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

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1 Executive 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.

1.1 Summary of Objective 1 Analysis

The analysis for Objective 1, which aims to explore and develop a methodology to link educational metrics with the impacts of climate change and environmental degradation, can be summarized as follows:

1.1.1 Development of the Climate-Mapped Educational Risk Index (CMER Index)

The study developed the Climate-Mapped Educational Risk Index (CMER), integrating data on extreme climate events and students' academic performance. Principal Component Analysis (PCA) was used to extract components that reveal the relationship between climate factors and educational risk. One of the extracted components shows a significant connection between anomalies in the duration of heavy rainfall and increased educational risk, as reflected in student learning outcomes. This methodology enhances the accuracy of the CMER Index by removing unrelated variability, offering a clearer reflection of educational risk linked to climate change. Compared to conventional index calculations that aggregate scores directly, this approach provides a more robust and reliable assessment of the specific risks associated with climate conditions.

The CMER Index was developed to provide detailed insights into educational risk at the school level. The index was designed to have a score range between 0 and 1, where a value closer to 1 indicates higher risk and a value closer to 0 indicates lower risk. To facilitate meaningful interpretation, the scale was categorized into three levels of risk: "Low Risk" (0 - 0.60), "Medium Risk" (0.60 - 0.80), and "High Risk" ($>$ 0.80). These thresholds were determined using Receiver Operating Characteristic (ROC) analysis to effectively distinguish educational risk.

Schools with a high CMER Index are more likely to have students with lower-than-expected learning outcomes. These lower academic performances are notably associated with anomalies in the duration of heavy rainfall, indicating a strong link between prolonged extreme weather events and educational risk. This approach ensures that the CMER Index provides a nuanced reflection of risk levels, enabling a clearer understanding of the degree of risk associated with climate change at the school level.

1.1.2 Geographical Distribution of the CMER Index

The distribution of CMER Index scores across Thailand was analyzed for the period between 2017 and 2021. It was found that 777 schools (2.95%) exhibited a high level of educational risk according to the CMER Index. Geographically, these high-risk schools were predominantly located in the southern provinces (e.g., Yala, Narathiwat, Pattani), northeastern provinces (e.g., Udon Thani, Nong Khai, Nakhon Phanom), central provinces (e.g., Nakhon Sawan, Phetchabun, Ayutthaya), and northern provinces (e.g., Mae Hong Son, Chiang Mai).

The analysis revealed that there are 24 provinces where the median CMER Index score exceeds 0.6, indicating that at least 50% of all schools within these provinces fall into the medium or higher risk categories. Among these provinces, Mae Hong Son, Narathiwat, and Yala have the highest median CMER scores. These three provinces also have the largest proportions of high-risk schools, with 39.6%, 37.6%, and 35.4% of all schools within each province classified as high-risk, respectively. In contrast, no high-risk schools were found in Bangkok, Phatthalung, Rayong, and Nonthaburi.

Additionally, there are 8 provinces where, despite having a low median CMER score (below 0.6), over 10% of the schools are classified as high-risk. These provinces are Uthai Thani, Ratchaburi, Loei, Phitsanulok, Chainat, Kamphaeng Phet, Chiang Mai, and Chiang Rai. This situation reflects potential educational inequalities in these areas that may be linked to extreme climate factors, indicating that even in provinces with an overall lower level of risk, certain schools face significant vulnerabilities related to climate impacts.

1.1.3 CMER Index Categorized by Educational Service Areas

The analysis reveals that in both Primary Educational Service Areas (PESA) and Secondary Educational Service Areas (SESA), the majority of schools fall into the Low Risk category. However, PESA displays a higher proportion of schools classified as Moderate and High Risk compared to SESA. While the average CMER scores for both service areas are similar across all risk levels, the concentration of High-Risk schools is notably lower in SESA.

