Technical Assistance for Mapping Education Data to Thailand Child-Sensitive Climate Change Risk

Siwachoat Srisuttiyakorn   Prapasiri Ratchapropapornkul
Kanit Srikularb   Watinee Omornpaisarnlort

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1 Exclusive Summary

Climate change and environmental degradation are significant global challenges, impacting many sectors, particularly education. This research focuses on examining the risks posed by climate-related disasters on the educational system in Thailand, with a particular emphasis on children. The sensitivity of children to these changes is a critical issue that needs to be explored and understood in order to help stakeholders develop effective strategies for addressing future challenges.

The research has two main objectives. The first is to explore and develop a methodology to identify relevant education metrics that highlight the actual or potential, direct or indirect, adverse effects of climate change and environmental degradation on children's participation in education and learning. The second objective is to identify the characteristics of schools, provinces, areas, and children that are exposed to significant risks from climate hazards, taking into account factors such as region, urban/rural settings, socio-economic status, disability, gender, age, and the location of schools in hardship areas.

This research represents an important step in connecting education data with climate risk factors, particularly by assessing the impact of these risks on children's education. The findings will support future policy planning and operational efforts to ensure that responses to environmental challenges are effective and aligned with the needs of the education system.

2 Introduction

In recent years, the frequency and severity of climate-related events—such as heatwaves, floods, droughts, and wildfires—have escalated, posing significant and continuous threats globally. These environmental changes have not only devastated critical infrastructure in sectors like the economy, agriculture, and public health, but they have also severely impacted education systems. Climate change exacerbates societal issues such as poverty, inequality, food insecurity, and the spread of climate-induced diseases (Adler et al., 2022). Children, in particular, are disproportionately vulnerable to these challenges, primarily due to their physiological immaturity and limited ability to adapt to extreme environmental conditions. According to UNICEF, children's health risks from climate impacts—such as respiratory diseases and heat-related illnesses—are significantly higher than those of adults. Currently, over 500 million children are already experiencing extreme heatwaves, and it is projected that by 2050, nearly 2 billion children will face even more frequent and severe climate events (UNICEF, 2021).

Various studies have been conducted to analyze the climate risk of different areas globally, including in Thailand. For instance, findings from the WorldRiskReport 2023 revealed that Thailand had a WorldRiskIndex score of 21.09, placing it at a very high-risk level and ranking 23rd out of 193 countries globally. In 2024, Thailand's risk score increased to 21.70, with the country's ranking improving to 21st out of 193 countries, reflecting a heightened vulnerability to climate risks over time (Auer-Frege et al., 2023, 2024). These findings align with those of the Global Climate Risk Index (CRI) published by Eckstein et al. (2021), which placed Thailand 9th out of 180 countries in terms of exposure to climate hazards between 2000 and 2019. Both reports underscore Thailand's significant vulnerability to climate-related disasters, such as floods and extreme heatwaves, which pose increasing threats to infrastructure, public health, and the country's educational system (Eckstein et al., 2021).

In addition to health risks, climate change has profound implications for education. Research from the World Bank indicates that over the past two decades, climate-induced disasters such as floods and droughts have led to prolonged school closures, exacerbating learning losses, increasing dropout rates, and threatening children's future opportunities (Adler et al., 2022; UNICEF, 2021).The IPCC's Synthesis Report 2023 also highlights that human-caused climate change is already affecting weather extremes globally, with vulnerable communities—including children—bearing disproportionate impacts. These effects are expected to intensify with further warming, amplifying risks to key infrastructure, health, and education systems, particularly in developing countries like Thailand (IPCC, 2023). These challenges are particularly critical for children in vulnerable regions like Thailand, where the intersection of climatic changes and educational access poses significant risks.

When considering the impact of climate risk on children through the Children's Climate Risk Index (CCRI), Thailand ranks 50th out of 163 countries, highlighting the country's exposure to climate-related vulnerabilities. The risks from climatic changes vary significantly and include extreme heat, flooding, droughts, and disease outbreaks. For instance, children in densely populated urban areas with less greenery are more susceptible to heat, while the 2011 floods had severe psychological and educational impacts on Thai children and those from migrant families, leading to school closures and the spread of waterborne diseases. Similarly, Thailand's most severe drought in 40 years caused widespread drinking water shortages, contributing to health issues such as childhood diarrhea, while rising temperatures have increased the prevalence of diseases like dengue fever, malaria, and Zika. These findings underscore Thailand's status as a high-risk country for climate-related impacts (UNICEF, 2021).

One method to mitigate these risks or impacts from climate changes and disasters is to reduce greenhouse gas emissions. The United Nations has campaigned for greenhouse gas emissions to be reduced to zero by 2050. This effort requires cooperation from both the public and private sectors. Thailand has set ambitious targets to achieve carbon neutrality by 2050 and net-zero greenhouse gas emissions by 2065. These targets are challenging and require clear, rapid, and comprehensive action, relying on cooperation from various sectors, especially the participation of the public within the country. Research supports that higher levels of public education can reduce the risks from climate changes and disasters, as education helps people understand climate conditions and issues, and develops necessary skills for adapting and coping with environmental changes (O'Neill et al., 2020). Education also raises awareness about the environmental impacts of human activities and the importance of sustainable practices, which can stimulate behavior changes and community participation in activities aimed at reducing climate change and disaster risks. Additionally, education influences policy promotion related to the climate, which are all factors that help mitigate the risks from climate changes and disasters, promoting the success of the goals for reducing greenhouse gas emissions to zero. (Rousell & Cutter-Mackenzie-Knowles, 2020)

However, with the increasing intensity and frequency of climate change and disasters, which create obstacles to children's access to and the quality of education, these conditions affect learners from early childhood through secondary education. The impacts of these factors vary depending on the type and severity of the situation. Severe climate disasters, such as heatwaves or floods, can lead to school closures, which in turn impact children's learning opportunities, reduce their learning efficiency, or hinder teachers' ability to manage the learning process. These conditions can also increase psychological stress among students and those involved. In less severe cases, such as rising temperatures or air pollution, these environmental factors may disrupt students' concentration in class and pose challenges to their full learning potential. These situations make it harder for children to access and receive education, increasing the risks posed by climate change and disasters and, ultimately, hindering progress toward the goal of reducing greenhouse gas emissions to zero (Adler et al., 2022; IPCC, 2023; UNICEF, 2021). These conditions also negatively impact students' academic performance. Numerous studies have found that extreme weather conditions, such as higher temperatures, are linked to decreased academic achievement, whether it be lower test scores or reduced concentration in the classroom (Adler et al., 2022; Zivin & Neidell, 2014). These situations affect long-term learning outcomes, particularly among students in areas with limited resources to adapt. Climate change thus becomes a significant factor influencing academic performance and the development of children's future potential.

However, these impacts are not uniformly distributed among all children. Area-specific studies have shown that the distribution of risks from the CCRI tends to differ by province. Provinces in the Northeast, such as Ubon Ratchathani, Nakhon Ratchasima, Si Sa Ket, Buriram, and Surin, and in the South, like Nakhon Si Thammarat, Songkhla, and Narathiwat, tend to have the highest climate risks for children. Moreover, within the same province or area, different groups of children are likely to experience varying impacts from these risks. For example, children from higher-income families and safer homes tend to be less affected by these risks compared to those from lower-income households. This indicates that the intersection of climate and non-climate factors, such as socio-economic status, access to infrastructure, and geographic location, plays a critical role in determining the overall vulnerability of children to climate-related risks.

This hypothesis aligns with the findings of the IPCC Summary for Policymakers 2022, which revealed that climate factors, such as extreme weather events, interact with non-climate factors, such as economic inequality, social status, and access to basic resources. This interaction increases the risks faced by vulnerable groups, particularly in urban areas, informal settlements, and regions lacking infrastructure. As a result, these populations are less capable of coping with the impacts of climate change, exacerbating the severity of its effects on economically and socially disadvantaged groups (Pörtner et al., 2022).

Based on a review of related research, the study by Thampanishvong et al. (2022) examines the risks of climate change in Thailand, focusing primarily on its impacts on children. However, this assessment is limited to the provincial level, creating indices to reflect children's vulnerability to climate change across regions. While these indices provide a useful overview of climate risk exposure, they generally operate on a broad scale, focusing only on provincial-level vulnerabilities. For instance, UNICEF's study highlights that children in different parts of Thailand are exposed to varying levels of risk, with some regions facing significantly higher threats. This uneven distribution of climate risks across provinces emphasizes the varying degrees of exposure and vulnerability, particularly in rural areas where children are more likely to be impacted by climate hazards.

Additionally, regression analysis from the study suggests a strong linkage between child-sensitive climate risk indices and socio-economic factors, showing that children in poorer, rural households are at greater risk due to lower adaptive capacity. Factors such as access to resources, infrastructure, and financial services were found to reduce overall climate risk for households with children, underscoring the importance of enhancing adaptive capacities.

The findings from the aforementioned research have provided policymakers and stakeholders with valuable insights into the climate-related risks faced by children, as well as the factors associated with those risks. However, this research has not specifically examined the risks related to education, which is a critical gap. Understanding the educational risks of climate change is essential because education plays a fundamental role in children's long-term development, future opportunities, and overall well-being. When climate-related disruptions affect access to and the quality of education, they can have profound, lasting consequences on children's ability to learn and thrive, ultimately impacting the country's future workforce and economic growth.

Moreover, the study was conducted at a provincial level, which, while providing a useful understanding of how risks are distributed across provinces, may still lack sufficient granularity. Many provinces in Thailand cover large geographic areas with diverse topographies and population characteristics. This variability means that climate risks, and their impact on different population groups, are likely to differ even within the same province. As a result, a province-wide analysis may not capture the specific risks experienced by more localized communities or schools within that province.

Additionally, while the study did include an analysis of factors that influence climate risks, these findings represent a national overview. In the context of Thailand's education system, varying local contexts—such as regional disparities, socio-economic differences, and infrastructural inequalities—are key factors that could influence the relationship between these factors and educational risks, particularly as they affect the resources available to students and schools.

Given these gaps, this research aims to develop a more focused and detailed analysis of educational risks from climate change. Specifically, this study will develop an educational risk index that correlates climate change impacts with student academic achievement and analyze the factors associated with this risk across different educational contexts. By doing so, this study will provide a clearer understanding of how climate risks intersect with education and inform the development of more targeted interventions to mitigate these risks.

The Climate-Mapped Educational Risk Index (CMER Index) is developed by combining extreme precipitation and temperature indices with student academic achievement data. The index integrates climate variables—such as the intensity, duration, and frequency of extreme weather events—with educational outcomes, particularly using the O-NET Score as a measure of academic achievement. To construct the index scale, Principal Component Analysis (PCA) was employed, capturing the major dimensions of climate extremes and their correlation with student performance.

In addition to constructing the CMER Index, this study explores the relationship between non-climate factors and educational risks by applying regularized regression. The analysis focuses on four main categories of non-climate factors: Geographical & Spatial Barriers, School Infrastructure & Connectivity, School Characteristics, and Student Characteristics. Based on the hypothesis that these relationships may vary across different regions due to diverse socio-economic and environmental contexts, the predictive models were constructed separately for each educational service area. This approach allows for a more nuanced analysis of how non-climate factors influence educational risks in different local settings.

The results from this analysis will generate insights that can support the design of targeted policies and resources to mitigate educational risks posed by climate change, ensuring that interventions are tailored to the specific needs and vulnerabilities of different regions and communities.

3 Research Objectives

The objective of this research project are as follows:

1. Explore and develop a methodology note to identify relevant education metrics to highlight the actual or potential, direct or indirect, adverse effect of climate change and environmental degradation on children's education participation and learning.
2. Identify characteristics of schools/provinces/areas and children where education is exposed to considerable risks of climate hazards, inter alia by region, urban/rural, socio-economic status, disability, gender, age, school hardship location, etc.

4 Research Conceptual Framework

The diagram in Figure 1 below illustrates the conceptual framework of this research, which consists of two main components. The first component focuses on the development of a Climate-Mapped Educational Risk Index (CMER Index). The second component involves analyzing the relationship between non-climate factors and the CMER Index. The details of these components are as follows:

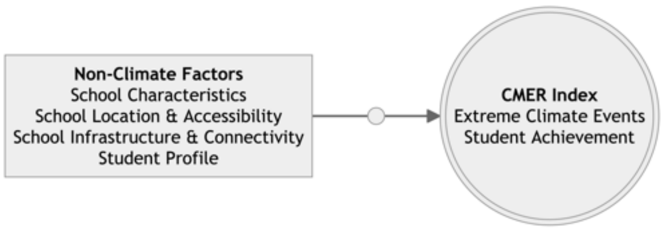

Figure 1: Research Conceptual Framework

The first part involves constructing the CMER Index, which assesses the educational risks associated with climate change. This index is developed by integrating extreme climate event data (such as excessive rainfall or rising temperatures) with student academic performance (such as O-NET scores). While the CMER Index helps identify schools and areas with heightened climate-related educational risks, it serves primarily as a tool for prioritizing further analysis. To design effective interventions, additional insights into non-climate factors—such as school infrastructure, geographical barriers, and socio-economic conditions—will be necessary to fully understand the context in which these risks occur.

The second part of the conceptual framework focuses on the analysis of non-climate factors that are likely to correlate with educational risks. These factors are grouped into four dimensions: School Characteristics, School Location & Accessibility, School Infrastructure & Connectivity, and Student Profile. This analysis is conducted under the hypothesis that the relationship between non-climate factors and the CMER Index varies by region, reflecting the diverse educational contexts across Thailand.

