

High-Resolution Climate Projections: An Interpolated Downscaling Methodology

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1. Introduction

Climate change poses significant challenges to countries in the Asia Pacific, where the impacts of rising temperatures, changing precipitation patterns, and glacial melt can have severe socio-economic and environmental consequences (ESCAP 2023). To develop targeted adaptation strategies, policymakers and researchers require high-resolution climate projections (Copernicus Climate Change Service, n.d.). However, General Circulation Models (GCMs) used in global climate studies often operate at coarse spatial resolutions (e.g., 100 km), making them insufficient for localized decision-making (Saha and Ravela, 2024). Downscaling techniques bridge this gap by refining coarse-resolution data to a finer scale, allowing for more accurate climate risk assessments at regional and local levels (Saha and Ravela, 2024).

This paper outlines an interpolated downscaling methodology produced jointly by ESCAP and NIES/AP-Plat. The methodology has been used to enhance Bhutan's climate projections, as detailed in the *Bhutan Climate Projection Report (2024)*. It explains how climate data was processed using Climate Data Operators (CDO) and shell scripting, and how bilinear interpolation was employed to produce high-resolution (1 km) datasets. The study demonstrates the methodology's practical application to the Asia Pacific region by presenting Bhutan's projected climate changes under various Shared Socioeconomic Pathways (SSPs).

To extend the interpolated downscaling methodology to extreme heat conditions, the paper further introduces a modified framework that integrates high-resolution temperature and humidity data to compute a spatially refined heat index across the Asia-Pacific region. The approach begins by processing minimum, maximum, and average temperature data, alongside near-surface relative humidity, using multi-model ensemble outputs from CMIP6 datasets. These datasets are downscaled to ~1 km resolution using bilinear interpolation and corrected for bias using historical WorldClim observations. Building upon this foundation, the methodology incorporates multi-threshold heat risk indicators developed by the World Bank (World Bank, n.d.), categorizing daily climate variables into actionable metrics such as hot days, tropical nights, and humidity risk days.

The apparent temperature—or heat index—is calculated using the Rothfusz regression equation (National Weather Service Weather Prediction Center, 2022), a widely accepted formulation based on temperature and relative humidity. The resulting values are adjusted for low- and high-humidity extremes and converted to Celsius for interpretation. Finally, the method classifies regions into categorical heat risk zones by combining exceedance thresholds of maximum temperature, minimum temperature, and heat index. These classifications are stored in GeoTIFF format, offering policymakers spatially explicit tools for identifying emerging hotspots of heat stress and guiding targeted adaptation responses across the region.

2. Literature review

Downscaling refers to the techniques used to refine and regionalize large scale climate model projections to provide localized climate information. It is critical for understanding climate change impacts at finer spatial scales. The climate projections from the GCMs often show systematic biases and uncertainty compared to the observational data which originate from the processes that either cannot be captured by the GCMs or simplified through parameterization due to its coarse scale (Alex Hall’s Research Group, n.d.) In order to utilize these results at finer scale, downscaling methods are essential. Broadly downscaling methodologies can be categorized into two main types: dynamic downscaling and statistical downscaling (Intergovernmental Panel on Climate Change, 2007). Each method has its advantages and disadvantages, which guides their applicability depending on specific research needs and available resources.

2.1 Dynamic Downscaling

Dynamic downscaling employs high-resolution regional climate models (RCMs) to simulate climate processes with a focus on physical realism. This approach captures the interactions of climate processes more effectively, but at a significantly higher computational cost, making it less practical for comprehensive regional studies over extensive timeframes (Alex Hall’s Research Group, n.d.; Intergovernmental Panel on Climate Change, 2007; Ashfaq, 2023) Moreover, dynamic downscaling can exhibit biases that require correction before use in impact assessments, limiting its usability without further adjustments (Ashfaq, 2023; Pacific RISA, n.d.).

Dynamical downscaling involves the use of RCMs that simulate atmospheric physical processes at finer spatial resolutions. This method provides a physically consistent representation of local climate processes and can effectively capture complex interactions between the atmosphere, land surface, and ocean (Tu & Duan, 2024; Fallah et al, 2025). However, dynamical downscaling is computationally intensive and often requires substantial data inputs, which can restrict its use to regions with adequate computational resources (Tu & Duan, 2024). Moreover, limited availability of RCM data makes this process more challenging for some regions. While dynamical downscaling generally yields more accurate representations of local climate patterns, it may still suffer from biases that necessitate correction before use in impact analyses (Ashfaq, 2023).

2.2 Statistical Downscaling

Statistical downscaling involves using statistical relationships between historical observation of the local climate and large-scale climate variables derived from global climate models (GCMs) or regional climate models (RCM) for the same historical period to generate high-resolution climate projections (Alex Hall's Research Group, n.d.). Statistical downscaling methods include regression-type models considering both linear and nonlinear relationships (Alex Hall's Research Group, n.d.). Statistical downscaling techniques vary in their complexity. While the simplest models simulate linear regression equations, the complex one can use statistical neural networks and weather generators (Pacific RISA, n.d.). The effectiveness of statistical downscaling improves with higher quality and longer durations of historical observed weather data.

This method is computationally less demanding, allowing for the generation of large ensembles of downscaled datasets relatively easily compared to dynamic approaches (Ashfaq, 2023). However, its main limitation lies in its inability to account for natural climate variability and extreme events, which are often poorly represented (Keller, Garner, Rao, Knipping, & Thomas, 2022). As a result, while statistically downscaled data can show little to no bias in historical periods, it may struggle with accuracy when forecasting future extreme weather events (Ashfaq, 2023; Pacific RISA, n.d.). Moreover, the method may not be applicable in certain regions due to the requirement for a specific quantity of historically observed data.

Both the methods are data driven, technically complex and resource intensive with varied levels. However, climate risk analysis often demands downscaled projections for pressing needs and might not afford technically intensive and time-consuming methods (Saha and Ravela, 2024). Moreover, the availability of observational data and the RCMs pose a big challenge in using either dynamic or statistical downscaling methods (Intergovernmental Panel on Climate Change, 2007). From that backdrop this paper proposes a spatial interpolation based downscaling method which is comparatively easy, less time and resource intensive than the other two conventional methods.

2.3 Interpolated Downscaling

Interpolated downscaling is an emerging method that combines aspects of both statistical and dynamical approaches. It utilizes interpolation techniques to generate high-resolution climate data from lower-resolution GCM outputs, offering a compromise between the computational efficiency of statistical methods and the physical accuracy of dynamical models (Tran Ahn and Taniguchi, 2018). This method typically involves resampling high-resolution variables and applying interpolation techniques to lower-resolution datasets to achieve a target spatial resolution. Interpolated downscaling is noted for its capability to maintain the spatial patterns of data while providing smoother transitions between pixels, thereby enhancing the overall accuracy of the projections (Shilengwe, Banda, & Nyambe, 2024; National Center for Atmospheric Research, n.d.). Unlike purely statistical methods, interpolated downscaling can leverage both historical data and spatial information effectively, leading to improved scenarios of localized climate conditions (Keller, Garner, Rao, Knipping, & Thomas, 2022). Moreover, the flexibility of interpolation allows it to adapt to various input data quality levels and resolutions, making it suitable for applications in regions with complex hydrogeological conditions, where traditional methods may falter (National Center for Atmospheric Research, n.d.).