In the Primary Educational Service Areas (PESA), regions with the highest CMER scores and a significant proportion of High-Risk schools are primarily located in the southern region, followed by the central and northern regions. Specifically:

- Southern Region: Yala Districts 2 and 3, and Narathiwat Districts 1 and 2 exhibit the highest educational risks, with more than 50% of schools classified as high-risk. These areas have notably high median CMER scores, indicating a strong link between climate factors and educational challenges.
- Central Region: Nakhon Sawan District 3, Phetchabun Districts 1 and 3, and Ang Thong also show elevated educational risk, with significant portions of schools categorized as high-risk. This suggests that central Thailand faces similar climate-related educational vulnerabilities.
- Northern Region: Chiang Mai District 5 and Mae Hong Son District 2 reflect trends of elevated risk, where the median CMER scores are high and a substantial number of schools fall into the high-risk category. This highlights that educational challenges linked to climate change are not isolated to any single region.

For the Secondary Educational Service Areas (SESA), two key regions stand out for having elevated CMER scores: Sing Buri-Ang Thong and Nong Khai. These areas exhibit a higher proportion of schools at risk, suggesting that educational vulnerabilities linked to climate change are also present in SESA, albeit to a lesser extent than in PESA regions.

The analysis of Research Objective 1 provides stakeholders with a valuable tool—the CMER Index—to pinpoint schools, areas, or educational service areas that face heightened educational risks associated with climate change. This index allows for a clear identification of vulnerable regions where targeted interventions are needed. However, designing effective interventions to support these high-risk schools may require more detailed information on the factors driving these risks. Therefore, the analysis under Research Objective 2 seeks to explore these underlying characteristics, aiming to provide a comprehensive understanding of the factors that contribute to educational vulnerability, thereby guiding more informed and strategic intervention planning.

1.2 Summary of Objective 2 Analysis

For Research Objective 2, the analysis aims to explore and identify the non-climate factors that contribute to educational vulnerabilities across different regions in Thailand, focusing on actionable elements that can be addressed through policy and intervention. By performing separate regressions for Primary Educational Service Areas (PESA) and Secondary Educational Service Areas (SESA), the analysis uncovers how school-related factors affect the Climate-Mapped Educational Risk Index (CMER Index).

The analysis incorporates these non-climate factors—categorized into school characteristics, location & accessibility, infrastructure & connectivity, and student profiles—because they represent controllable elements that can be influenced by decision-makers. In contrast to climate factors, which are largely beyond human control, these factors offer practical opportunities for strategic interventions. By understanding their impact on educational outcomes, the Risk-Importance Matrix (RIM) serves as a tool to highlight regions and schools where targeted policies can effectively mitigate educational risks and improve outcomes related to climate change.

1.2.1 Summary of Influential Non-Climate Factors

The analysis of non-climate factors influencing the CMER Index was conducted separately for Primary Educational Service Areas (PESA) and Secondary Educational Service Areas (SESA). By examining these factors, the research offers targeted insights into educational vulnerabilities across different regions and provides guidance for tailored policy interventions. Key Findings are as follows:

PESA Regions

- Small School Size is a notable driver of educational risk, with smaller schools frequently facing resource and administrative limitations. A significant portion of these regions show a strong association between smaller school size and heightened educational risk.
- Accessibility Issues play a critical role, including “Hard to Reach” and “School Distance” factors. Geographic inaccessibility, due to remoteness or school-community distances, significantly elevates educational risk across a sizable number of regions.
- Lack of Infrastructure contributes to increased educational risks in certain areas. Inadequate access to services like electricity, water, and internet negatively affects the ability to maintain stable learning environments.

- Poverty and Younger Students have a relatively lower impact on CMER but still present notable risks in certain areas, particularly where socioeconomic disparities are more pronounced.

SESA Regions

- Small School Size has an even more pronounced effect on educational risk, with most regions exhibiting a strong association between limited resources in smaller schools and increased risk.
- School Distance and Infrastructure Deficiencies moderately affect risk, with accessibility and basic infrastructure continuing to be relevant factors in some areas.
- Younger Students show slight vulnerability, particularly contrasting with the trends observed in PESA regions.

Overall Insights and Implications

The most significant factor influencing educational risk across both PESA and SESA is school size, with a stronger impact observed in SESA regions. This finding underscores the need for resource allocation, administrative support, and infrastructure improvements specifically for smaller schools. Additionally, accessibility challenges, including school distance and remoteness, necessitate interventions to improve transportation and access to schools. Finally, the role of infrastructure and poverty, while moderate, suggests that holistic approaches are needed to ensure all students have equitable access to resources.

