. Berl. 2014, 145, 62–79.

25. Yi, C.; An, S.M.; Kim, K.R.; Kwon, H.G.; Min, J.S. Surface micro-climate analysis based on urban morphological characteristics: Temperature deviation estimation and evaluation. Atmos. Korea 2016, 26, 445–459.

26. Grimmmond, C.S.B.; Roth, M.; Oke, T.R.; Au, Y.C.; Best, M.; Betts, R.; Carmichael, G.; Cleugh, H.; Dabberdt, W.; Emmanuel, R.; et al. Climate and more sustainable cities: Climate information for improved planning and management of cities (producers/capabilities perspective). Procedia Environ. Sci. 2010, 1, 247–274.

27. Bechtel, B.; Wiesner, S.; Zakšek, K. Estimation of dense time series of urban air temperatures from multitemporal geostationary satellite data. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2014, 7, 4129–4137.

28. Hoffmann, P.; Krueger, O.; Schlünzen, K.H. A statistical model for the urban heat island and its application to a climate change scenario. Int. J. Climatol. 2012, 32, 1238–1248.

29. Arnolds, D.; Böhner, J.; Bechtel, B. Spatio-temporal variance and meteorological drivers of the urban heat island in a European city. Theor. Appl. Climatol. 2017, 128, 43–61.

30. Robert, S.; Foresti, L.; Kanevski, M. Spatial prediction of monthly wind speeds in complex terrain with adaptive general regression neural networks. Int. J. Climatol. 2013, 33, 1793–1804.

31. Caillouet, L.; Vidal, J.P.; Sauquet, E.; Gra, B. Probabilistic precipitation and temperature downscaling of the twentieth century reanalysis over France. Clim. Past. 2016, 12, 635–662.

32. Oh, J.-H.; Kim, T.; Kim, M.-K.; Lee, S.-H.; Min, S.-K.; Kwon, W.-T. Regional climate simulation for Korea using dynamic downscaling and statistical adjustment. J. Meteorol. Soc. Jpn. Ser. II 2004, 82, 1629–1643.

33. Kim, K.B.; Kwon, H.-H.; Han, D. Bias correction methods for regional climate model simulations considering the distributional parametric uncertainty underlying the observations. J. Hydrol. 2015, 530, 568–579.

34. Maraun, D.; Wetterhall, F.; Ireson, A.M.; Chandler, R.E.; Kendon, E.J.; Widmann, M.; Brienen, S.; Rust, H.W.; Sauter, T.; Thomeßl, M.; et al. Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user. Rev. Geophys. 2010, 48, doi:10.1029/2009RG000314.

35. Dallavalle, J.P. A perspective on the use of model output statistics in objective weather forecasting. In Proceedings of the 15th Conference on Weather Analysis and Forecasting, Norfolk, VA, USA, 19–23 August 1996; Volume 15, pp. 479–482.

36. Fuentes, U.; Heimann, D. An improved statistical-dynamical downscaling scheme and its application to the alpine precipitation climatology. Appl. Clim. 2000, 65, 119–135.

37. Imbert, A.; Benestad, R.E. An improvement of analog model strategy for more reliable local climate change scenarios. Appl. Clim. 2005, 82, 245–255.

38. Keramitsoglou, I.; Kiranoudis, C.T.; Weng, Q. Downscaling geostationary land surface temperature imagery for urban analysis. IEEE Geosci. Remote Sens. Lett. 2013, 10, 1253–1257.

39. Park, J.; Jang, D.H. Application of MK-PRISM for interpolation of wind speed and comparison with Co-kriging in South Korea. Gisct. Remote Sens. 2016, 53, 421–443, doi:10.1080/15481603.2016.1192373.

40. Daly, C.; Neilson, R.P.; Phillips, D.L. A statistical-topographic model for mapping climatological precipitation over mountainous terrain. J. Appl. Meteorol. 1994, 33, 140–158.

41. Daly, C.; Gibson, W.P.; Taylor, G.H.; Johnson, G.L.; Pasteris, P. A knowledgebased approach to the statistical mapping of climate. Clim. Res. 2002, 22, 99–113.

42. Yi, C.; Shin, Y.; Roh, J.W. Development of an Urban High-Resolution Air Temperature Forecast System for Local Weather Information Services Based on Statistical Downscaling. Atmosphere 2018, 9, 164.