Interpolated downscaling can be particularly advantageous in scenarios where high-resolution data is needed, but resources are limited for running complex dynamical models (Tran Ahn and Taniguchi, 2018). Additionally, by leveraging historical climate patterns, interpolated downscaling can produce robust projections for localized areas while minimizing the computational burden associated with dynamical simulations (Ashfaq, 2023).

Interpolation-based downscaling methods, such as bilinear interpolation and inverse-distance weighting (IDW), provide a cost-effective alternative to statistical or dynamic downscaling methods. Studies have shown that bilinear interpolation, while simplistic, can perform well in capturing broad climate trends in regions with complex topography (Liu, Feng, Yang, Hu, & Li, 2019). Interpolated downscaling is a widely employed technique to bridge the gap between coarse-resolution climate models and the fine-scale data required for specific applications.

Interpolated downscaling effectively maintains the spatial characteristics of the data. By using techniques like bilinear interpolation, which considers the values of surrounding pixels, the method reduces the risk of introducing artificial artifacts that can arise from statistical methods that may oversimplify relationships between variables (Intergovernmental Panel on Climate Change, 2007). This is particularly important in climate modeling, where the accurate representation of spatial patterns is crucial for applications such as water resource management and ecosystem assessments (Intergovernmental Panel on Climate Change, 2007; Serifi, Günther, & Ban, 2023).

Another advantage of interpolated downscaling lies in its flexibility to integrate various datasets. High-resolution datasets can be directly resampled to match the desired resolution, and lower-resolution datasets can be interpolated accordingly. This allows for the inclusion of diverse datasets, enabling researchers to utilize all available information effectively (Shilengwe, Banda, & Nyambe, 2024). The approach is adaptable, accommodating changes in data sources without requiring substantial reconfiguration of the methodology.

Interpolated downscaling allows for straightforward comparison with observed data. Since it operates on existing datasets and enhances their resolution, the resulting outputs can be easily validated against high-resolution ground truth data. This comparability is vital for assessing the accuracy and reliability of downscaled products, thereby enhancing confidence in their use for decision-making processes related to climate change impacts (National Center for Atmospheric Research, n.d.; Serifi, Günther, & Ban, 2023).

As many climate datasets are often coarsened due to storage limitations or computational constraints, interpolated downscaling helps recover some of the high-resolution information that is otherwise lost (National Center for Atmospheric Research, n.d.). This is particularly beneficial in cases where archived simulations were conducted at lower resolutions, allowing researchers to extract useful insights from historical data without incurring the high costs associated with re-simulations or extensive statistical modeling (Earth System Model Evaluation Tool [ESMValTool] Community, n.d.).

Comparisons between interpolated methods and traditional statistical downscaling revealed that interpolated approaches, such as the use of a MOS-Analog technique (Keller, Garner,

Rao, Knipping, & Thomas, 2022), produced more reliable precipitation projections for future climate scenarios. This was particularly evident in the work done by Shilengwe, Banda, and Nyambe (2024) which emphasized that interpolated methods can better represent spatial variability, crucial for local decision-making (Keller, Garner, Rao, Knipping, & Thomas, 2022; Shilengwe, Banda, & Nyambe, 2024).

Recent advancements in machine learning have further enhanced the capabilities of interpolated downscaling. For instance, generative diffusion-based downscaling techniques have demonstrated superior accuracy in recovering high-resolution climate data from lower-resolution outputs. By employing machine learning models, researchers achieved remarkable results in terms of capturing fine-scale details, which are often lost in conventional downscaling methods (Geoscience Blog, 2023; Colley, 2024).

3. ESCAP Downscaling methodology validation in Bhutan- an interpolated technique to downscale global climate datasets in Asia and the Pacific

Bhutan's unique topography and microclimatic variations make it challenging to derive accurate climate projections using coarse-resolution GCM data. Despite advances in downscaling techniques, the lack of locally refined datasets has hindered precise risk assessments (Saha and Ravela, 2024). This paper addresses this gap by applying an interpolated downscaling methodology to improve Bhutan's climate projections, facilitating better-informed adaptation strategies. The methodology has been used by the National Centre for Hydrology and Meteorology, Royal Government of Bhutan in the latest Climate Change Projection Report, 2024.

The aim of the methodology is to:

- (1) Develop high-resolution (1 km) climate projection datasets for Bhutan by downscaling CMIP6 GCM outputs,
- (2) Apply bilinear interpolation to refine temperature and precipitation data for the historical (1971-2000) and future (2021-2100) periods under various SSPs,
- (3) Bias correct downscaled projections against observed datasets from WorldClim, and
- (4) Demonstrate the practical application of downscaled projections in assessing climate risks for Bhutan.

3.1 Data and Methodology

Following two primary data sources were used for this method. All the data are open source.

- (1) The WorldClim historical climate data is used in this study for bias correction of the CMIP6 climate projection data. WorldClim data is developed from spatially interpolated monthly climate data for global land areas at a very high spatial resolution (approximately 1 km²). It includes monthly estimation of the variables aggregated across a target temporal range of 1970–2000, using data from between 9000 and 60 000 weather stations. The data is preferred

over CMIP6 historical data considering its spatial resolution and the topographical nature of Bhutan.

(2) The future climate data is sourced from the CMIP6 global climate projection dataset. The models provide output for both historical periods and the future. Ten climate models were chosen from the CMIP6 models based on the primary and secondary climate models specified by ISIMIP3b (Inter-Sectoral Impact Model Intercomparison Project [ISIMIP], 2022). The selection of primary models was based on parameters such as the process representation, structural independence, climate sensitivity, and performance in the historical period. According to ISIMIP (2022), the better-performing CMIP6 models are AWI-CM-1-1-MR, CESM2, CESM2-WACCM, GFDL-CM4, GFDL-ESM4, HadGEM3-GC31-LL, MPI-ESM1-2-HR, MPI-ESM1-2-LR, MRIESM2-0, SAM0- UNICON and UKESM1-0-LL. Additionally, based on the availability of the required variables GFDL-ESM4, MPI-ESM1-2-HR, MRI-ESM2-0 and UKESM1-0-LL as potential primary models. Another model providing data for potential variables is IPSLCM6A-LR. Apart from these, 5 other secondary climate models were selected based on the criteria mentioned above (ISIMIP, 2022). Among the five models—GFDL-ESM4, MPI-ESM1-2-HR, MRI-ESM2-0, IPSL-CM6A-LR, and UKESM1-0-LL—there are notable differences in climate sensitivity, which can influence projection outcomes. It is important to note that some models may exhibit the "hot model" tendency, projecting higher-than-observed warming and potentially overestimating future temperature changes. The hot model issue can affect ensemble means and the robustness of climate impact assessments. Considering a broad range of models helps to mitigate this bias and improve the reliability of projections (Hausfather, Marvel, Schmidt, Nielsen-Gammon, & Zelinka, 2022).