In conclusion, this analysis points to the critical role of addressing school size, accessibility, and infrastructure readiness to mitigate educational risks. A tailored, region-specific approach that enhances support for small schools, improves access in remote areas, and strengthens infrastructure will be crucial to promote equitable educational outcomes and resilience across both PESA and SESA regions.

1.2.2 Risk-Importance Matrix

The researcher developed the Risk-Importance Matrix (RIM) as an analytical tool to assess educational risks associated with climate anomalies across Primary Educational Service Areas (PESA) and Secondary Educational Service Areas (SESA). The RIM categorizes these areas based on the Climate-Mapped Educational Risk (CMER) Index and the relative importance (RI) of various non-climate factors, such as school size, socioeconomic conditions, and accessibility. The aim is to identify strategic focus groups for tailored interventions, ensuring efficient resource allocation and policymaking to mitigate educational vulnerabilities.

Key Group Classifications within RIM

Strategic Focus Group: The RIM highlights regions with high CMER and significant RI scores as priority areas for immediate policy action. These regions face compounded risks due to climate and non-climate factors, warranting urgent support. The classification criteria include CMER values slightly below 0.60 to encompass regions with moderate risk yet significantly influenced by specific non-climate factors. Regions surpassing an RI score of 40% are emphasized, pointing to a pronounced influence of factors like "Small School," "School Distance," or "Lack of Infrastructure" on educational risk.

Development Priority and Monitoring Groups: To delineate regions with varying degrees of risk, a diagonal boundary separates districts into either Development Priority or Monitoring categories based on their CMER values (ranging from 0.6 to 0.2) and RI scores. The Development Priority group includes districts with moderate to high risk and clear associations with influential factors, while the Monitoring group consists of regions with moderate to low CMER values but a strong link to non-climate factors, ensuring continued observation to preempt potential escalation in risk.

Low-Risk Group: Districts exhibiting very low CMER Index values, with minimal influence from non-climate factors, fall under the Low-Risk category. These areas currently show stable educational conditions and require the least immediate intervention but are still monitored to maintain their status and address any emerging vulnerabilities.

Regions with Multiple Influential Factors

Some PESA regions, like Narathiwat Area 1, Chiang Mai Area 5, and SESA regions, Sing Buri & Ang Thong, face complex educational challenges driven by multiple non-climate factors. For instance:

- Narathiwat Area 1 is impacted by both poverty and school distance, highlighting the combined influence of socioeconomic difficulties and accessibility challenges.
- Chiang Mai Area 5 experiences heightened risk due to remoteness and school distance, suggesting that access to education is significantly hindered by location and travel difficulties.
- Sing Buri & Ang Thong is influenced by both "Small School" and "Lack of Infrastructure," with RI scores of 84.76 and 70.72, respectively. The combination of these factors suggests that limited school size and infrastructure deficiencies together significantly contribute to educational risk in this region.

The analysis of these regions indicates that the interplay of factors such as location, poverty, school size, and infrastructure can compound educational risks. Targeted interventions addressing these combined influences are crucial for reducing overall risk effectively.

Regions Dominated by a Single Factor

Other regions are primarily influenced by a single dominant factor:

- Small School: A prominent factor across both PESA and SESA regions, particularly in Narathiwat Area 2, Yala Area 1, Nakhon Phanom Area 1, Chachoengsao Area 1, and several SESA regions like Phra Nakhon Si Ayutthaya, Chachoengsao, and Ubon Ratchathani & Amnat Charoen. These smaller schools, often with limited resources and support, are strongly associated with higher educational risks.
- Poor Family: Regions like Pattani Area 3, Kalasin Area 3, Chainat, and Khon Kaen Area 1 face challenges mainly tied to socioeconomic factors, reflecting how poverty directly correlates with increased educational vulnerability.
- Lack of Infrastructure: A critical factor in Mae Hong Son Area 2, Nong Khai Area 1, Udon Thani Area 2, Tak Area 2, and Sisaket & Yasothon. These areas suffer from limited access to basic services, such as electricity, water, and internet, exacerbating educational challenges.
- School Distance: Particularly influential in Trang Area 2, Chachoengsao Area 2, and Khon Kaen Area 5, where the distance between schools and community centers significantly affects access and student outcomes.