In this research, Educational Service Areas (ESAs) have been selected as the geographic unit of analysis. The selection of ESAs is crucial because each area covers specific geographic regions that align with the climate data grids used in the study. This alignment allows for a precise connection between climate risks and the schools and regions affected. Moreover, ESAs serve as administrative units responsible for formulating and managing school policies, making them suitable for policy-oriented analysis. The structure of the ESAs enables policy recommendations to be more effectively tailored to specific regions. By analyzing how non-climate factors correlate with the CMER Index across different ESAs, the study aims to provide important insights for the development and implementation of localized education policies. These policies can then be adapted to address both climate risks and other factors, ensuring that the interventions are context-sensitive and effective in mitigating educational risks.

5 Scope of Works and Methodologies

This research focuses on assessing the educational risks faced by students due to climate change across schools under the Office of the Basic Education Commission (OBEC) in Thailand. Specifically, this research seeks to address the gap left by previous studies, by developing a comprehensive Climate-Mapped Educational Risk Index (CMER), which combines key climate variables with educational outcomes to assess levels of risk. While earlier research has focused on general climate vulnerabilities, this study aims to fill the void in understanding how climate risks specifically impact education. In addition, the study will investigate non-climate factors—such as school infrastructure, geographical barriers, and socio-economic conditions—to gain a deeper understanding of how these elements correlate with climate risks across different educational contexts. The insights gathered from this analysis will inform the development of targeted interventions to mitigate the educational risks posed by climate change, ultimately contributing to more resilient education systems in vulnerable regions.

5.1 Variables and Data Sources

The data used in this study is divided into two parts: climate data, spanning the periods 1970-2005 and 2017-2021, with the unit of analysis being a 25x25 square kilometer grid, and non-climate (education) data, covering the period 2017-2021, with the unit of analysis being individual schools. The details are as follows:

5.1.1 Climate Data

The climate data used in this study is derived from the Southeast Asia Climate Downscaling/Coordinated Regional Climate Downscaling Experiment Southeast Asia (SEACLID/CORDEX Southeast Asia) Project, Phase II: High-resolution Analysis of Climate Extremes over Key Areas in Southeast Asia (http://www.rucore.ru.ac.th/seaclid-cordex-phase2). The data has been downscaled to high resolution using a combination of General Circulation Models (GCMs) and Regional Climate Models (RCMs) to account for two greenhouse gas concentration scenarios: RCP4.5 and RCP8.5, which represent moderate and high levels of greenhouse gas emissions, respectively. These simulations were applied across several regions in Southeast Asia to assess future climate risks and extreme events.

The results from the selected GCM models were downscaled into a 25x25 square kilometer grid, resulting in a total of 2,691 grid cells specifically within Thailand. This downscaling allows for a highly detailed analysis of climate variability across specific areas in the country. The granularity of the grid provides a more accurate understanding of localized climate patterns, which is crucial for forecasting extreme climate events and assessing their potential impacts on various sectors, including education and communities affected by climate change. The grid layout is illustrated in the Figure 2.

Further information and an assessment of the impact on children in Thailand can be found in the report by Thampanishvong et al. (2022), which explores the effects of climate change and environmental degradation on children in Thailand. The report highlights the unequal distribution of risks across different regions and emphasizes the vulnerability of rural communities, which are more susceptible to climate risks.

Table 1 presents a list of **the extreme precipitation data** used in the research. The Extreme Precipitation Data table provides a structured overview of various indices

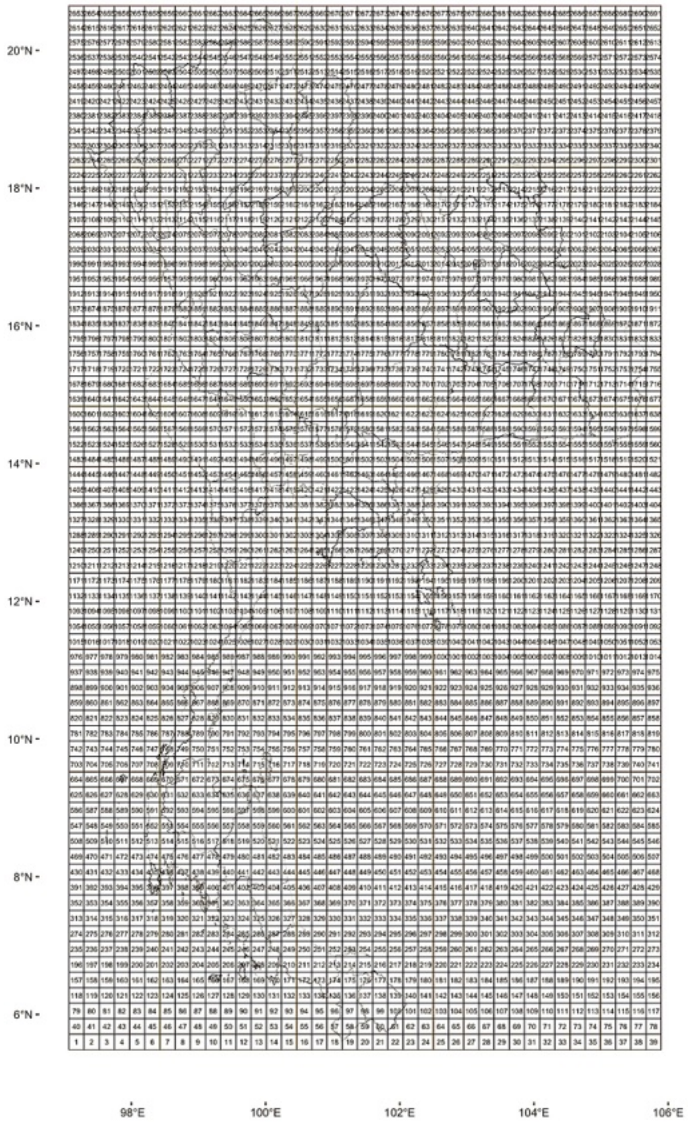

Figure 2: Map of 25x25 km Grid Cells Over Thailand

that measure the key aspects of extreme precipitation events. These indices are divided into three main dimensions: intensity, frequency, and duration.

The intensity dimension captures the magnitude of rainfall events, with indices such as Rx1day, which measures the maximum total precipitation in a single day, and Rx5day, which tracks the maximum precipitation over any consecutive 5-day period. Additionally, R95p and R99p reflect the annual sum of precipitation on days exceeding the 95th and 99th percentiles, respectively, indicating the most extreme rainfall events in a year.

The frequency dimension assesses how often heavy rainfall occurs, using indices like R10mm and R20mm, which count the number of days in a year where daily precipitation equals or exceeds 10 mm and 20 mm, respectively. These measures help quantify how frequently significant rain events happen within a year.

Lastly, the duration dimension focuses on the persistence of rainy periods. The CWD (Consecutive Wet Days) index measures the longest stretch of consecutive days with at least 1 mm of precipitation, providing insight into prolonged wet conditions during the year.

Table 1: Climate Data: Extreme Precipitation Data

Index	Definition	Unit	Category
Rx1day	Maximum 1-day precipitation total	mm	Intensity
Rx5day	Maximum 5-day precipitation total	mm	Intensity
R95p	Annual sum of daily precipitation $>$ 95th percentile	mm	Intensity
R99p	Annual sum of daily precipitation $>$ 99th percentile	mm	Intensity
R10mm	Annual number of days when precipitation $\geq$ 10 mm	days	Frequency
R20mm	Annual number of days when precipitation $\geq$ 20 mm	days	Frequency
CWD	Maximum annual number of consecutive wet days (i.e., when precipitation $\geq$ 1 mm)	days	Duration

The Extreme Temperature Data in Table 2 summarizes key indices used to measure various aspects of extreme temperature events. These indices are divided into three primary dimensions: intensity, frequency, and duration, which together provide a comprehensive picture of temperature extremes over time.

The intensity dimension focuses on the severity of temperature extremes. For instance, indices such as TXx and TNx measure the highest maximum and minimum daily temperatures within a year, reflecting how extreme heat waves can become during a given period. These indices provide insight into how extreme temperature peaks occur in different regions.

The frequency dimension captures how often extreme temperatures occur, using indices such as TX90p and TN90p, which represent the percentage of days within a year when the maximum and minimum temperatures exceed the 90th percentile, respectively. These measures help quantify how frequently high-temperature events take place, indicating the frequency of heat waves or unusually warm nights over the course of the year.

The duration dimension looks at the persistence of these temperature extremes. Indices such as WSDI (Warm Spell Duration Index) measure the length of consecutive days when the daily maximum temperature exceeds the 90th percentile, providing a measure of how prolonged heat events are in a given region. This can be critical for understanding the long-term stress that extended periods of extreme heat can place on communities, infrastructure, and ecosystems.

Table 2: Climate Data: Extreme Temperature Data

Index	Definition	Unit	Category
TXx	Monthly Maximum value of daily max temperature	°C	Intensity
TNx	Monthly Maximum value of daily min temperature	°C	Intensity
TXn	Monthly Minimum value of daily max temperature	°C	Intensity
TNn	Monthly Minimum value of daily min temperature	°C	Intensity
DTR	Monthly mean difference between TX and TN	°C	Intensity
TX10p	Share of days when Tmax < 10th percentile	% of days	Frequency
TN10p	Share of days when Tmin < 10th percentile	% of days	Frequency
TX90p	Share of days when Tmax > 90th percentile	% of days	Frequency
TN90p	Share of days when Tmin > 90th percentile	% of days	Frequency
CSD	Annual number of days with at least 6 consecutive days when Tmin < 10th percentile	days	Duration
WSD	Annual number of days with at least 6 consecutive days when Tmax > 90th percentile	days	Duration

Together, the indices for both extreme precipitation and extreme temperature provide a comprehensive view of climate-related events, capturing the intensity, frequency, and duration of extreme weather patterns. The precipitation indices quantify rainfall intensity in millimeters, while the frequency and duration are measured in days, offering valuable insights into risks such as flooding, soil erosion, and infrastructure damage. Similarly, the temperature indices assess heat intensity by measuring maximum and minimum temperatures, while tracking the frequency and persistence of heat waves or warm spells. By analyzing both sets of indices together, this integrated perspective helps to understand how extreme weather events, whether through excessive rainfall or extreme heat, manifest across different dimensions and regions. Such detailed insights are essential for assessing the risks these climate extremes pose to both human and environmental systems, providing a critical foundation for managing the impacts of climate change, particularly in vulnerable regions.

5.1.2 Non-Climate Data

The non-climate data is categorized into five main dimensions: School Demographics, School Location & Accessibility, School Infrastructure and Connectivity, and Student Profile. All data is at the school level and pertains to schools under the Office of the Basic Education Commission (OBEC). The data is further classified into schools affiliated with the Primary Educational Service Areas and those affiliated with the Secondary Educational Service Areas. The details of each dimension are as follows:

The school characteristics component includes basic information about the schools, such as the school name, address, affiliated educational service area, and school size. This data was collected from the Basic School Information Database of the Office of Basic Education Commission (OBEC) and the Data Management Center (DMC) under the Ministry of Education, Thailand, for the academic years 2017 and 2021. The data covers a total of 30,112 schools across Thailand.

The school location & accessibility component consists of four key variables: the longitude and latitude coordinates of the school, the distance from the district center, the type of hardship location (whether the school is in a remote or hard-to-reach area), and the degree of difficulty in accessing the school.

The longitude and latitude coordinates were collected using the school's name and address, with the coordinates retrieved from the Google Maps API. The distance from the district center was calculated using the Haversine formula, which measures the shortest distance between two points on a sphere. This data covers 29,748 schools. Finally, The data on the type of hardship location and the degree of difficulty in accessing the school is based on the announcement from the Office of the Basic Education Commission (OBEC) regarding the designation of 1,441 schools located in special areas (remote highland areas and island areas) under the project aimed at creating opportunities and reducing educational disparities at the local level. This data is from the fiscal year 2022-2023, as per the announcement dated August 10, 2022 (Office of the Basic Education Commission (OBEC), 2023).

The school infrastructure & connectivity component includes information on the school's infrastructure, such as the availability and type of electricity, water supply, and internet connectivity. This data was collected by the researchers through web scraping from the OBEC assets information website (Office of the Basic Education Commission (OBEC), 2024), with the scraping conducted between September 2-3, 2024, covering a total of 28,136 schools.

The student profile data The data includes the percentage of students from low-income families in each school. This information is sourced from the O-NET score database and the student profile database provided by the National Institute of Educational Testing Service (NIETS).

The student achievement data includes O-NET exam scores in Mathematics, Science, Thai, and English from the academic years 2017-2021. This data is averaged at the school level and is categorized into three education levels: Grade 6, Grade 9, and Grade 12.

Table 3: Non-Climate Data

Dimensions	Source
School Characteristics: (1) School name (2) Address (3) School size	OBEC Basic School Information Database & Data Management Center (2017, & 2021)
School Location & Accessibility: (1) Longitude and latitude (2) Distance from district center (3) Type of hardship location (4) Degree of accessibility difficulty	Google Maps API & OBEC Announcement on Special Areas (2022)
School Infrastructure & Connectivity: Availability and type of (1) Electricity (2) Water supply (3) Internet connectivity	OBEC Assets Information Website (2024)
Student Profile: (1) O-NET scores in Mathematics, Science, Thai, and English (2) Percentage of students from low-income families	NIETS O-NET Score Database (2017-2021)

5.2 Data Preprocessing and Analysis

This research divides the data analysis into two main components. The first component focuses on analyzing climate and student achievement data to construct the Climate-Mapped Educational Risk Index (CMER Index), addressing the first research objective. The second component examines the relationship between non-climate factors and the CMER Index within each educational service area, addressing the second research objective.