The method leverages the Climate Data Operators (CDO) toolset and shell scripting to automate large-scale data processing. We followed a three-step methodology (for details of the codes please refer to the annex):

Step 1: Data Acquisition and Preprocessing

- **Climate Model Data:** Multidimensional data from CMIP6 GCM datasets for temperature (minimum, maximum and average) and precipitation were obtained from the *Center for Climate Change Adaptation (CCCCA)*, *AP-Plat-Pro* (National Institute for Environmental Studies, n.d.) for all the 10 chosen GCMs (CCCCA Data Server, 2022). The climate change scenario considered for this study are SSP1 2.6, SSP3 7.0 and SSP5 8.5 for both historical (1971-2000) and future (2021-2100) time periods. The data files come as a stack of data layers in near-term (2021-2040), mid-term (2061-2080) and long-term (2081-2100) intervals as per IPCC conventions.
- **Observed Climate Data:** Observed global data were collected for temperature (minimum, maximum and average) and precipitation for the historical time period (1971 – 2000) from WorldClim version 2.1 (30 seconds ~1 km²) database (WorldClim. n.d.).
- **Region Extraction:** Bhutan's geographical extent (88°E–93°E, 26°N–29°N) was extracted from both the global climate projection datasets for all the time scales and scenarios as well as WorldClim observed climate data (1971-2000). A fine-resolution grid definition file (30

seconds $\sim 1 \text{ km}^2$) was created using the geographical extent of Bhutan and then based on the extent, the number of rows and columns in the intended downscaled raster were calculated.

- **Temporal Splitting of the Climate Model Data:** Monthly climate data files were created for each year between 1971-2000 and 2021-2100.
- **Calculation of mean values of the variables:** Average values of temperature and precipitation were calculated for each month of all the years between 1971-2000 and 2021-2100.

This is repeated for other time periods namely 2021-2040 (near-term), 2041-2080 (mid-term) and 2081-2100 (long-term) climate projection data for all the scenarios. All the pre-processing steps were replicated for all the climate projection models under consideration followed by calculating an ensemble mean of all the models.

Step 2: Downscaling Using Bilinear Interpolation

- **Interpolation Execution:** Bilinear interpolation was performed on the ensemble mean outputs. (Refer Section 2.3 on bilinear interpolation)

Step 3: Bias Correction

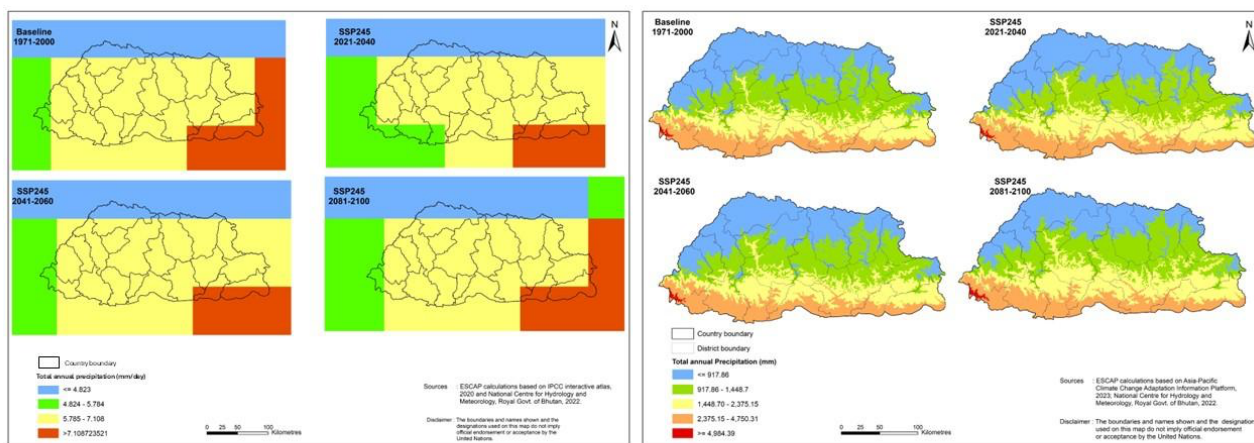
- **Bias Correction:** Climate model biases were corrected in reference to the WorldClim data first by calculating the difference between model historical data (1971-2000) and the model projection data for a specific time period and scenario and then adding the difference with WorldClim historical data for monthly files of each future year and scenario.

3.2 Results from Bhutan validation

The application of interpolated downscaling in Bhutan's climate projections yielded crucial insights as noted in the *Climate Change Projection Report 2024 (Figure 1)*. The findings indicate a pronounced warming trend, particularly in the northern and central regions, where minimum temperatures are projected to rise faster than maximum temperatures. This has significant implications for Bhutan's glacial systems, as increased warming is expected to accelerate glacial melt, thereby affecting water resources, ecosystems, and human settlements.

The method demonstrates that fine-scale climate projections are not just a technical exercise but a critical foundation for informed policymaking. By improving Bhutan's ability to anticipate climate risks, downscaling methodologies like bilinear interpolation provide a cost-effective tool for guiding national adaptation strategies, enhancing climate resilience, and protecting lives and livelihoods in the face of a changing climate.

Figure 1 Comparison of the global climate model data and the downscaled data for precipitation of Bhutan



3.3. Modification of the methodology to downscale heat variables for heat index

This method leverages the Climate Model Data Operators (CDO) toolset and shell scripting to automate large-scale data processing, along with Python-based climate model data processing libraries for statistical analyses. It integrates multi-threshold heat risk metrics developed by the World Bank (World Bank, n.d), which assess day-time maximum temperatures, nighttime minimum temperatures, and a combined heat index. These metrics serve as a baseline for evaluating changing and intensifying extreme heat conditions over different time scales, identifying where and when extreme heat is most likely to occur. The downscaling codes are provided in Annex 2.

For our analysis, we utilized CanESM5, selected for its high Equilibrium Climate Sensitivity (ECS) and its applicability to assessing projected climate risks in the Asia-Pacific region. CanESM5's ECS of 5.6°C positions it among the models projecting the most significant warming, making it particularly relevant for evaluating extreme heat conditions under high-emission scenarios (Hausfather, 2019).