1.3 Summary of Recommendations

The recommendations outlined below are based on the CMER analysis, aiming to address educational risks exacerbated by climate anomalies across different regions in Thailand. The strategic measures suggested are designed to guide policymakers in targeted interventions, improve resource allocation, and enhance educational resilience. By focusing on key factors such as school size, socioeconomic challenges, infrastructure, and access, these recommendations provide a roadmap for developing comprehensive strategies to support vulnerable schools and ensure equitable educational outcomes.

1. **Utilizing the CMER Index for Targeted Identification and Management of Climate-Related Educational Risk**

The CMER Index provides a comprehensive framework to identify schools and regions facing significant educational risks due to climate anomalies, offering a holistic approach that includes not just flooding but also indirect climate impacts. Policymakers are encouraged to use the CMER Index for proactive planning and to prioritize areas for timely intervention.

2. **Leveraging Resilient Schools as Models for Climate-Adapted Education Management**

Schools that demonstrate resilience against climate-related risks, despite being located in high-risk areas, offer valuable insights for policy development. Studying their best practices can help formulate strategies to build climate resilience across vulnerable schools.

3. **Addressing the Vulnerabilities of Small Schools to Enhance Educational Resilience**

Small schools are significantly impacted by educational risks related to climate factors. Targeted support, including resource allocation, capacity building for staff, collaborative networks, and localized support mechanisms, is recommended to strengthen their resilience and reduce risk.

4. **Tailored Interventions for Regions with Multiple Influential Factors**

For regions like Narathiwat, Chiang Mai, and Sing Buri & Ang Thong, where multiple non-climate factors contribute to educational risks, a customized approach is necessary. Focused strategies should address the interplay of factors like poverty, remoteness, and infrastructure challenges.

5. **Tailored Interventions for Regions Dominated by a Single Factor**

Areas where a single non-climate factor, such as "Small School," "Poor Family," or "Lack of Infrastructure," predominantly influences educational risk require focused interventions addressing the primary driver. Specific support strategies should be developed based on the unique needs of each region to ensure impactful risk mitigation.

By implementing these targeted strategies, policymakers can effectively enhance educational resilience and support vulnerable regions in managing climate-related educational risks.

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:

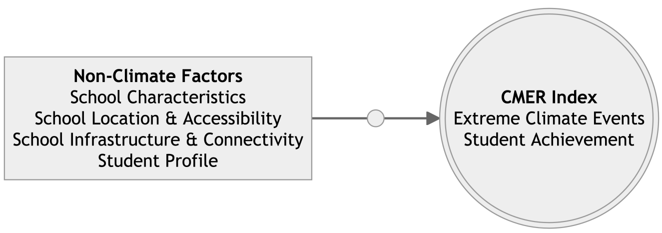

Figure 1: Research Conceptual Framework

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

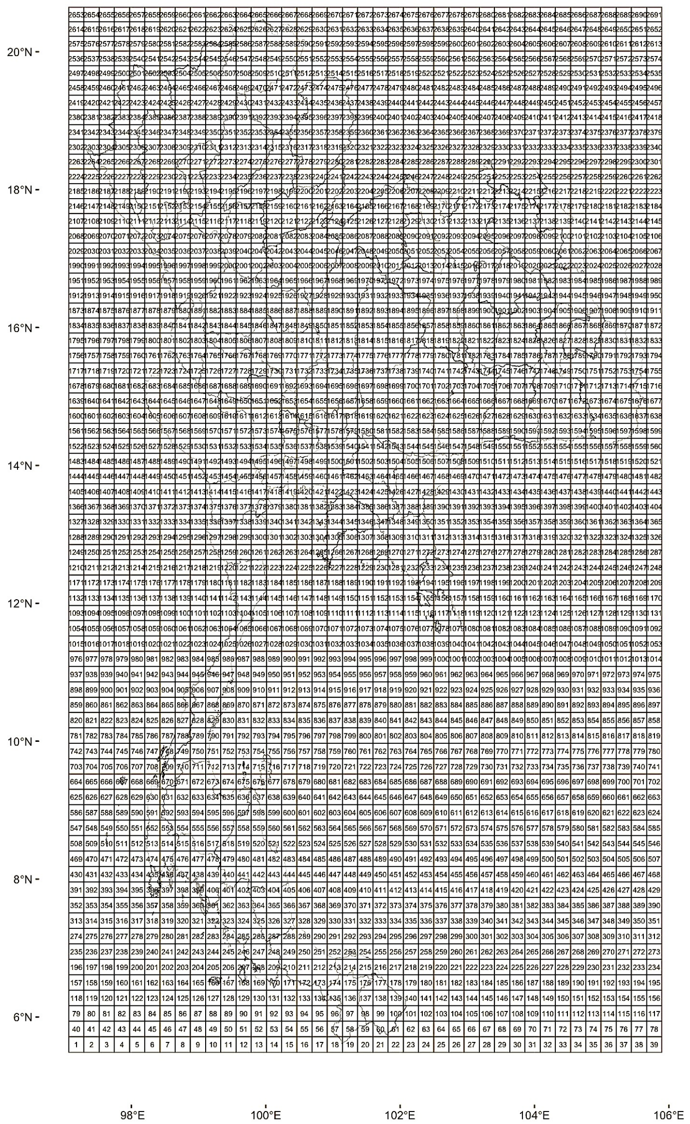

Figure 2: Map of 25x25 km Grid Cells Over Thailand

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 (Google, 2024). 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.

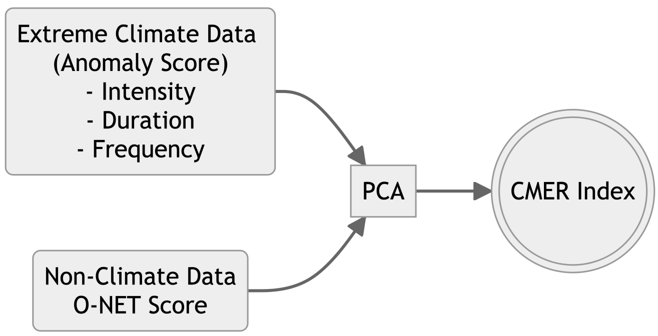

Figure 3: analytical framework for constructing the CMER Index

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.