The results from both parts of the analysis will not only help identify high-risk schools and areas but also provide deeper insights into the school characteristics and educational factors associated with CMER Index risks in each region. This understanding will facilitate the development of targeted recommendations aimed at mitigating these risks effectively. The details of data preparation and analysis for each research objective are as follows:

5.2.1 Research Objective 1: Constructing the CMER Index

The process of constructing the CMER Index begins with utilizing extreme climate data (including precipitation and temperature indices), which are calculated into anomaly scores. These anomaly scores are derived from the difference between climate data during the study period (2017-2021) and the baseline period (1970-2005), reflecting deviations in extreme rainfall and temperature across different regions. This data is then combined with student academic achievement, represented by aggregated O-NET exam scores in four subjects: mathematics, science, Thai language, and social studies.

Principal Component Analysis (PCA) is employed to integrate these variables, reducing the data's dimensionality while preserving the most critical variance. The result is a composite index that captures the combined correlation between extreme climate factors and academic achievement. These correlations include both direct and indirect relationships between climate variables and educational outcomes.

In this analysis, the selected principal components must contain information about educational risks, particularly components where climate factors exhibit an inverse correlation with academic achievement. This means that as the intensity of extreme climate events increases, student achievement scores decrease, indicating a higher educational risk in areas more affected by extreme climate conditions.

By focusing on such components, the analysis provides a comprehensive educational risk index that identifies high-risk areas and schools. This index will support targeted interventions to mitigate the negative impacts of climate change on education effectively.

The diagram in Figure 3 below illustrates the analytical framework for constructing the CMER Index.

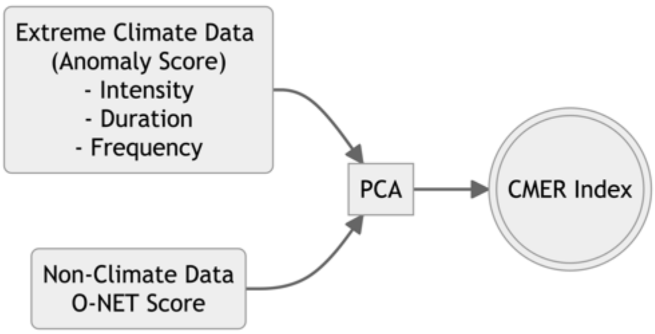

Figure 3: analytical framework for constructing the CMER Index

The diagram in Figure 4 illustrates the detailed steps involved in the data preprocessing and analysis for Research Objective 1, which aims to construct the Climate-Mapped Educational Risk Index (CMER Index).

The first component of the process focuses on the climate data, which includes precipitation and temperature datasets. The data undergoes several stages of preprocessing:

1. Tidying the data: The data is reshaped, filtered, and aligned across the different climate variables.

2. Normalization: The climate data is normalized to ensure consistency.

3. Calculation of composite indices: The indices for intensity, duration, and frequency of climate extremes are calculated.

4. Splitting the data: The climate data is divided into two time periods, the baseline (1970-2005) and the study period (2017-2021).
5. Anomaly score calculation: An anomaly score is calculated by comparing the study period with the baseline period. This score represents the deviation of current climate conditions from historical averages.

Simultaneously, the second component involves processing the non-climate data from the DMC and O-NET datasets:

1. Tidying DMC and O-NET data: The school profile and O-NET scores are tidied, reshaped, and aligned.
2. Merging DMC and O-NET data: The two datasets are merged to combine school profile data with student achievement data.
3. Normalization of O-NET scores: The O-NET scores across four subjects (Math, Science, Thai, and English) are normalized.
4. Calculation of the achievement score: A composite index for achievement (Ach Score) is calculated from the O-NET data.

Next, the school location data is processed to obtain the geographic coordinates (longitude and latitude) for each school using the Google Maps API. The distance between each school and the corresponding climate grid cell is calculated using the Haversine distance formula. Schools are mapped into the climate grid based on the shortest distance to a grid cell.

Finally, the climate and non-climate data are merged to create a complete dataset, which is then analyzed using Principal Component Analysis (PCA). PCA is applied to extract the key components representing the educational risks associated with extreme climate events. The final output is the CMER Index, which ranges from 0 to 1 and reflects the level of educational risk due to climate change in each region.

This comprehensive process enables a systematic and integrated analysis of climate and non-climate factors, providing insights into the risks that climate extremes pose to student achievement across different areas in Thailand.

5.2.2 Research Objective 2: Analyzing Non-Climate Factors

In the data analysis for the second objective, regularized regression will be employed as the primary technique to assess the relationship between non-climate factors and the CMER Index, which was developed in the first objective. The goal of this analysis is to understand how factors such as school characteristics, accessibility challenges, school resources, and students' socio-economic status affect educational risks across different educational service areas.

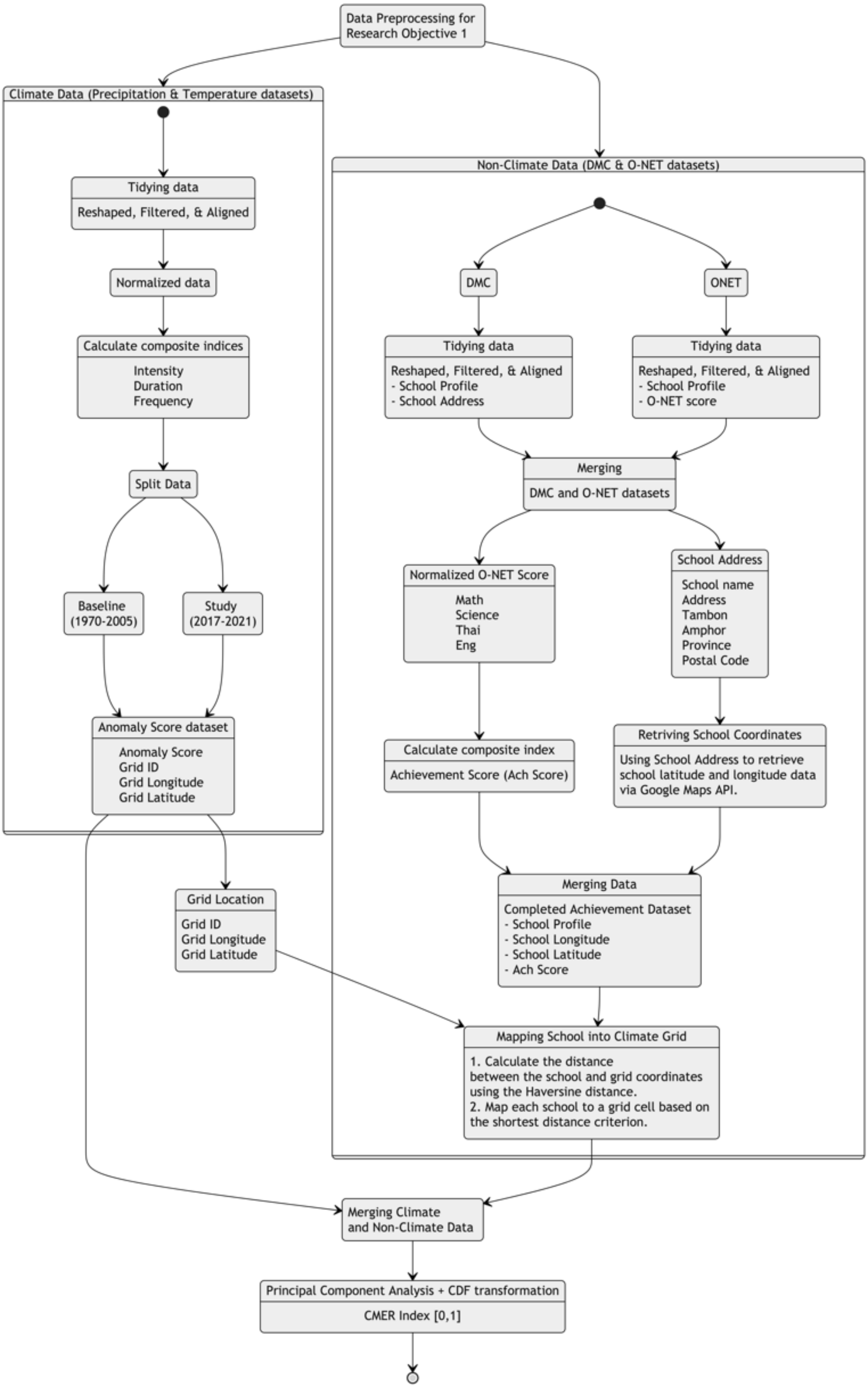

Figure 4: Data Preprocessing and Analysis for Research Objective 1

In the preprocessing stage, the CMER Index from the first objective will be combined with the non-climate data consisting of four dimensions: School Characteristics, School Location & Accessibility, School Infrastructure & Connectivity, and Student Profile. The integration of these datasets is straightforward since the climate and student achievement data for each school have already been matched and merged in the previous step.

The detailed analysis framework for Research Objective 2, as presented in the diagram, outlines how various school-related factors are analyzed to assess their relationship with the Climate-Mapped Educational Risk Index (CMER Index). These factors are divided into four main categories:

1. **School Characteristics:** This dimension includes the size of the school, classified into four categories: small (S), medium (M), large (L), and extra-large (XL). School size is a critical factor in understanding how resources and capacity may influence educational risks related to climate change.

2. **School Location & Accessibility:** This category encompasses the distance of the school from the district center, and the degree of accessibility.

- Distance from the District Center: Measured in kilometers, this variable indicates the geographical remoteness of the school from the nearest administrative center, which may affect access to resources and support.

- Degree of Accessibility Difficulty: The ease of accessing the school is classified into four levels—ranging from “not difficult” to “most difficult”—which provides insight into how challenging it may be for students to attend school regularly, particularly during extreme weather events.

3. **School Infrastructure & Connectivity:** This dimension focuses on the Infrastructure Readiness Score, which is calculated based on the availability of essential services such as electricity, water supply, and internet access at the school. The score ranges from 0 to 1, where a higher score indicates better infrastructure readiness, contributing to the school’s capacity to manage climate-related disruptions.

4. **Student Profile:**

- Percentage of Low-Income Students: This variable is transformed into a categorical dummy variable for schools under the Primary Educational Service Areas (PESA). It distinguishes between schools where the majority of students come from low-income families (>50%) and those where low-income students are a minority.

- Student Level: Refers to the grade levels of students, specifically focusing on Grade 6, Grade 9, and Grade 12. Analyzing this variable provides valuable insights into how educational risks may vary across different age groups. This approach helps to identify potential disparities in vulnerabilities between younger and older students, highlighting how students in primary school may face different challenges compared to those in secondary school, which supports the development of targeted interventions for each group.

The use of regularized regression addresses the issue of multicollinearity, which is common in large datasets, allowing for more precise identification of the factors that influence educational risk. The analysis will be conducted separately for each educational service area, distinguishing between Primary Educational Service Areas (PESA) and Secondary Educational Service Areas (SESA), to capture regional differences in educational contexts.

The results from this analysis will help identify which non-climate factors are significantly associated with the CMER Index in each educational service area. This information will provide insights for targeted recommendations and actionable strategies to mitigate educational risks posed by climate change in specific regions.

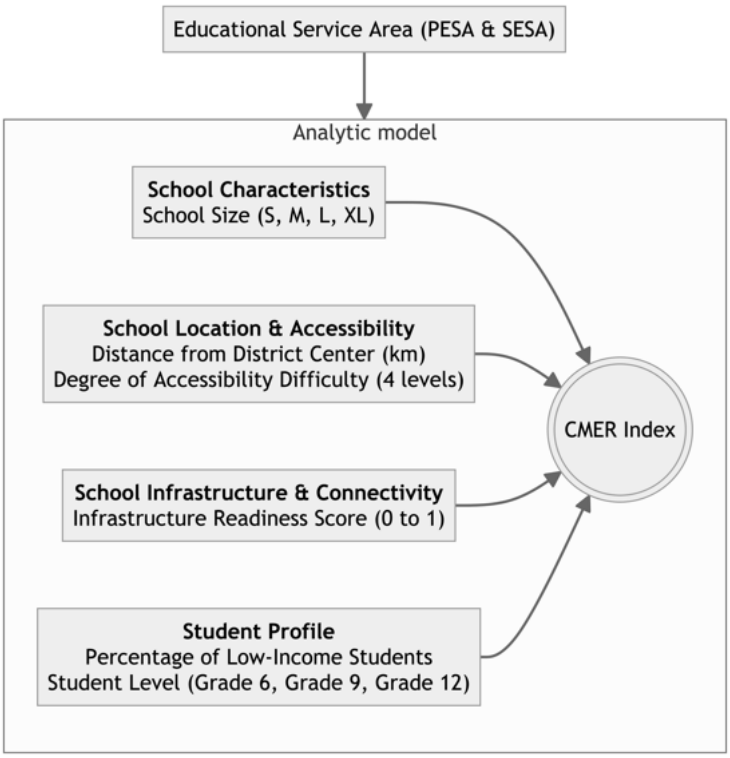

Figure 5: Analysis Framework for Research Objective 2

6 Research Results

This chapter presents the results of the data analysis, which is divided into two parts corresponding to the research objectives.