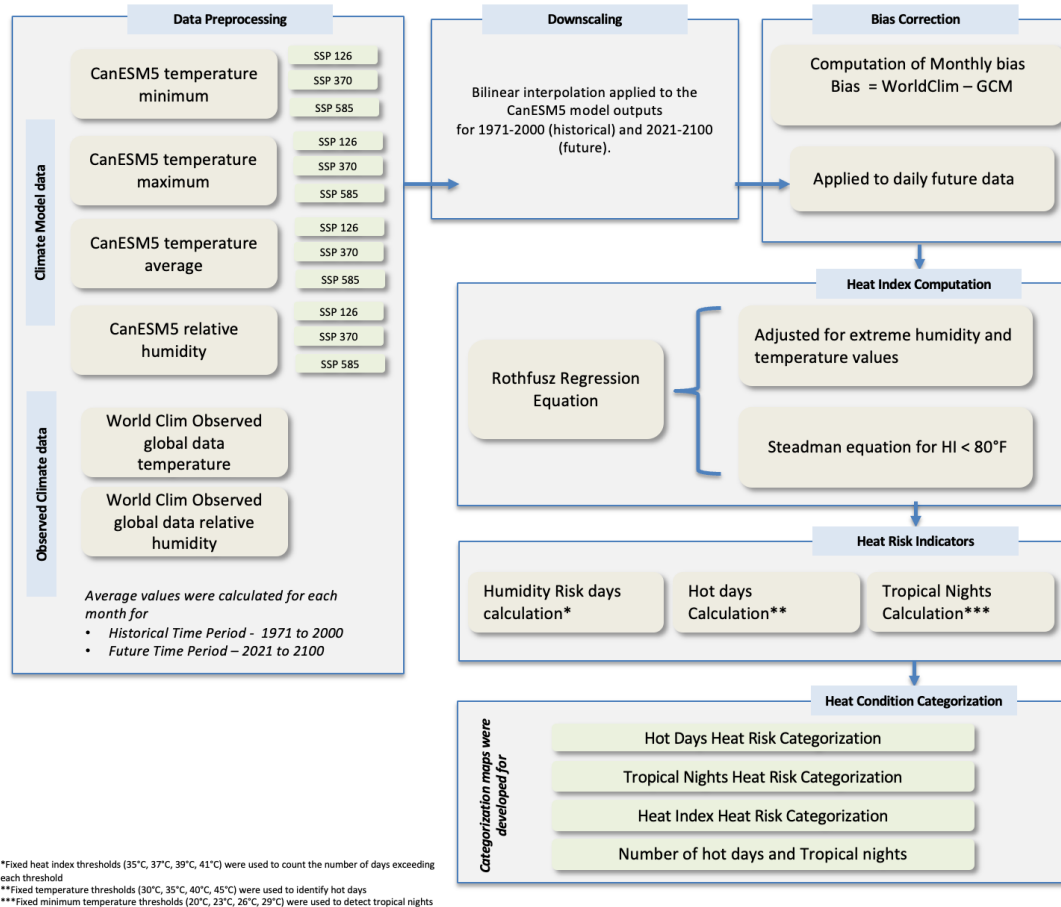


Figure 2 Heat Index Methodology

Step 1: Data Preprocessing

- 1) **Climate Model Data:** Multidimensional data from CMIP6 GCM datasets for temperature (minimum, maximum, and average) and Near-Surface Relative Humidity were obtained from NASA Earth Exchange (NEX-GDDP-CMIP6) for the CanESM5 model. The climate change scenarios considered in this study are SSP1 2.6, SSP3 7.0, and SSP5 8.5 for both historical (1971-2000) and future time periods (2021-2100).
- 2) **Observed Climate Model Data:** Observed global data for temperature and Near-Surface Relative Humidity for the historical period (1971 – 2000) were obtained from WorldClim version 2.1 at a 30-second (~1 km²) resolution.
- 3) **Calculation of mean values of the variables:** The average values of temperature and near-surface relative humidity were calculated for each month from 1971 to 2000 using the climate CanESM5 historical data.

Step 2: Downscaling Using Bilinear Interpolation

Interpolation Execution: Bilinear interpolation was applied to the CanESM5 model outputs for all years between 1971-2000 (historical) and 2021-2100 (future).

Step 3: Bias Correction

Bias Correction: The difference between monthly values of WorldClim historical data and the the CanESM5 historical data (1971-2000) was computed. This monthly difference was used to correct daily projection data:

- 1) Temporal Splitting of the Climate Model Data: Monthly Climate Model Data files were created for each year between 1971-2000 for the CanESM5 data.
- 2) Calculation of mean values of the variables: Average values of temperature and Near-Surface Relative Humidity were calculated for each month of all the years between 1971-2000.
- 3) Computing the difference between the monthly values of WorldClim historical data and monthly CanESM5 historical data (1971-2000).
- 4) Applying Monthly Difference to Daily Data: Applying the correction by adding this difference to the CanESM5 projection daily data for each future year and scenario.

Since observational data from WorldClim (~1 km²) is only available at a monthly scale, the monthly difference was used as a proxy for daily data bias correction factors.

Step 4: Heat Index Computation

The heat index (HI) represents the apparent temperature based on temperature (T) and relative humidity (RH). It was computed using the Rothfusz regression equation, which was developed through multiple regression analysis and documented in the 1990 National Weather Service (NWS) Technical Attachment (National Weather Service Weather Prediction Center, 2022).

Rothfusz Regression Equation:

$$HI = -42.379 + (2.04901523 * T) + (10.14333127 * RH) - (0.22475541 * T * RH) - (0.00683783 * T * T) - (0.05481717 * RH * RH) + (0.00122874 * T * T * RH) + (0.00085282 * T * RH * RH) - (0.00000199 * T * T * RH * RH)$$

where:

- 1) T = Temperature (°F)
- 2) RH = Relative Humidity (%)
- 3) HI = Heat Index (°F)

Conditional Adjustments for Extreme Conditions:

- 1) If $RH < 13\%$ and $80^{\circ}F \leq T \leq 112^{\circ}F$, a low-humidity adjustment was applied:

$$\text{ADJUSTMENT} = [(13 - \text{RH}) / 4] * \text{sqrt}([(17 - |T - 95|) / 17])$$

- 2) If $\text{RH} > 85\%$ and $80^\circ\text{F} \leq T \leq 87^\circ\text{F}$, a high-humidity adjustment was applied:

$$\text{ADJUSTMENT} = [(\text{RH} - 85) / 10] * [(87 - T) / 5]$$

- 3) For HI values below 80°F , a simplified Steadman's equation (National Weather Service Weather Prediction Center, 2022) was used:

$$\text{HI} = 0.5 * [T + 61.0 + ((T - 68.0) * 1.2) + (\text{RH} * 0.094)]$$

Step 5: Humidity Risk Days Calculation

- 1) Fixed heat index thresholds (35°C , 37°C , 39°C , 41°C) were used to count the number of days exceeding each threshold. (greater or equal to Threshold)
- 2) Annual and period average humidity risk days were computed and stored in NetCDF and GeoTIFF formats.