43. Shin, Y.; Yi, C. Statistical downscaling of urban-scale air temperatures using an analog model output statistics technique. Atmosphere 2019, 10, 427.

44. Yi, C.Y.; Eum, J.H.; Choi, Y.J.; Kim, K.R.; Scherer, D.; Fehrenbach, U.; Kim, G.H. Development of Climate Analysis Seoul (CAS) maps based on landuse and meteorological model. J. Korean Assoc. Geogr. Inf. Stud. 2011, 14, 12–25.
45. Shin, S.C.; Kim, M.K.; Suh, M.S.; Rha, D.K.; Jang, D.H.; Kim, C.S.; Kim, Y.H. Estimation of high resolution gridded precipitation using GIS and PRISM. *Atmosphere* 2008, 18, 71–81.
46. Park, S.H.; Choi, S.J. Hierarchical Gaussian process model for regression. In *Korean Information Science Society Conference; Korean Institute of Information Scientists and Engineers: Seoul, Korea*, 2010; pp. 66–67.
47. Lee, K.M.; Kim, K.Y.; Oh, U.; Yoo, S.K.; Song, B.S. Prediction of Multi-Physical Analysis Using Machine Learning. *J. IEEE* 2016, 20, 94–102.
48. Matulla, C.; Zhang, X.; Wang, X.L.; Wang, J.; Zorita, E.; Wagner, S.; von Storch, H. Influence of similarity measures on the performance of the analog method for downscaling daily precipitation. *Clim. Dyn.* 2008, 30, 133–144.
49. Gutiérrez, J.M.; San-Martín, D.; Brands, S.; Manzanas, R.; Herrera, S. Reassessing statistical downscaling techniques for their robust application under climate change conditions. *J. Clim.* 2013, 26, 171–188.
50. Radanovics, S.; Vidal, J.-P.; Sauquet, E.; Daoud, A.B.; Bontron, G. Optimising predictor domains for spatially coherent precipitation downscaling. *Hydrol. Earth Syst. Sci.* 2013, 17, 4189–4208.
51. Turco, M.; Quintana-Segui, P.; Llasat, M.C.; Herrera, S.; Gutiérrez, J.M. Testing MOS precipitation downscaling for ensembles regional climate models over Spain. *J. Geophys. Res. Atmos.* 2011, 116, 1–14.
52. Mardia, K.V. Spatial discrimination and classification maps. *Commun. Stat. Theory Methods* 1984, 13, 2181–2197.
53. Mardia, K.V.; Watkins, A.J. On multimodality of the likelihood in the spatial linear model. *Biometrika* 1989, 76, 289–295.
54. Mardia, K.V. Maximum likelihood estimation for spatial models. In *Spatial Statistics: Past. Present and Future; Monograph; Institute of Mathematical Geography: Ann Arbor, MI, USA*, 1990; Volume 12, pp. 203–253.
55. Liaw, A.; Wiener, M. Classification and regression by random forest. *R News* 2002, 2, 18–22.
56. Cherkassky, V.; Ma, Y. Practical selection of SVM parameters and noise estimation for SVM regression. *Neural Netw.* 2004, 17, 113–126.
57. Yi, C.; Kim, K.R.; An, S.M.; Choi, Y.J.; Holtmann, A.; Jänicke, B.; Fehrenbach, U.; Scherer, D. Estimating spatial patterns of air temperature at building-resolving spatial resolution in Seoul, Korea. *Int. J. Clim.* 2016, 36, 533–549.
58. Shmueli, G. To explain or to predict? *Stat. Sci.* 2010, 25, 289–310.
59. Hamdi, R.; Schayes, G. Sensitivity study of the urban heat island intensity to urban characteristics. *Int. J. Climatol.* 2008, 28, 973–982.
60. Bottyán, Z.; Unger, J. A multiple linear statistical model for estimating the mean maximum urban heat island. *Theor. Appl. Climatol.* 2003, 75, 233–243.
61. Unger, J.; Sümeghy, Z.; Gulyás, Á.; Bottyán, Z.; Mucsi, L. Land-use and meteorological aspects of the urban heat island. *Meteorol. Appl.* 2001, 8, 189–194.

© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).