The first research objective focuses on exploring and developing a methodology to identify relevant educational metrics that highlight the actual or potential direct or indirect adverse effects of climate change and environmental degradation on children's education participation and learning. The analysis in this section centers on the creation and evaluation of the Climate-Mapped Educational Risk Index (CMER), which integrates extreme climate data with student academic achievement. The results from constructing this index will address the first research objective by helping to identify high-risk areas or schools that are particularly vulnerable to the impacts of climate change.

The second research objective involves analyzing and identifying the characteristics of schools, provinces, areas, and children that are exposed to considerable risks from climate hazards. This includes factors such as region (urban/rural), socio-economic status, disability, gender, age, and the location of schools in hard-to-reach areas. The analysis focuses on understanding how non-climate factors—such as school characteristics, school location and accessibility, school infrastructure, and student profiles—are associated with the CMER index within different educational service areas. This will help provide insights into the specific factors that influence educational risks in various contexts, supporting the development of targeted policy interventions.

The results of the analysis for each section are as follows:

6.1 Results for Research Objective 1:

The first objective of this research is to identify and develop a methodology that links climate-related factors with educational outcomes. This aims to capture how climate change, particularly extreme weather events, may impact children's participation and performance in education. The analysis for this objective focuses on developing the Climate-Mapped Educational Risk (CMER) Index, which integrates extreme climate data and student achievement metrics. In this section, we present the results of the Principal Component Analysis (PCA) used to construct the CMER Index, followed by an analysis of the index itself to assess its implications for educational risk. The details of these analyses are as follows:

6.1.1 Principal Component Analysis Results (PCA) for CMER Index Construction

This section presents the results of the PCA analysis aimed at creating a scale for the educational risk index associated with extreme climate anomalies. The analysis is divided into two parts. The first part highlights the percentage of variance explained by each principal component, categorized by extreme precipitation and temperature anomalies. The results illustrate how much of the original dataset's variance can be captured by the principal components for both precipitation and temperature anomalies, as shown in Figure 6.

The second part, which is crucial, focuses on the component loadings between the extreme precipitation anomalies and student achievement outcomes. This section reveals the relationship between precipitation anomalies—such as intensity, frequency, and duration—and student achievement, showing how these variables contribute to the principal components. These loadings are represented in the component scale in Figure 7, providing key insights into the association between climate anomalies and educational performance.

The Percentage of Variance Explained by Each Principal Component (PC)

The bar charts in Figure 6 present the percentage of variance explained by each principal component (PC) for both extreme precipitation and extreme temperature data, along with student achievement (O-NET scores) across three grade levels (Grade 6, Grade 9, and Grade 12). Each chart provides insights into how much variance in the original dataset is captured by the principal components. The height of the bars reflects the contribution of each component in explaining the data's variance.

From these charts, it is evident that the first principal component (PC1) consistently captures the largest proportion of variance, explaining approximately 40% across all grade levels for both climate variables. The second and third components (PC2 and PC3) combined explain around 25%, while the fourth component (PC4) captures roughly 7-8%.

Component Loadings from Principal Component Analysis (PCA)

The following analysis presents a bar chart displaying the component loadings from the Principal Component Analysis (PCA) for both extreme climate indices (precipitation and temperature) and student achievement across the four principal components and three student grade levels. These loadings represent the strength and direction of the relationship between each variable (rows) and the respective principal components (columns). High absolute values of the loadings indicate that the variable has a

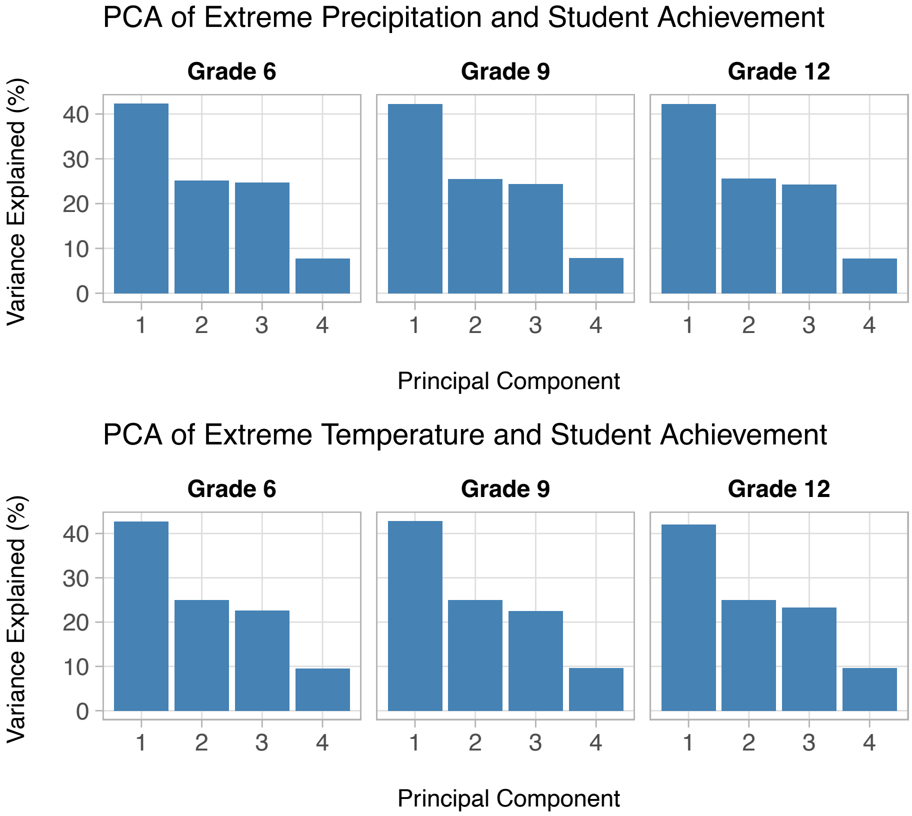

Figure 6: Percentage of Variance Explained by Principal Components of Extreme Climate and Student Achievement

strong correlation with the principal component, reflecting how much that variable contributes to defining the meaning of the component.

Figure 7 below presents the bar chart of the component loadings from the analysis. Key elements of the chart include the Y-axis, which lists the variables used in the analysis, such as precipitation intensity, frequency, duration, and student achievement. The X-axis shows the loading values, representing the strength and direction of each variable's contribution to the principal components. Values closer to -1 or 1 indicate strong correlations, while values near 0 suggest weak or no correlation. Each section (PC1 to PC4) illustrates how the variables relate to the different components. Blue bars indicate positive correlations, meaning that as the variable increases, so does the component, while red bars represent negative correlations, where an increase in the variable corresponds to a decrease in the component.

When examining Figure 7 (upper), particularly in PC3, we observe an inverse relationship between Precipitation Duration and student achievement. Precipitation Duration has a positive loading in PC3, indicating that as the duration of extreme rainfall increases, it is positively associated with higher values in PC3. This suggests that prolonged extreme rainfall durations are linked to an increase in climate-related educational risk. Conversely, student achievement shows a negative loading in PC3, implying that higher student achievement is inversely related to this risk. In other words, in areas where educational risk (PC3) is high, student achievement tends to be lower, reflecting a greater risk of poorer academic performance.

In contrast, Figure 7 (lower) shows no clear pattern between extreme temperature factors and student achievement that can be combined into a coherent risk scale. No principal components derived from the variance and covariance of these variables seem to capture educational risk.

Thus, PC3 of Extreme Precipitation and Student Achievement emerges as a robust measure of educational risk. Prolonged rainfall duration correlates with increased educational risk, while higher academic performance (higher student achievement) correlates with lower risk. This relationship supports the use of PC3 as a key factor in the **Climate-Mapped Educational Risk Index (CMER)**, where longer rainfall durations correspond with higher educational risk and lower student achievement.

6.1.2 Descriptive Analysis of CMER Index

This section "Descriptive Analysis of CMER Index" focuses on a detailed exploration of the Climate-Mapped Educational Risk (CMER) Index, examining its distribution, categorization, and geospatial patterns. This analysis is crucial to understanding the nature and extent of educational risks across different dimensions, such as student grade levels and geographic regions.

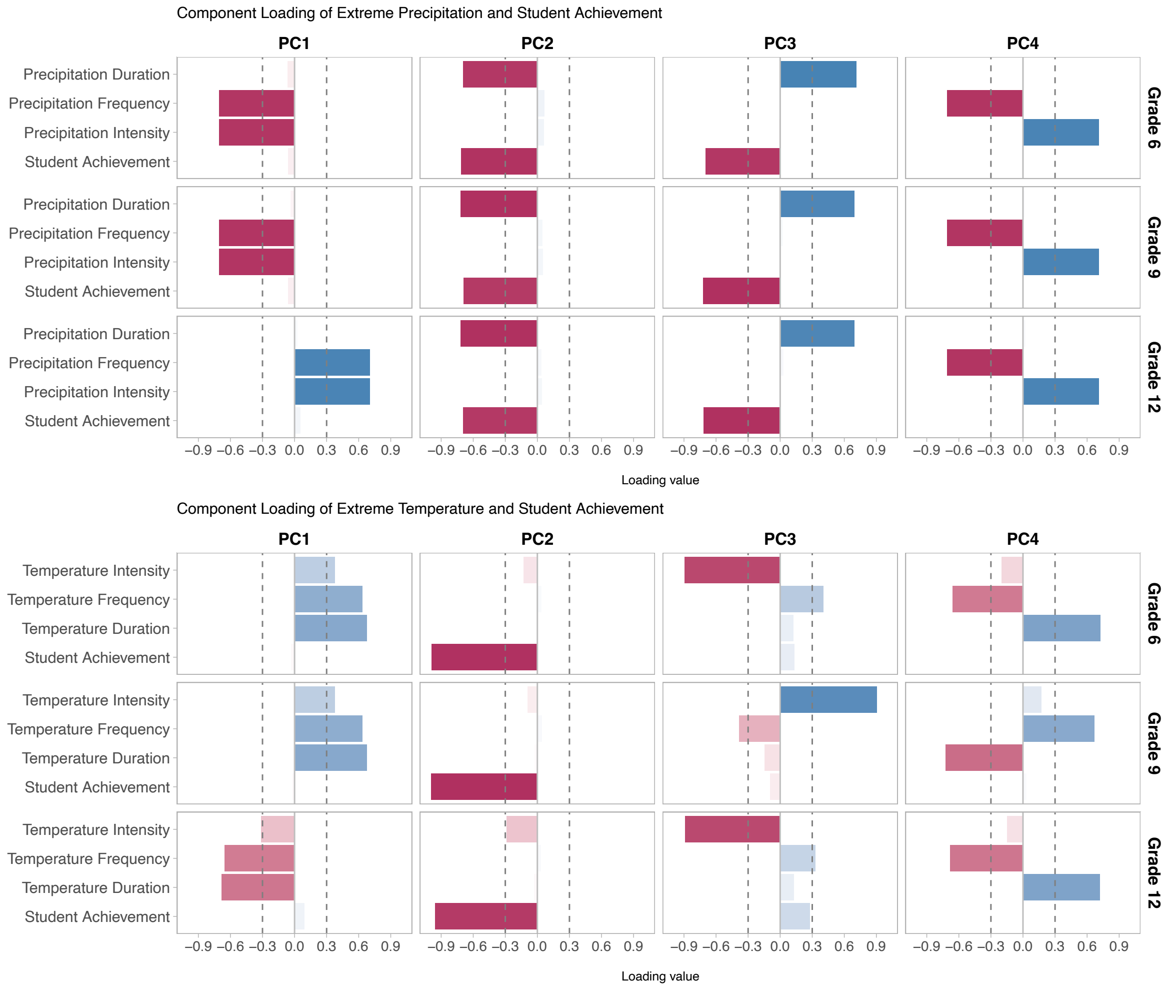

Figure 7: Component Loading of Extreme Precipitaion, and Student Achievement

Summary of CMER Index

The Climate-Mapped Educational Risk Index (CMER) scores, as derived from the Principal Component Analysis (PCA) discussed in the previous section, are standardized and have a possible range from negative infinity to positive infinity, which can make interpreting the risk levels challenging. To improve interpretability, the researcher transformed the risk index scores into a [0,1] range using a cumulative distribution function (CDF) based on the t-distribution. This transformation confines the CMER Index to a bounded scale, making the interpretation of risk levels more intuitive. The Table 4, and Figure 8 below display the distribution of the risk index scores, categorized by student grade level.

The distribution of the CMER Index across all grade levels (Grade 6, Grade 9, and Grade 12) shows a relatively consistent pattern. The mean CMER Index for all levels is around 0.5, with most values falling between 0.4 and 0.63 (the interquartile range). The minimum values across grades are close to 0, while the maximum values approach 1, indicating a broad range of potential risk levels.

This consistency in the distribution suggests that the educational risks related to climate anomalies are similarly spread across different student grade levels. The histograms provide a visual confirmation of this pattern, showing a concentration of CMER Index values around the middle of the scale, with fewer schools exhibiting either extremely low or high risk levels.

Table 4: Summary of CMER Risk Index Categorized by Student Level

Student Level	Mean	SD	Min	Q1	Median	Q3	Max
Grade 6	0.515	0.167	0.009	0.403	0.526	0.634	0.979
Grade 9	0.518	0.160	0.000	0.423	0.534	0.631	0.947
Grade 12	0.505	0.160	0.046	0.397	0.515	0.614	0.967

Optimizing CMER Risk Cut-Offs with ROC Analysis

To provide clearer interpretation of the CMER Index, we will determine cut-off points that reflect the risk levels of schools. The CMER Index will be categorized into three levels: low, moderate, and high risk. This categorization will be based on student achievement scores and the use of ROC analysis. Given that student achievement scores are standardized, specific thresholds will help define the risk levels more precisely.