Step 6: Hot Days Calculation

- 1) Fixed temperature thresholds (30°C , 35°C , 40°C , 45°C) were used to identify hot days, where daily maximum temperatures exceeded the threshold.
- 2) Annual and period average hot day count was recorded and stored in NetCDF and GeoTIFF formats.

Step 7: Tropical Nights Calculation

- 1) Fixed minimum temperature thresholds (20°C , 23°C , 26°C , 29°C) were used to detect tropical nights, where daily minimum temperatures remained above the threshold overnight.
- 2) Annual and period average of tropical night counts were stored in NetCDF and GeoTIFF formats.

Step 8: Heat Condition Categorization

Heat condition categorization (**Number of Hot Days and Tropical Nights with Humidity**) was performed based on exceedance of heat index, maximum temperature, and minimum temperature thresholds, using the following classification:

1. Heat Risk categories were developed based on the exceedance of heat index, maximum temperature, and minimum temperature thresholds.
2. The following fixed thresholds were used for classification:
 - Daily Max Temperature (tasmax): 30°C , 35°C , 40°C , 45°C

- Nighttime Min Temperature (tasmin): 20°C, 23°C, 26°C, 29°C
 - Heat Index (HI): 35°C, 37°C, 39°C, 41°C
3. GeoTIFF raster data from each threshold were processed to generate annual exceedance counts.
 4. A multi-level classification system was applied, ensuring that the highest severity category was assigned first when multiple conditions were met.
 5. A final categorized GeoTIFF output was produced, providing a spatial representation of Heat Risk severity across regions.

Additionally, specific categorization maps were generated for:

- A. Hot Day Heat Risk Categorization
- B. Tropical Night Heat Risk Categorization
- C. Heat Index Heat Risk Categorization
- D. Number of Hot Days and Tropical Nights

Final Outputs

Annual and multi-year datasets for heat index, humidity risk days, extreme heat days, tropical nights, and heat condition categorization were generated.

3.4. Limitations of the Interpolation-Based Downscaling Method

Despite its utility in refining climate projections for Bhutan, the interpolation-based downscaling method has several limitations that must be acknowledged. One primary constraint is that the approach relies solely on a selection of global climate models (GCMs) as its source data while excluding regional climate models (RCMs) (Tefera, Ray, & Wooten, 2021). Since RCMs incorporate finer-scale atmospheric processes specific to regional topography and climate dynamics, their absence may lead to over- or under-estimations of key climate variables at the sub-national level. The limited scope of input data can result in biases that affect the accuracy of localized climate risk assessments, particularly in areas with highly variable microclimates.

Another challenge is the uncertainty in accuracy when compared to statistical or dynamical downscaling methods. While interpolation techniques such as bilinear interpolation provide computational efficiency, the lack of statistically or dynamically downscaled climate data for Bhutan makes it difficult to validate their precision against more sophisticated techniques. Statistical downscaling methods, which establish empirical relationships between large-scale climate variables and local observations, and dynamical downscaling, which employs high-resolution climate models nested within GCMs, may offer more physically consistent representations of local climate patterns (Wilby, Dawson, & Barrow, 2002 ; World Meteorological

Organization [WMO] 2021). However, due to the absence of benchmark datasets for Bhutan, the degree of uncertainty in the interpolated results remains unknown.

A further limitation of bilinear interpolation is its tendency to smooth out sharp spatial gradients, which could lead to underestimation due to complex terrains in Bhutan. The method assumes a linear transition between data points, which leads to an artificial smoothing effect, potentially masking localized extreme climate events such as sudden temperature drops in high-altitude regions or extreme precipitation events associated with convective storms (Latombe et al 2018). Further exploration of hybrid approaches that integrate interpolation with bias correction and machine learning techniques for improved accuracy could mitigate these challenges.

In summary, while interpolation-based downscaling provides a pragmatic and computationally efficient solution for enhancing Bhutan's climate projections, its inherent limitations highlight the need for further methodological refinements. Incorporating regional climate models, multi-method validation, and hybrid statistical approaches could enhance the robustness of future downscaling efforts, ensuring more reliable climate risk assessments for Bhutan's diverse landscapes.

3.5 Conclusion

This methodology demonstrates the utility of interpolated downscaling in enhancing climate projections for Bhutan and will be used to further downscale climate data on temperature and precipitation in the Asia Pacific region. The findings provide policymakers with fine-scale climate insights crucial for adaptation planning. The methodology is expanded in the ESCAP Asia Pacific Risk and Resilience Portal and being used in conjunction with machine learning to improve accuracy and incorporate multi-model ensembles for uncertainty reduction for the Asia Pacific region.

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ANNEX 1: Codes for downscaling methodology - average temperature

Followings are the sample code to downscale average temperature for January from MIROC6 GCM.

Abbreviations

tas-Average temperature, Mrc6 – MIROC6, hi-Historical, BTN – Bhutan, WC-WorldClim, DIF-Difference, BC- Bias corrected

Step 1: GCM

1.1: Extract region

- Historical

`cdo sellonlatbox,88,93,26,29 tas_mrc6hi01_1971_2000_01.nc tmp1971-2000_01BTN.nc`

- Future

`cdo sellonlatbox,88,93,26,29 tas_mrc68501_2071_2100_01.nc tmp2071-2100_01BTN.nc`

1.2: Split year and month

- Historical

cdo splityearmon tmp1971-2000_01BTN.nc tmp_BTN_

- Future

cdo splityearmon tmp2071-2100_01BTN.nc tmp_BTN_

1.3: Ensemble mean

- Historical

```
cdo ensmean tmp_BTN_197101.nc tmp_BTN_197201.nc tmp_BTN_197301.nc
tmp_BTN_197401.nc tmp_BTN_197501.nc tmp_BTN_197601.nc tmp_BTN_197701.nc
tmp_BTN_197801.nc tmp_BTN_197901.nc tmp_BTN_198001.nc tmp_BTN_198101.nc
tmp_BTN_198201.nc tmp_BTN_198301.nc tmp_BTN_198401.nc tmp_BTN_198501.nc
tmp_BTN_198601.nc tmp_BTN_198701.nc tmp_BTN_198801.nc tmp_BTN_198901.nc
tmp_BTN_199001.nc tmp_BTN_199101.nc tmp_BTN_199201.nc tmp_BTN_199301.nc
tmp_BTN_199401.nc tmp_BTN_199501.nc tmp_BTN_199601.nc tmp_BTN_199701.nc
tmp_BTN_199801.nc tmp_BTN_199901.nc tmp_BTN_200001.nc tmp_BTN_1971-2000_01.nc
```