In determining the cut-off points for the CMER using ROC, we incorporate student achievement scores, which serve as a key educational outcome, to establish risk level thresholds. The first step involves setting the criteria for low and very low academic

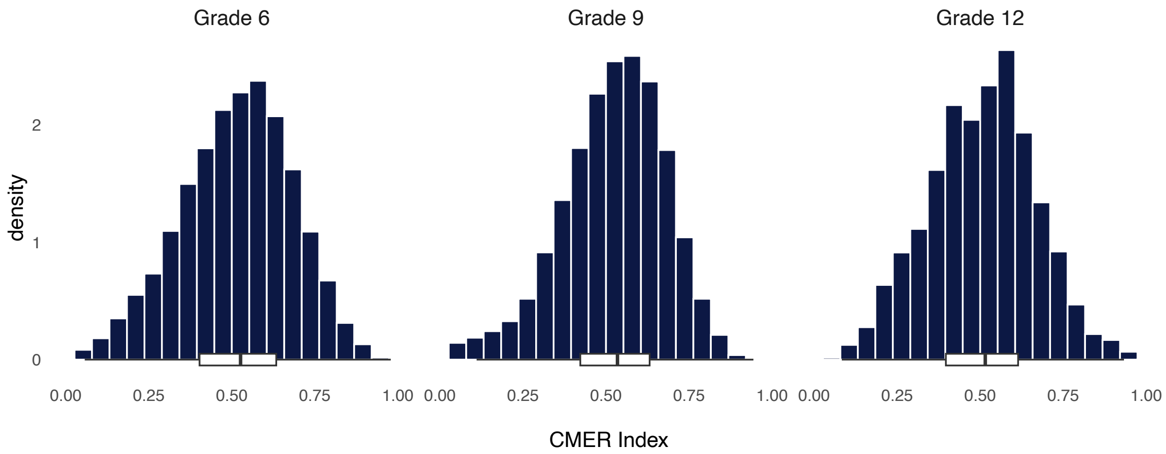

Figure 8: Histogram of School CMER Index categorized by student level

performance. Since achievement scores are measured as standardized scores, we define scores below -0.5 (i.e., 0.5 standard deviations below the mean) as indicating low academic performance and scores below -2.5 (i.e., 2.5 standard deviations below the mean) as indicating very low academic performance.

The ROC (Receiver Operating Characteristic) curve is a graphical tool used to evaluate the performance of various cut-offs for the Climate-Mapped Educational Risk Index (CMER). It allows us to determine the most effective threshold for classifying schools where student achievement scores (low and very low) are negatively impacted by extreme climate events.

The ROC curve plots two critical metrics:

1. True Positive Rate (Sensitivity): This measures the proportion of schools correctly identified as being at moderate or high risk on the CMER scale. For example, schools where student achievement is significantly underperforming due to climate-related risks.

2. False Positive Rate (1 - Specificity): This measures the proportion of schools incorrectly classified as moderate or high risk when, in reality, they are not.

In this analysis, the ROC curve (presented in Figure 9) is used to determine the optimal cut-off points for the CMER Index, which identifies schools with moderate and high risk levels.

- **Moderate-risk cut-off: A threshold of 0.60 was selected**, achieving a sensitivity of 0.80. This means that 80% of schools identified as moderate risk are correctly classified based on student achievement. The corresponding specificity is 0.79, indicating that 79% of schools not at moderate risk are correctly excluded. The AUC (Area Under the Curve) for this cut-off is 0.88, which indicates good overall performance in distinguishing moderate-risk schools from others. An AUC closer to 1.0 reflects stronger classification accuracy, meaning the model is effective at identifying schools at moderate risk.

- **High-risk cut-off: A threshold of 0.80 was determined**, resulting in perfect sensitivity of 1.00—meaning that all schools at high risk were accurately identified. The specificity for this cut-off is 0.95, indicating that 95% of schools not at high risk are correctly excluded. The AUC for this cut-off is 0.98, demonstrating near-perfect accuracy. This means the model is highly effective at distinguishing high-risk schools, ensuring almost no high-risk schools are missed.

Overall, these ROC analyses identify 0.60 and 0.80 as the optimal cut-off values for classifying schools into moderate and high-risk categories, respectively. These thresholds were selected to ensure a balance between sensitivity and specificity, providing an accurate and meaningful framework for identifying schools that are at the greatest educational risk due to extreme climate conditions. This approach, as outlined by Unal (2017), helps in defining the optimal cut-points that maximize the performance of the classification model.

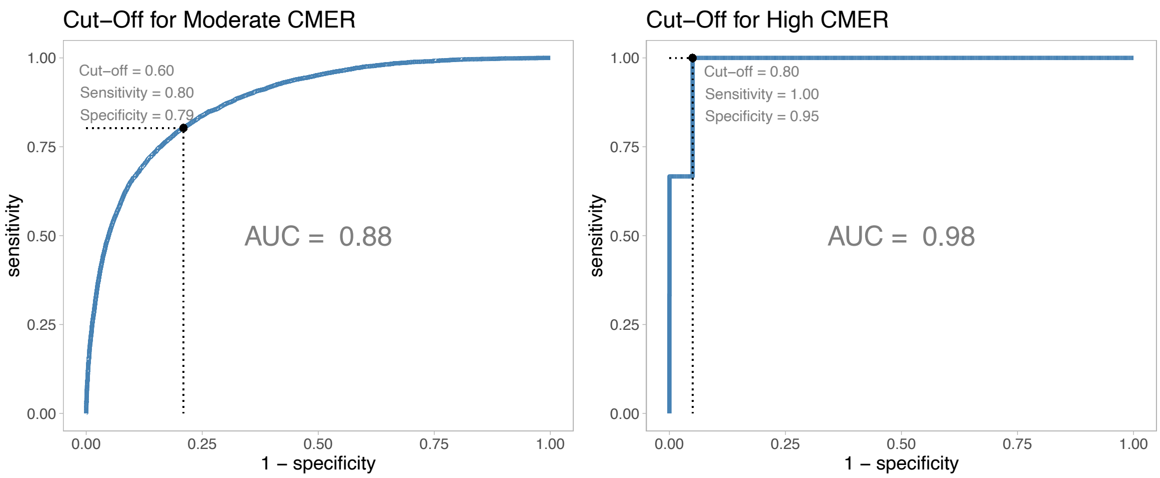

Figure 9: ROC Curve for Determining the Cut-off of the CMER Index

Distribution of CMER Index Categorized by Risk Level and Educational Service Area

The analysis presented in Table 5 categorizes schools into three risk levels—Low Risk, Moderate Risk, and High Risk—based on the cut-off points.

- **Low Risk:** The majority of schools, totaling 17,954, fall into this category. The average CMER score for these schools is 0.42, with a standard deviation of 0.13, indicating some variability within this group. The CMER scores range from a minimum of 0.01 to a maximum of 0.60.

- **Moderate Risk:** A smaller subset of 7,580 schools is classified as moderate risk. These schools have an average CMER score of 0.68, with a tighter standard deviation of 0.05, suggesting less variability among schools in this group. The CMER scores range from 0.60 to 0.80.
- **High Risk:** This category includes 777 schools, representing those at the highest level of risk. The average CMER score in this group is 0.84, with a standard deviation of 0.04, indicating even less variability. CMER scores in this group range from 0.80 to 0.98.

Table 5: Summary of Risk Level Analysis for Schools

Risk Level	Count	Average Risk	Standard Deviation	Minimum	Maximum
Low Risk	17954	0.42	0.13	0.01	0.60
Moderate Risk	7580	0.68	0.05	0.60	0.80
High Risk	777	0.84	0.04	0.80	0.98

The Table 6 provides a summary of the distribution of school risk levels within the Primary Educational Service Area (PESA) and the Secondary Educational Service Area (SESA). Additionally, analyzing CMER separately for PESA and SESA allows for a more targeted approach in understanding and addressing the specific challenges faced by primary and secondary education sectors. This differentiation provides a clearer picture of where interventions might be most effectively applied, aligning the risk assessment more closely with the unique characteristics and needs of each service area.

- Within the PESA, the majority of schools fall under the Low Risk category, accounting for 16,291 schools (approximately 68.2% of total PESA schools), with an average risk score of 0.42 and a standard deviation of 0.13. The risk scores in this group range from a minimum of 0.01 to a maximum of 0.60. In the Moderate Risk category, there are 7,070 schools (around 29.7%), with an average risk score of 0.68 and a standard deviation of 0.05, and risk scores spanning from 0.60 to 0.80. High Risk schools account for only 777 schools (about 3.2% of PESA schools), with an average risk score of 0.84, a standard deviation of 0.04, and scores ranging from 0.80 to 0.98.
- For SESA, the Low Risk category also dominates, with 1,663 schools (approximately 76.8% of total SESA schools), having an average risk score of 0.43 and a standard deviation of 0.13. The risk scores for this group range from 0.04 to 0.60. The Moderate Risk category comprises 510 schools (around 23%), with an average risk score of 0.67, a standard deviation of 0.05, and scores between 0.60 and 0.80. Only 12 schools (about 0.5% of SESA schools) fall into the High Risk category, with an average score of 0.83, a standard deviation of 0.02, and scores ranging from 0.80 to 0.86.

The analysis indicates that in both PESA and SESA, most schools are categorized as Low Risk. However, PESA shows a higher proportion of schools in the Moderate and High Risk categories compared to SESA. The average risk scores for both educational service areas are similar across risk levels, but the concentration of High Risk schools is notably lower in SESA.

Table 6: Summary of Risk Level Analysis for Schools Categorized by Educational Service Area

Risk Level	Count	Average Risk	Standard Deviation	Minimum	Maximum
PESA					
Low Risk	16291	0.42	0.13	0.01	0.60
Moderate Risk	7070	0.68	0.05	0.60	0.80
High Risk	765	0.84	0.04	0.80	0.98
SESA					
Low Risk	1663	0.43	0.13	0.04	0.60
Moderate Risk	510	0.67	0.05	0.60	0.80
High Risk	12	0.83	0.02	0.80	0.86

Geospatial Distribution of School CMER Index

The map in Figure 10 provides a visual representation of the distribution of the Climate-Mapped Educational Risk (CMER) Index across Thailand's primary (PESA) and secondary (SESA) educational service areas. When comparing this visual data with the summary table above, several connections can be observed.

Each point on the map represents a school, with the color gradient reflecting its respective CMER Index score. The visualization aims to provide an overview of the distribution of educational risks within each service area. In the map, lighter points signify schools with higher CMER Index scores, indicating a greater risk for the students in those schools. It is important to note that this visualization does not compare the density of high-risk schools across different affiliation directly, as the number of schools offering each affiliation varies. Instead, the focus is on understanding how the educational risks are geographically distributed for each grade level, offering insights into the regional spread of student risk within schools.

- The left map, representing PESA, shows a more concentrated distribution of moderate and high-risk schools in various regions across the country, particularly in the north, northeast, central, and southern regions. This aligns with the summary table, which shows a higher proportion of schools classified as Moderate and High Risk within PESA areas (around 32.5%).

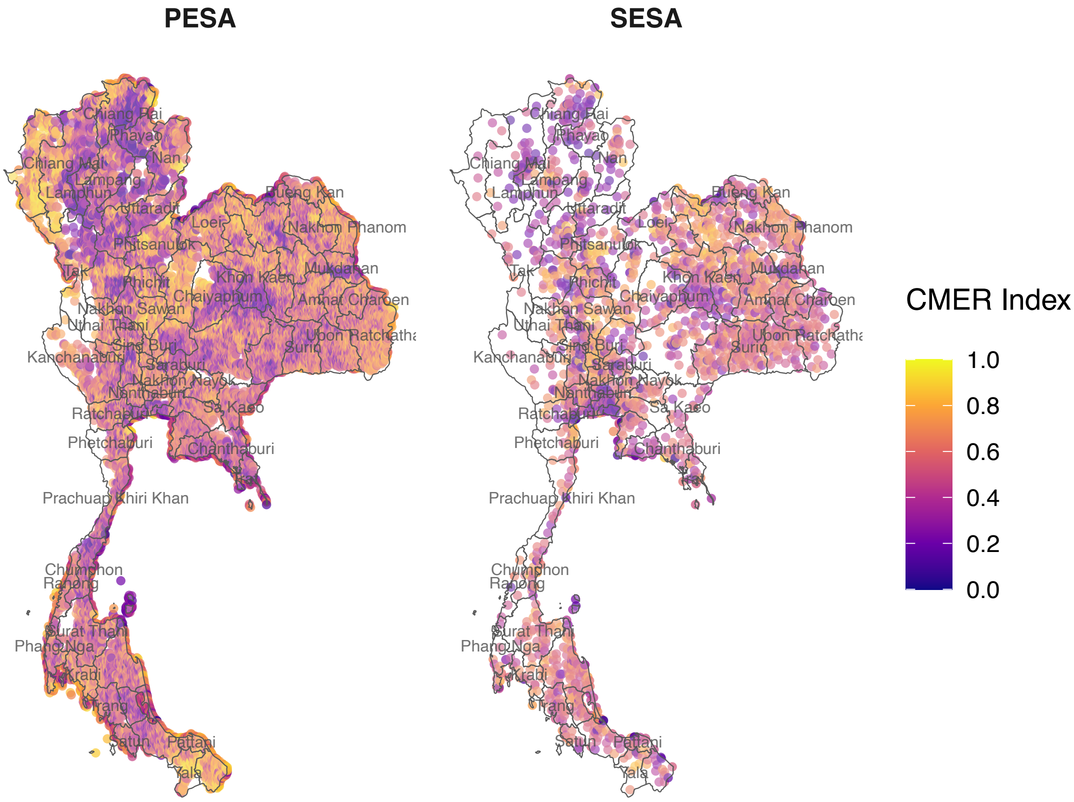

Figure 10: Geospatial Distribution of School CMER Index Categorized by Student Level (2017-2021)