- Future

```
cdo ensmean tmp_BTN_207101.nc tmp_BTN_207201.nc tmp_BTN_207301.nc
tmp_BTN_207401.nc tmp_BTN_207501.nc tmp_BTN_207601.nc tmp_BTN_207701.nc
tmp_BTN_207801.nc tmp_BTN_207901.nc tmp_BTN_208001.nc tmp_BTN_208101.nc
tmp_BTN_208201.nc tmp_BTN_208301.nc tmp_BTN_208401.nc tmp_BTN_208501.nc
tmp_BTN_208601.nc tmp_BTN_208701.nc tmp_BTN_208801.nc tmp_BTN_208901.nc
tmp_BTN_209001.nc tmp_BTN_209101.nc tmp_BTN_209201.nc tmp_BTN_209301.nc
tmp_BTN_209401.nc tmp_BTN_209501.nc tmp_BTN_209601.nc tmp_BTN_209701.nc
tmp_BTN_209801.nc tmp_BTN_209901.nc tmp_BTN_200001.nc tmp_BTN_2071-2100_01.nc
```

1.4: Downscaling

- Historical

cdo remapbil,grid30s_BTN.txt tmp_BTN_1971-2000_01.nc tmp_BTN_30s_1971-2000_01.nc

- Future

cdo remapbil,grid30s_BTN.txt tmp_BTN_2071-2100_01.nc tmp_BTN_30s_2071-2100_01.nc

Step 2: WorldClim historical data (1970-2000)

2.1 translate tif to netcdf

```
gdal_translate -of netCDF wc2.1_30s_tavg_01.tif tmp_WC_1970-2000_01.nc
```

2.2 Extract Bhutan region

```
cdo sellonlatbox,88,93,26,29 tmp_WC_1970-2000_01.nc tmp_WC_BTN_1970-2000_01.nc
```

Step 3: Bias correction

3.1 Calculate difference between 2071-2100 and 1971-2000

```
cdo      sub      tmp_BTN_30s_2071-2100_01.nc      tmp_BTN_30s_1971-2000_01.nc  
tmp_DIF_BTN_30s_2071-2100_1971-2000_01.nc
```

3.2 Add the difference with WorldClim historical data

```
cdo add tmp_DIF_BTN_30s_2071-2100_1971-2000_01.nc tmp_WC_BTN_1970-2000_01.nc  
tmp_BC_BTN_2071-2100_01.nc
```

ANNEX 2: Modified codes for downscaled heat assessments

Step 1: Downscaling Using Bilinear Interpolation

A grid information file is required for spatial interpolation of climate model outputs. This file defines the spatial resolution, and extent of the target study area.

A text file (e.g., `grid\_<study\_area>.txt`) is created with the following specifications:

Example Grid File Structure:

```
gridtype= lonlat
xsize= <number_of_grid_cells_x>
ysize= <number_of_grid_cells_y>
xfirst= <longitude_of_first_grid_point>
yfirst= <latitude_of_first_grid_point>
xinc= <grid_spacing_in_longitude>
yinc= <grid_spacing_in_latitude>
```

Parameters:

gridtype= lonlat → Defines the grid as latitude-longitude (geographic coordinate system).

xsize / ysize → Specifies the number of grid cells along longitude and latitude; calculated as (longitude_range / xinc) and (latitude_range / yinc), respectively.

xfirst / yfirst → Defines the longitude and latitude of the first (top-left) grid point.

xinc / yinc → Sets the resolution of the grid in degrees (spacing between grid points).

Usage in Downscaling and Interpolation:

This grid file is used in bilinear interpolation to align climate model outputs to the study area's resolution:

```
cdo remapbil,grid_<study_area>.txt <input_file> <output_file>
```

Key Considerations:

- 1) Ensure the grid extent covers the study area of interest.
- 2) The resolution (xinc, yinc) should match the required analysis scale.

Step 2: Bias Correction

- 1) Temporal Splitting of the Climate Model Data:

```
cdo splitmon input.nc output_
```

- 2) Calculation of mean values of the variables



```
cdo timmean "$file" "tasmin_day_<study_area>_${year}_01_timmean.nc"
```

Parameters:

- timmean → Computes the time-averaged (mean) value for the entire time dimension of the input dataset.
- \$file → Input NetCDF file containing Climate Model Data for a specific month and year.
- tasmin_day_<study_area>_\${year}_01_timmean.nc → Output file storing the computed mean values for January (01) of the given year.

3) Computing the difference between the monthly values of **WorldClim historical data and monthly climate CanESM5 historical data (1971-2000)**.

Command for Computing the Difference:

```
cdo sub tmp_WC_${VAR}_30s_1971-2000_${MON}.nc \
    tmp_CM_${VAR}_historical_30s_1971-2000_${MON}.nc \
    tmp_DIF_historical_${VAR}_${MON}.nc
```

Parameters:

- sub → Computes the pixel-wise difference between two datasets.
- tmp_CM_\${VAR}_historical_30s_1971-2000_\${MON}.nc → CanESM5 historical dataset for the variable (\$VAR) and month (\$MON).
- tmp_WC_\${VAR}_30s_1971-2000_\${MON}.nc → WorldClim historical dataset for the same variable and month.
- tmp_DIF_historical_\${VAR}_\${MON}.nc → Output file storing the computed difference for the given variable and month.

4) **Applying Monthly Difference to Daily Data**

Apply the same monthly correction value to all daily data in that month:

```
cdo add \
    "processed_${VAR}_${month}.nc" \
    "tmp_DIF_historical_${VAR}_${month}.nc" \
    "bias_corrected_${VAR}_${month}.nc"
```

Parameters:

- processed_\${VAR}_\${month}.nc → Future daily Climate Model Data (processed, interpolated, and converted if needed).
- tmp_DIF_historical_\${VAR}_\${month}.nc → Monthly bias correction value.
- bias_corrected_\${VAR}_\${month}.nc → Final bias-corrected daily Climate Model Data.

Step 3: Heat Index Computation

- 1) Heat index values were extracted from the NetCDF files, ensuring coordinate reference system (CRS) consistency and correcting any latitude ordering.
- 2) Temperature was converted from Kelvin to Fahrenheit for the heat index calculation, then converted back to Celsius for output.
- 3) The Rothfusz regression formula was applied to estimate the heat index, with adjustments for low and high humidity conditions

Script:

```
import os, glob

import xarray as xr

import numpy as np

import rasterio

from rasterio.transform import Affine

from rasterio.crs import CRS

# Input and output directories

future_tas_folder = "<path_to_temperature_data>"

future_rh_folder = "<path_to_humidity_data>"

output_dir_nc = "<path_to_output_netcdf>"

output_dir_tif = "<path_to_output_geotiff>"

os.makedirs(output_dir_nc, exist_ok=True)

os.makedirs(output_dir_tif, exist_ok=True)
```

```
# Retrieve and sort NetCDF files

nc_files_tas = sorted(glob.glob(os.path.join(future_tas_folder, "*.nc")))
nc_files_rh = sorted(glob.glob(os.path.join(future_rh_folder, "*.nc")))

# Load NetCDF data and assign CRS
def load_and_fix_crs(nc_file, var_name):
    ds = xr.open_dataset(nc_file)
    data = ds[var_name].rio.write_crs("EPSG:4326")
    if data.coords["lat"][0] < data.coords["lat"][-1]:
        data = data.sel(lat=slice(None, None, -1))
    return data.where(data != 1e+20, np.nan)

# Compute heat index using temperature (°F) and relative humidity (%)
def compute_heat_index(tas_f, rh):
    simple_HI = 0.5 * (tas_f + 61.0 + ((tas_f - 68.0) * 1.2) + (rh * 0.094))
    HI = np.where(
        simple_HI < 80, simple_HI,
        -42.379 + 2.04901523 * tas_f + 10.14333127 * rh
        - 0.22475541 * tas_f * rh - 0.00683783 * tas_f**2
        - 0.05481717 * rh**2 + 0.00122874 * tas_f**2 * rh
        + 0.00085282 * tas_f * rh**2 - 0.00000199 * tas_f**2 * rh**2
    )
    low_humidity = (rh < 13) & (tas_f >= 80) & (tas_f <= 112)
    high_humidity = (rh > 85) & (tas_f >= 80) & (tas_f <= 87)
    sqrt_term = np.clip((17 - np.abs(tas_f - 95)) / 17, 0, None)
    HI = np.where(low_humidity, HI - ((13 - rh) / 4) * np.sqrt(sqrt_term), HI)
    HI = np.where(high_humidity, HI + ((rh - 85) / 10) * ((87 - tas_f) / 5), HI)
    return (HI - 32) * 5/9 # Convert Fahrenheit to Celsius
```

Convert dataset to GeoTIFF format

```
def save_to_geotiff(data, output_tif):
```

```
    lat, lon = data.coords["lat"].values, data.coords["lon"].values
```

```
    if lat[0] < lat[-1]:
```

```
        data = data[:, ::-1, :]
```

```
    pixel_width = (lon.max() - lon.min()) / (len(lon) - 1)
```

```
    pixel_height = (lat.max() - lat.min()) / (len(lat) - 1)
```

```
    transform = Affine.translation(lon.min() - pixel_width / 2, lat.max() + pixel_height / 2) *  
    Affine.scale(pixel_width, -pixel_height)
```

```
    with rasterio.open(output_tif, "w", driver="GTiff", height=data.shape[1], width=data.shape[2],  
count=data.shape[0], dtype=np.float32, crs=CRS.from_epsg(4326), transform=transform) as dst:
```

```
        for i in range(data.shape[0]):
```

```
            dst.write(data[i].values.astype(np.float32), i + 1)
```

Process each NetCDF file

```
for nc_file_tas, nc_file_rh in zip(nc_files_tas, nc_files_rh):
```

```
    year = os.path.basename(nc_file_tas).split("_")[-1].split(".nc")[0]
```

```
    tas = load_and_fix_crs(nc_file_tas, "tas")
```

```
    rh = load_and_fix_crs(nc_file_rh, "hurs")
```

```
    tas, rh = xr.align(tas, rh, join="outer", fill_value=np.nan)
```

```
    tas_f = (tas - 273.15) * 9/5 + 32 # Convert Kelvin to Fahrenheit
```

```
    heat_index = xr.apply_ufunc(compute_heat_index, tas_f, rh, input_core_dims=[["time", "lat",  
"lon"], ["time", "lat", "lon"]], output_core_dims=[["time", "lat", "lon"]], vectorize=True,  
dask="allowed").rename("heat_index")
```

```
    heat_index.to_netcdf(os.path.join(output_dir_nc, f"heat_index_{year}.nc"))
```

```
    save_to_geotiff(heat_index, os.path.join(output_dir_tif, f"heat_index_{year}.tif"))
```

```
print("Heat index computation completed.")
```

Step 4: Humidity Risk Days Calculation

- 1) Future heat index values were extracted and analyzed to **count the number of days** where the heat index exceeded **fixed thresholds** (35°C, 37°C, 39°C, 41°C).
- 2) Each threshold exceedance was recorded and stored as an annual count.
- 3) Multi-year period averages were computed to assess long-term trends in humidity risk days.