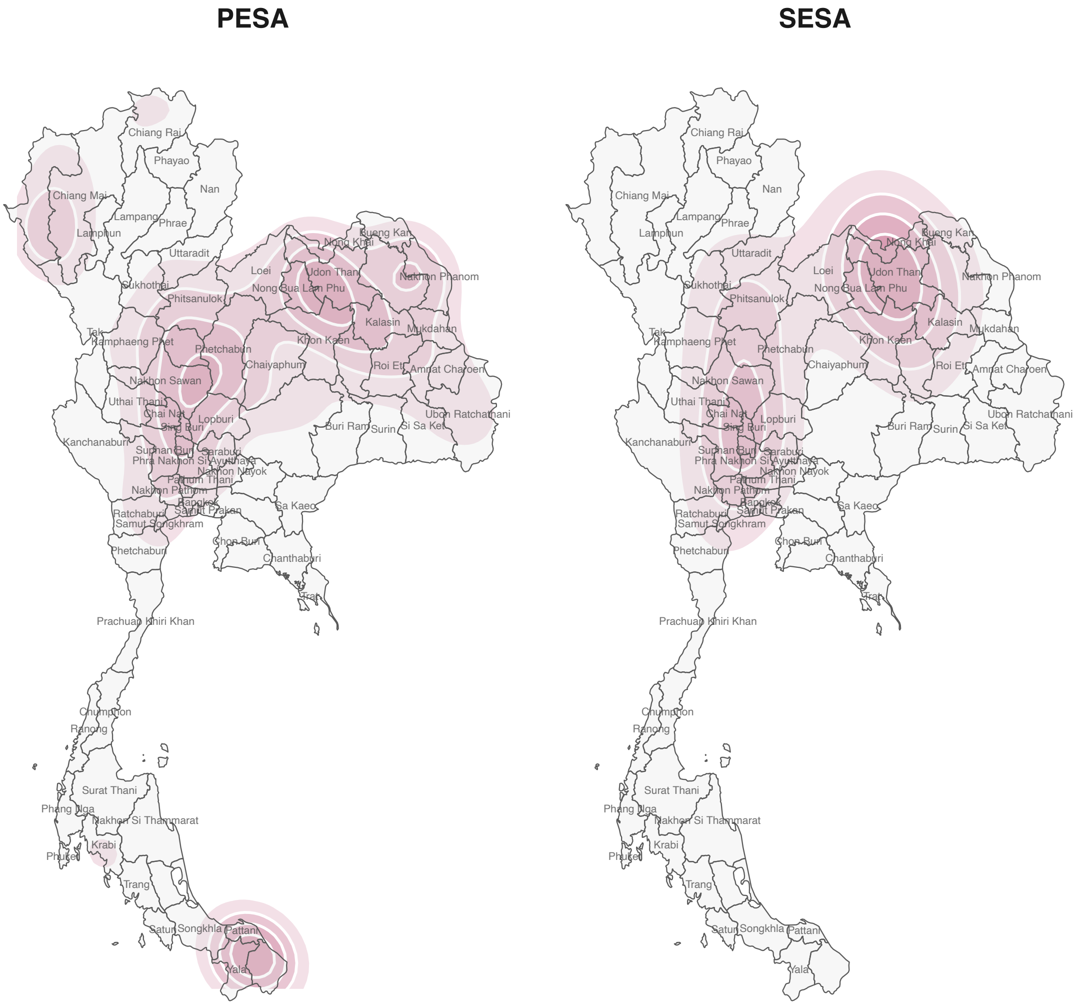

Figure 11: Contour Map of School with High Level of CMER (CMER > 0.8) Categorized by Educational Service Area (2017-2021)

- Meanwhile, the right map illustrates the distribution of the CMER Index in secondary educational service areas (SESA). According to the table, around 23.9% of SESA schools fall under moderate or high Risk categories, with only about 0.5% classified specifically as High Risk. The map shows that these schools are dispersed across various regions.

To enhance the previous visualization of high-risk schools, the researcher mapped school-level CMER data onto a contour map of Thailand (see Figure 11). This map illustrates the density of high-risk schools across both PESA and SESA. The contour plots indicate that high-risk levels are consistently found in provinces across all regions: the southern region (Yala and Narathiwat), northeastern region (Udon Thani, Nong Khai, and Nakhon Phanom), central region (Nakhon Sawan, Phetchabun, and Phitsanulok), and northern region (Mae Hong Son, Chiang Mai, and Chiang Rai) throughout the study period.

Figure 11 illustrates the density of high-risk schools within PESA (left) and SESA (right) across Thailand. The contour plots emphasize regions with the highest concentration of schools identified as having a high CMER Index. For PESA, dense clusters of high-risk schools are distributed across multiple regions. In the northern region, provinces like Mae Hong Son, and Chiang Mai, show high-risk levels. The northeastern region exhibits significant concentrations in Udon Thani, Nong Khai, Nong Bua Lam Phu, Nakhon Phanom, and Kalasin. In the central region, provinces such as Nakhon Sawan, Phetchabun, Phitsanulok, and Ayutthaya stand out as high-risk areas. The southern region highlights Yala, Narathiwat, Pattani, and Krabi.

The SESA contour map shows clusters primarily in the central and northeastern regions, indicating that while the distribution of high-risk schools is broader across PESA regions, SESA schools tend to have more concentrated clusters of risk, particularly in these two regions. Notably, both the central and northeastern regions emerge as high-risk areas for both PESA and SESA schools. This pattern suggests that these regions are particularly vulnerable across different educational service areas.

6.1.3 Provincial Descriptive Analysis of CMER Risk

To provide a clearer and more comprehensive overview of CMER risk, the analysis examines the CMER Index at the provincial level. This approach allows for a more detailed assessment of the geographic distribution of educational risks, offering insights into how these risks vary across different provinces and highlighting key areas that may require attention or targeted interventions. By focusing on the provincial breakdown, the analysis aims to better illustrate the spatial patterns of educational vulnerability within the context of climate-related challenges.

The CMER scores at the provincial level are calculated using the median, which serves as a central measure representing the typical level of risk for each province.

The analysis is divided into two main sections: (1) presenting the overall risk levels and the number of high-risk schools in each province, and (2) illustrating the trends in educational risk across provinces over the study period from 2017 to 2021. The details are as follows:

CMER Risk Levels and High-Risk School Distribution Across Provinces

The Figure 12 below, provides a comprehensive overview of educational risks across provinces in Thailand. On the left, the map displays the median CMER by province, with the lighter colors representing provinces that have a higher median CMER value. This visualization aims to show the geographic distribution of educational risks, offering insight into how risks vary at the provincial level.

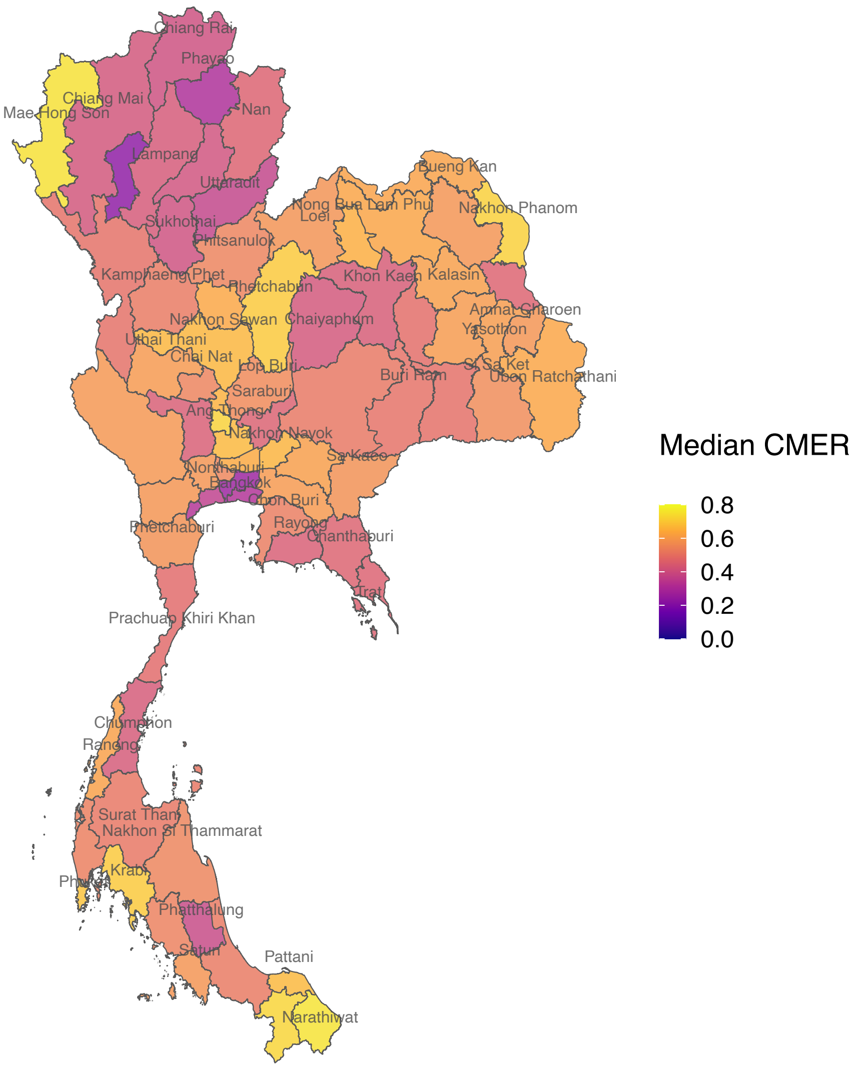

Figure 12: CMER Index Categorized by Province

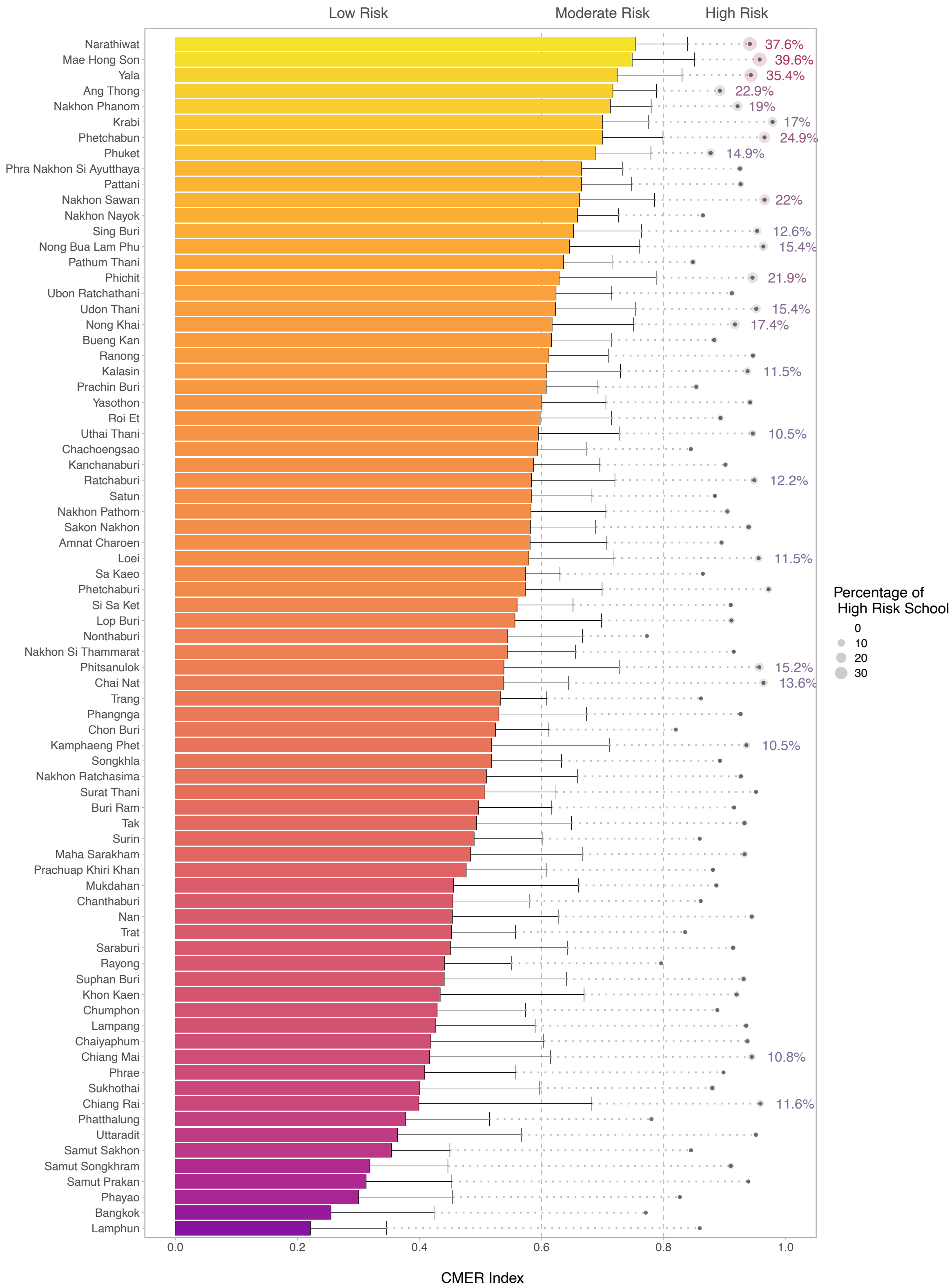

Figure 13: Provincial Distribution of CMER Index and Percentage of High-Risk Schools

The analysis reveals that provinces with a high median CMER are distributed across various regions of Thailand. In the Northern Region, provinces like Mae Hong Son stand out with elevated median values. In the Northeastern Region, provinces such as Nakhon Phanom, Nong Khai, Nong Bua Lam Phu, Udon Thani, and Ubon Ratchathani show a notable concentration of educational risk. The Central Region also includes several provinces with high median CMER values, including Phetchabun, Nakhon Sawan, Uthai Thani, and Phra Nakhon Si Ayutthaya. Additionally, the Southern Region shows particular hotspots of risk, notably in Yala, Narathiwat, and Krabi. These findings indicate a widespread geographic distribution of educational risk across different parts of the country, emphasizing the need for region-specific interventions.