Script:

```
import os

import glob

import xarray as xr

import numpy as np

import rasterio

from rasterio.transform import Affine

from rasterio.crs import CRS

# Input and output directories

future_hi_folder = "<path_to_future_heat_index_data>"

output_dir_nc = "<path_to_output_netcdf>"

output_dir_tif = "<path_to_output_geotiff>"

os.makedirs(output_dir_nc, exist_ok=True)

os.makedirs(output_dir_tif, exist_ok=True)

# Retrieve and sort NetCDF files

nc_files = sorted(glob.glob(os.path.join(future_hi_folder, "*.nc")))

# Heat index thresholds in Celsius

THRESHOLDS_C = {35, 37, 39, 41}
```

```
# Load NetCDF data and assign CRS
```

```
def load_and_fix_crs(nc_file):
```

```
    ds = xr.open_dataset(nc_file)
```

```
    heat_index = ds["heat_index"].rio.write_crs("EPSG:4326")
```

```
    if heat_index.coords["lat"][0] < heat_index.coords["lat"][-1]:
```

```
        heat_index = heat_index.sel(lat=slice(None, None, -1))
```

```
    return heat_index
```

```
# Detect days exceeding the heat index threshold
```

```
def detect_humidity_risk_days(data, threshold):
```

```
    return (data >= threshold).sum(axis=0).astype(np.uint16)
```

```
# Convert dataset to GeoTIFF format
```

```
def save_to_geotiff(data, output_tif):
```

```
    lat, lon = data.coords["lat"].values, data.coords["lon"].values
```

```
    if lat[0] < lat[-1]:
```

```
        data, lat = data[::-1], lat[::-1]
```

```
    pixel_width = (lon.max() - lon.min()) / (len(lon) - 1)
```

```
    pixel_height = (lat.max() - lat.min()) / (len(lat) - 1)
```

```
    transform = Affine.translation(lon.min() - pixel_width / 2, lat.max() + pixel_height / 2) *  
    Affine.scale(pixel_width, -pixel_height)
```

```
    with rasterio.open(
```

```
output_tif, "w", driver="GTiff", height=data.shape[0], width=data.shape[1], count=1,  
dtype=str(data.dtype),
```

```
crs=CRS.from_epsg(4326), transform=transform
```

```
) as dst:
```

```
dst.write(data.values, 1)
```

```
# Store annual and multi-year averages
```

```
annual_risk_counts = {threshold: [] for threshold in THRESHOLDS_C}
```

```
period_risk_counts = {threshold: [] for threshold in THRESHOLDS_C}
```

```
# Process each NetCDF file
```

```
for nc_file in nc_files:
```

```
    year = int(os.path.basename(nc_file).split("_")[-1].split(".nc")[0])
```

```
    heat_index = load_and_fix_crs(nc_file)
```

```
    lat, lon = heat_index.coords["lat"], heat_index.coords["lon"]
```

```
for threshold_c in THRESHOLDS_C:
```

```
    risk_day_counts = xr.apply_ufunc(  
        detect_humidity_risk_days,
```

```
        heat_index,
```

```
        xr.full_like(heat_index, threshold_c),
```

```
        input_core_dims=[["time"], ["time"]],
```

```
        output_core_dims=[[]],
```

```
        vectorize=True,
```

```
        dask="allowed",
```

```
)
```

```
risk_day_counts = xr.DataArray(  
    risk_day_counts,
```

```

risk_day_counts, coords={"lat": lat, "lon": lon}, dims=["lat", "lon"],
name=f"humidity_risk_days_{threshold_c}C"
)

annual_risk_counts[threshold_c].append(risk_day_counts)
period_risk_counts[threshold_c].append(risk_day_counts)

risk_day_counts.to_netcdf(os.path.join(output_dir_nc,
f"humidity_risk_days_{threshold_c}C_{year}.nc"))

save_to_geotiff(risk_day_counts,                                os.path.join(output_dir_tif,
f"humidity_risk_days_{threshold_c}C_{year}.tif"))

# Compute and save multi-year averages
for threshold_c, counts in period_risk_counts.items():
    if counts:
        period_avg = xr.concat(counts, dim="year").mean(dim="year")
        period_avg.to_netcdf(os.path.join(output_dir_nc,
f"humidity_risk_days_avg_{threshold_c}C.nc"))
        save_to_geotiff(period_avg,                                os.path.join(output_dir_tif,
f"humidity_risk_days_avg_{threshold_c}C.tif"))

print("Humidity risk days computation completed.")

```

Step 5: Hot Days Calculation & Step 6: Tropical Nights Calculation

Following the same approach as humidity risk days, **fixed temperature thresholds** were applied to identify hot days and tropical nights using climate model projections.

Hot Days Calculation (Step 6)

- Criteria: Days where daily maximum temperature (tasmax) exceeds fixed thresholds.
- Thresholds: 30°C, 35°C, 40°C, 45°C.
- Output: Count of days per year and multi-year period where daily maximum temperature surpasses each threshold.

Tropical Nights Calculation (Step 7)

- Criteria: Nights where daily minimum temperature (tasmin) remains above fixed thresholds.
- Thresholds: 20°C, 23°C, 26°C, 29°C.
- Output: Count of nights per year and multi-year period where daily minimum temperature stays above each threshold.

Step 7: Heat Condition Categorization

- 1) Heat Risk categories were assigned based on exceedance of **heat index (HI)**, **maximum temperature (tasmax)**, and **minimum temperature (tasmin)**.
- 2) The classification was based on fixed thresholds:
 - **Daily Max Temperature (tasmax): 30°C, 35°C, 40°C, 45°C.**
 - **Nighttime Min Temperature (tasmin): 20°C, 23°C, 26°C, 29°C.**
 - **Heat Index (HI): 35°C, 37°C, 39°C, 41°C.**
- 3) For each threshold, the number of days exceeding the threshold was identified.
- 4) If at least **0.5 days per year** exceeded the threshold, the location was classified into a heat category.
- 5) Categories were assigned in **descending order** to ensure higher-risk conditions take precedence.

Script:

```
import os

import rasterio

import numpy as np


# Input & Output Paths

input_folder = "<path_to_input_data>"

output_tif = os.path.join(input_folder, "Heat_Categorization.tif")

os.makedirs(input_folder, exist_ok=True)


# Heat Thresholds

tasmax_thresholds = [30, 35, 40, 45]

tasmin_thresholds = [20, 23, 26, 29]
```

```
hi_thresholds = [35, 37, 39, 41]
```

```
# Load GeoTIFF File Paths
```

```
tasmax_files = {t: os.path.join(input_folder, f"count_tasmax_above_{t}C.tif") for t in  
tasmax_thresholds}
```

```
tasmin_files = {t: os.path.join(input_folder, f"count_tasmin_above_{t}C.tif") for t in  
tasmin_thresholds}
```

```
hi_files = {t: os.path.join(input_folder, f"count_HI_above_{t}C.tif") for t in hi_thresholds}
```

```
# Read GeoTIFF Files
```

```
def read_raster(file_path):
```

```
    if os.path.exists(file_path):
```

```
        with rasterio.open(file_path) as src:
```

```
            return src.read(1), src.meta
```

```
    return None, None
```

```
# Initialize Heat Category Map
```

```
heat_category, meta = None, None
```

```
# Assign Heat Categories (Highest First)
```

```
for level in reversed(range(4)):
```

```
    tmax_thresh,    tmin_thresh,    hi_thresh    =    tasmax_thresholds[level],  
tasmin_thresholds[level], hi_thresholds[level]
```

```
    exceed_tmax, tmax_meta = read_raster(tasmax_files[tmax_thresh])
```

```
    exceed_tmin, tmin_meta = read_raster(tasmin_files[tmin_thresh])
```

```
    exceed_hi, hi_meta = read_raster(hi_files[hi_thresh])
```

```
    if meta is None:
```

```
        meta = tmax_meta or tmin_meta or hi_meta
```

```
    if exceed_tmax is None or exceed_tmin is None or exceed_hi is None:
```

```
        continue
```



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```
exceed_tmax = exceed_tmax >= 0.5
exceed_tmin = exceed_tmin >= 0.5
exceed_hi = exceed_hi >= 0.5
if heat_category is None:
    heat_category = np.zeros_like(exceed_tmax, dtype=np.uint8)
    heat_category = np.where((exceed_tmax | exceed_tmin | exceed_hi) & (heat_category ==
0), level + 1, heat_category)

# Save Heat Categorization as GeoTIFF
def save_to_geotiff(data, output_tif, meta):
    if meta:
        meta.update(dtype=rasterio.uint8, count=1)
        with rasterio.open(output_tif, "w", **meta) as dst:
            dst.write(data.astype(rasterio.uint8), 1)

    if heat_category is not None:
        save_to_geotiff(heat_category, output_tif, meta)
    else:
        print("No valid data available to save.")

print("Heat Condi
```