Figure 13 presents a bar chart detailing the distribution of the CMER Index across provinces. Each bar's length indicates the median CMER value for a province, and the error bars extending from each bar represent the third quartile (Q3) values. Dotted lines extending beyond the error bars show the maximum CMER values for the provinces. Additionally, the size of the points at the end of each line corresponds to the percentage of high-risk schools in each province. Annotations on the chart specifically highlight the percentage of schools with high CMER risk, focusing on provinces where more than 10% of schools are classified as high risk.

The analysis identifies 24 provinces with a median CMER above 0.6, indicating that over 50% of schools within these provinces face at least moderate to high educational risk. These provinces are spread across various regions in Thailand as follows: (1) Southern Region: 6 provinces, including Narathiwat, Yala, Krabi, Phuket, Pattani, and Ranong; (2) Northern Region: 1 province, Mae Hong Son; (3) Central Region: 8 provinces, namely Ang Thong, Phra Nakhon Si Ayutthaya, Nakhon Sawan, Nakhon Nayok, Pathum Thani, Phetchabun, Sing Buri, and Phichit; (4) Northeastern Region: 8 provinces, comprising Nakhon Phanom, Ubon Ratchathani, Udon Thani, Nong Bua Lam Phu, Nong Khai, Bueng Kan, Kalasin, and Yasothon; and (5) Eastern Region: 1 province, Prachin Buri. The geographic distribution of these high-risk provinces highlights that educational risks associated with extreme climate conditions are present across multiple regions of the country, indicating a widespread issue that requires attention on a national scale.

Among the provinces analyzed, 15 stand out with over 10% of their schools classified as high-risk. Mae Hong Son leads with 39.6% of its schools identified as high-risk, followed by Narathiwat (37.6%), and Yala (35.4%). Other notable provinces include Ang Thong with 22.9% of high-risk schools and Phetchabun with 24.9%. Nakhon Sawan, which has 22.0% high-risk schools, also shows a significant presence of educational vulnerabilities, while Krabi and Phuket have 17.0% and 14.9%, respectively. In the northeastern region, Nakhon Phanom (19.0%), Nong Bua Lam Phu (15.4%), Udon Thani (15.4%), and Nong Khai (17.4%) are among the provinces with a substantial percentage of high-risk schools. Sing Buri (12.6%), Phichit (21.9%), and Kalasin

(11.5%) further illustrate the widespread nature of high educational risks across different regions. These figures highlight areas with concentrated educational challenges tied to climate vulnerabilities.

Additionally, it was found that certain provinces, despite having a median CMER below 0.6, still have more than 10% of their schools classified as high-risk. These provinces include Uthai Thani, Ratchaburi, Loei, Phitsanulok, Chainat, Kamphaeng Phet, Chiang Mai, and Chiang Rai. This suggests that educational inequality in these areas may be influenced by extreme climate factors.

Trends in Provincial CMER Risk Over Time

In the Figure 14, The top plot illustrates the Precipitation Duration Anomaly, which shows the variations in the duration of rainfall in Thailand from 2017 to 2021. The horizontal axis represents the studied years, while the vertical axis displays the anomaly values, indicating how the duration of rainfall deviates from the long-term average. The points on the graph represent the median anomaly for each year, and the vertical error bars indicate the interquartile range (IQR), showing the spread between the 25th and 75th percentiles.

The bottom plot presents a boxplot of the CMER Index at the provincial level over the same period, displaying the distribution of educational risk across different provinces each year. The CMER Index values are categorized by year, and each boxplot reflects the variation and trends of educational risk within provinces.

A comparison of both plots reveals that changes in the Precipitation Duration Anomaly are associated with shifts in the educational risk levels of provinces. In years with higher anomalies, there is a noticeable increase in provinces with elevated CMER Index values, with many median boxplot values exceeding 0.6. This indicates an increase in the number of schools facing high educational risk. Particularly in 2018 and 2019, more than 50% of provinces had a median CMER Index at or above the moderate risk level. The observed trend highlights the vulnerability of the educational system in these provinces, which correlates with changes in weather patterns. Conversely, in years when the Precipitation Duration Anomaly is lower, the number of provinces facing educational risk also tends to decrease. For instance, in 2020 and 2021, there is a noticeable drop in the number of provinces with moderate or high CMER Index levels. The observed fluctuations reinforce the relationship between educational risk and climate anomalies, highlighting the importance of monitoring these factors over time.

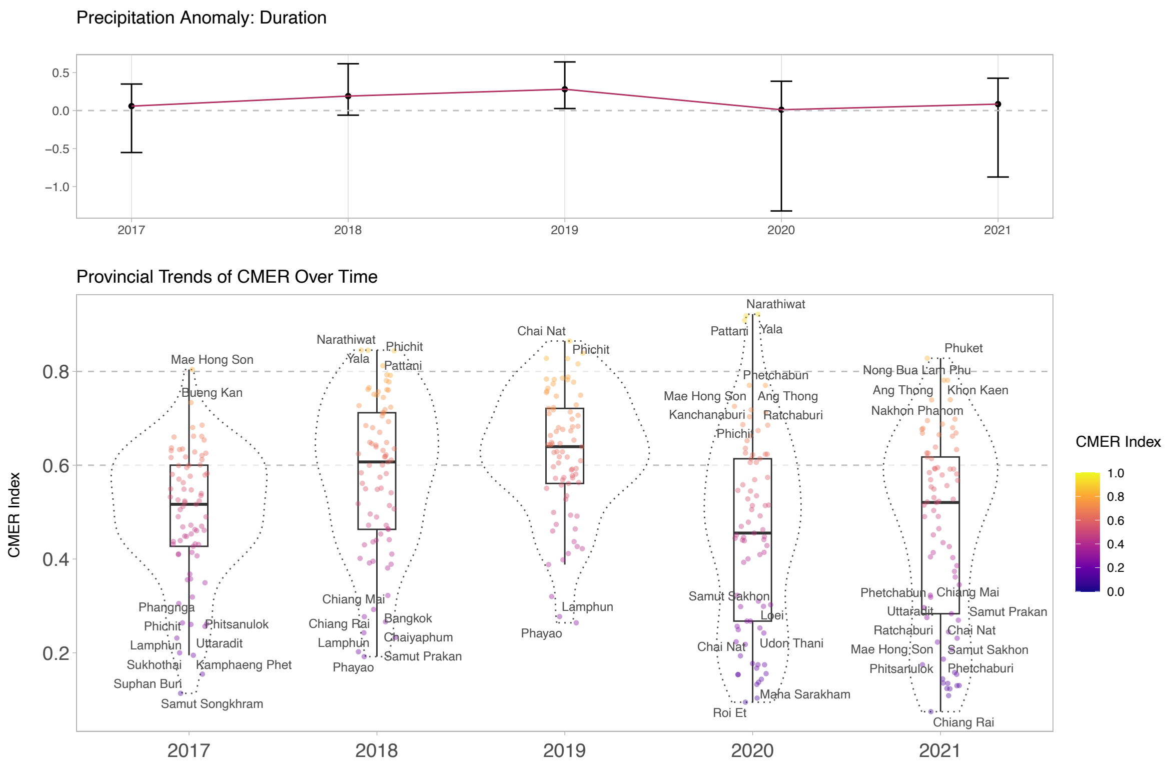

Figure 14: Provincial Trends of Precipitation Anomaly and CMER Over Time

6.1.4 Distribution of CMER Index at Educational Service Area Level

This section presents the analysis of the CMER Index at the educational service area level, categorized into two sections: Primary Educational Service Area (PESA) and Secondary Educational Service Area (SESA).

6.1.5 Geospatial Distribution of CMER Index

This section of the analysis presents the distribution of the CMER Index across multiple levels, including school, provincial, and educational service area distributions, from different perspectives. The objective is to provide a comprehensive understanding of educational risk across various dimensions, enabling users to grasp the nuances and implications of the data across different geographical and administrative units. This multifaceted approach allows for a clearer interpretation of the risks faced by schools and regions, offering an informed foundation for future policy.

Distribution of CMER Index at the School Level

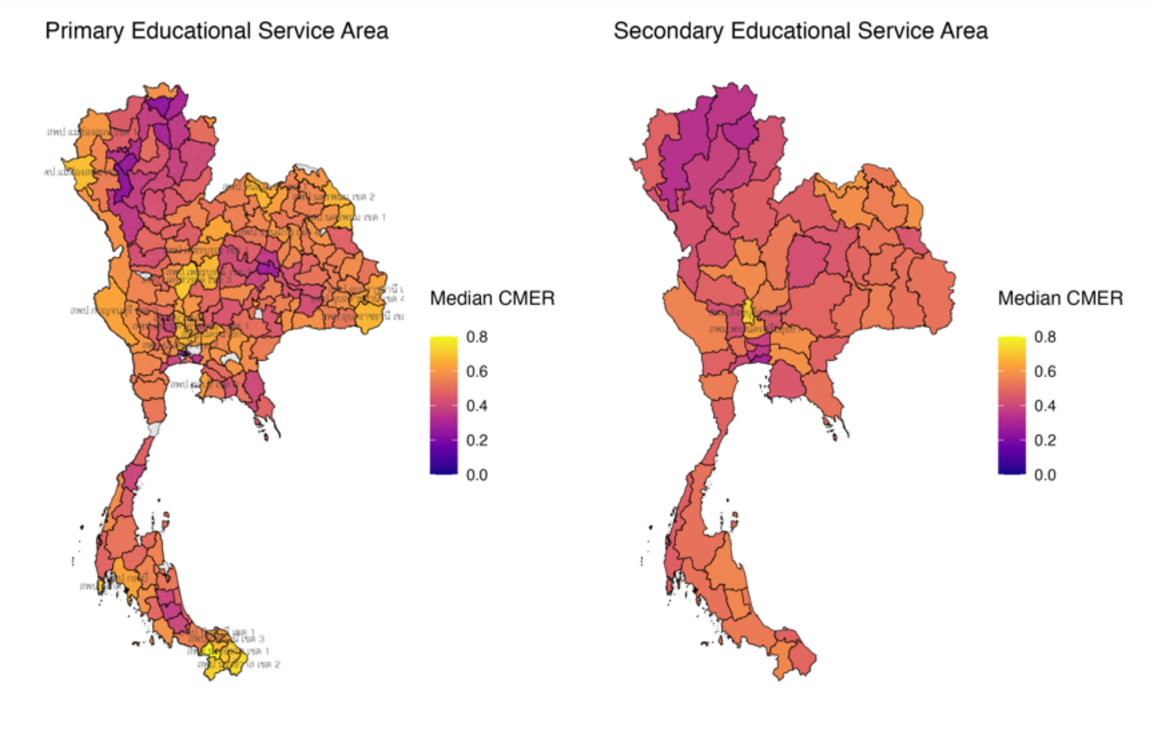

Figure 15: Median of CMER Categorized by Educational Service Area

6.1.5.1 CMER Index at The Province Level

The Figure 16 display a percentage of schools with high CMER risk levels in each province. The map on the left illustrates the geographical distribution of provinces with schools that fall under the high CMER (Climate-Mapped Educational Risk) category. When examined by region, it reveals that Southern Thailand has prominent provinces with high-risk schools, including Yala, Narathiwat, and Krabi. In Northern Thailand, provinces with a high percentage of high-risk schools include Mae Hong Son, Chiang Mai, Lampang, and Chiang Rai. In Northeastern Thailand, provinces such as Nong Khai, Nakhon Phanom, Udon Thani, and Nong Bua Lam Phu are highlighted. In Central Thailand, notable provinces include Ang Thong, Phetchabun, Nakhon Sawan, Sing Buri, Saraburi, Phra Nakhon Si Ayutthaya, and Nakhon Pathom. Additionally, in Western Thailand, Ratchaburi and Phetchaburi also stand out for having a higher percentage of high-risk schools. The darker colors on the map represent provinces with a greater percentage of schools facing high CMER risk.

The bar chart on the right provides a detailed ranking of provinces based on the percentage of schools classified as high-risk. Yala ranks highest with 22.2% of schools at high risk, followed by Narathiwat at 16.4% and Mae Hong Son at 13.5%. Other notable provinces include Ang Thong at 11.9%, Phetchabun at 11.4%, and Nakhon Sawan at 10.8%. This analysis highlights the areas where schools face the greatest risk and require attention and targeted educational interventions.

Figure 16 provides an analysis of the percentage of schools with a high CMER Index categorized by educational service areas, specifically the Primary Educational Service Area (PESA) on the left and the Secondary Educational Service Area (SESA) on the right. The maps use a color gradient to illustrate the percentage of schools within each educational area classified as having a high CMER risk level, with darker shades indicating a higher percentage of at-risk schools.

The analysis reveals distinct geographic patterns of educational risk across Thailand. For PESAs, there is a notable concentration of high-risk schools in several regions. In contrast, the distribution within SESAs appears more dispersed, with fewer areas showing concentrated risk among secondary schools.

- **Southern Region:** PESA zones such as Narathiwat (1 and 2), Yala (1), Pattani (3), and Krabi show a substantial proportion of schools classified as high risk, suggesting vulnerability due to factors like geographic isolation, socio-economic challenges, or exposure to extreme weather events.
- **Northern Region:** High-risk PESAs are found in Mae Hong Son (2), Chiang Mai (5), Chiang Rai (4), and Lampang (1 and 4). These risks may relate to mountainous topography, remote communities, and challenges in resource access.

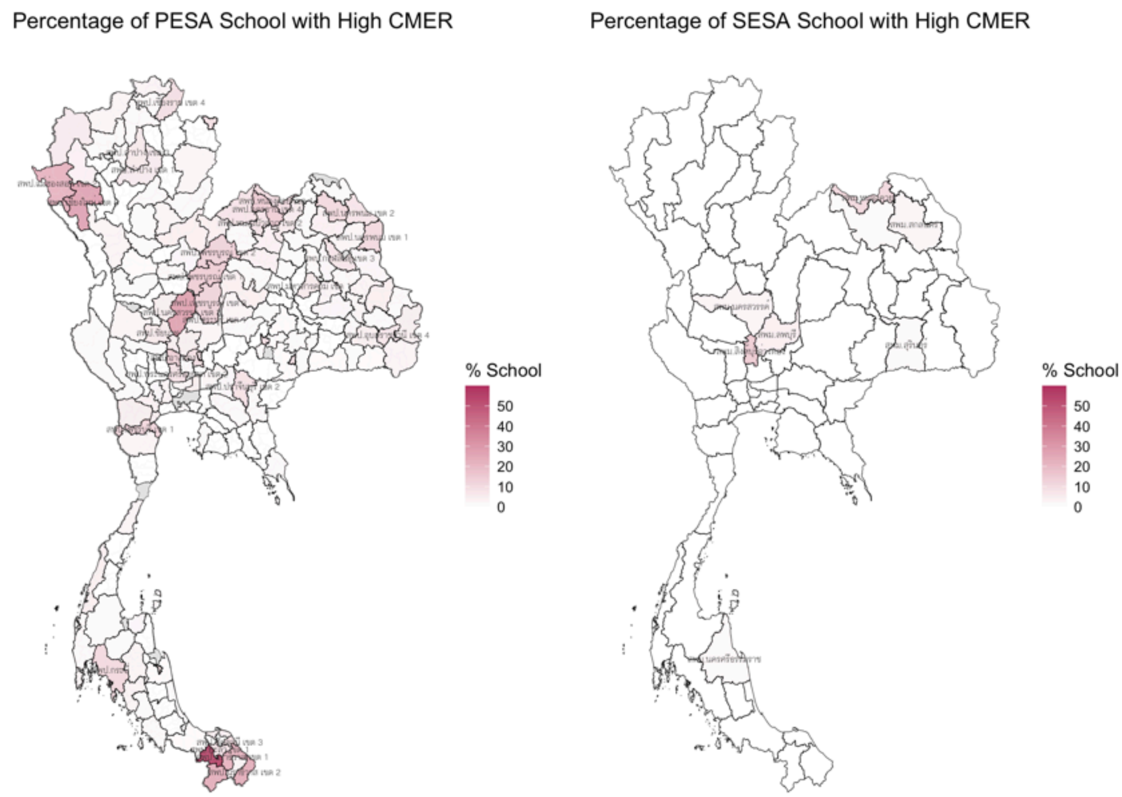

Figure 16: The Percentage of Schools with High CMER Index by Educational Service Area

- **Upper Northeastern Region:** Several PESAs stand out for high-risk status, including Nong Khai (1), Nakhon Phanom (1 and 2), Udon Thani (4), and Nong Bua Lam Phu (2), reflecting educational challenges exacerbated by climate variability.
- **Central Region:** High-risk zones are identified in Nakhon Sawan (3) and Phetchabun (1, 2, and 3), suggesting that climate-related educational challenges extend beyond traditionally vulnerable or remote regions.
- **SESA Distribution:** The SESA map demonstrates a more dispersed pattern of high-risk secondary schools, indicating that secondary education risks are more evenly spread, unlike the concentrated high-risk areas observed in primary education.

Overall, the analysis shows that high CMER risks are distributed across multiple regions, with specific hotspots in the south, north, and northeastern areas of Thailand. These findings underscore the need for localized risk assessments to better understand the vulnerabilities tied to climate risks in educational contexts, providing an informed basis for further exploration and potential development of targeted support and interventions.

6.2 Results for Research Objective 2:

Identify characteristics of schools/provinces/areas and children where education is exposed to considerable risks of climate hazards, inter alia by region, urban/rural, socio-economic status, disability, gender, age, school hardship location, etc.

7 Discussion and Recommendation

8 References

9 Appendices

Temporal Distribution of School CMER Index

The contour maps presented in Figure 18 provide a temporal overview of the distribution of high-risk schools across Thailand from 2017 to 2021, highlighting areas where the CMER Index consistently indicates heightened educational risk.

The contour map presented in Figure 18 illustrates areas in Thailand with schools identified as having high educational risk, categorized by the study years from 2017 to

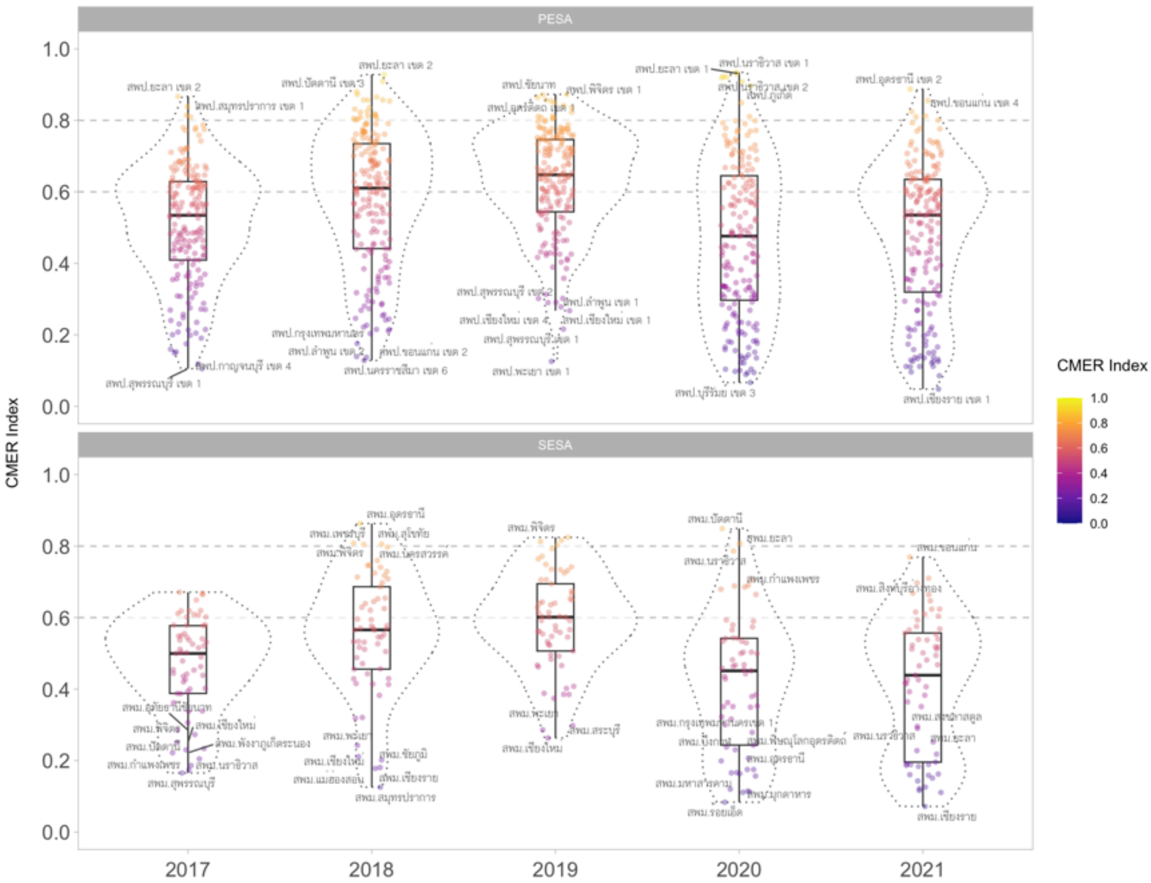

Figure 17: Boxplot of Temporal Distribution of CMER Index by PESA and SESA (2017-2021)

2021. The analysis reveals that the southern region, particularly in provinces like Yala, Narathiwat, and Pattani; the central region, including Nakhon Sawan, Phetchabun, Phitsanulok, and Phra Nakhon Si Ayutthaya; and the northeastern region, such as Nakhon Phanom, Nong Khai, Udon Thani, and Nong Bua Lam Phu, consistently show areas with a high level of risk. While the northern region may not have as many high-risk schools as other regions, specific provinces such as Mae Hong Son, Chiang Mai, and Chiang Rai exhibit a tendency towards higher educational risk as well.

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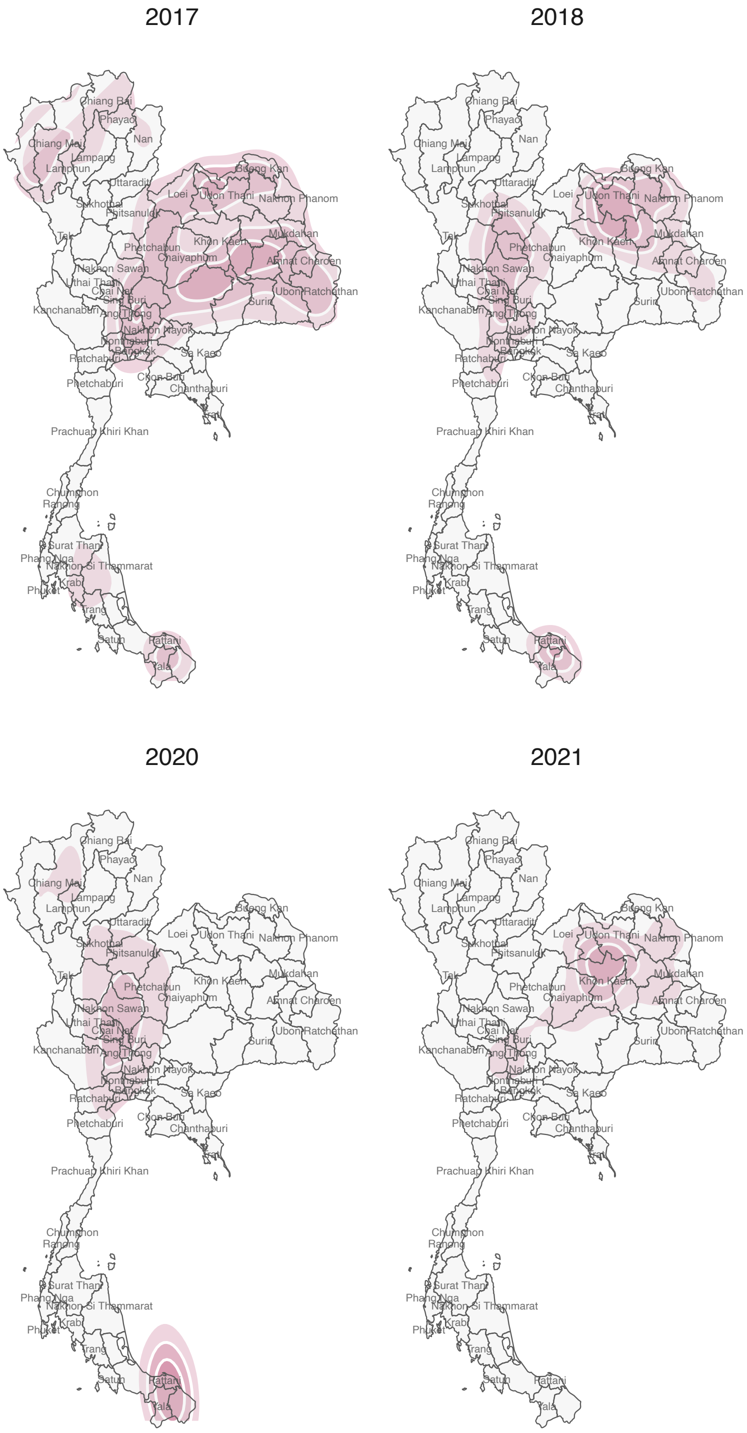

Figure 18: Temporal Contour Map of High CMER School (2017-2021)

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