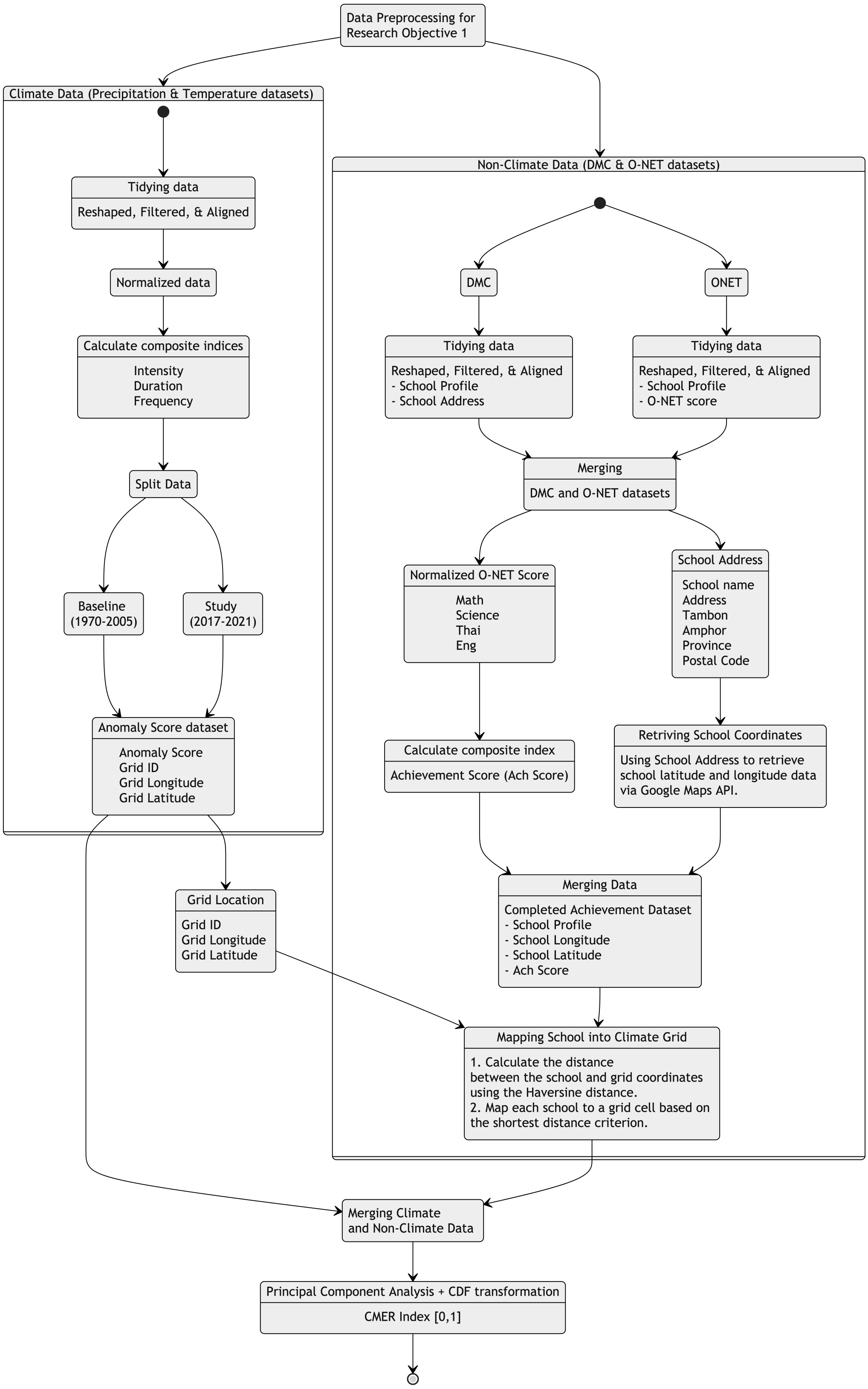

Figure 4: Data Preprocessing and Analysis for Research Objective 1

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 (Kuhn & Wickham, 2020).

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.

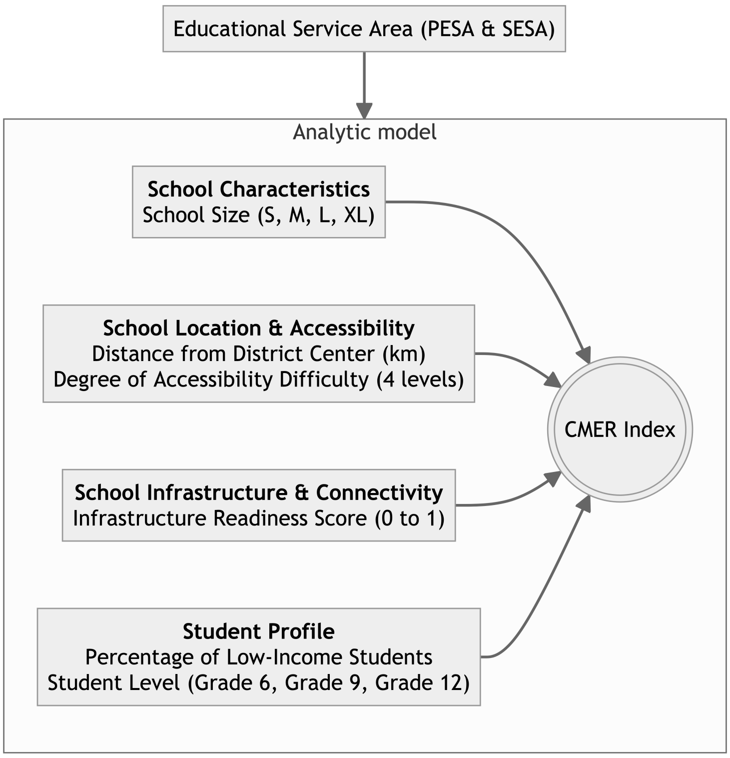

Figure 5: Analysis Framework for Research Objective 2

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

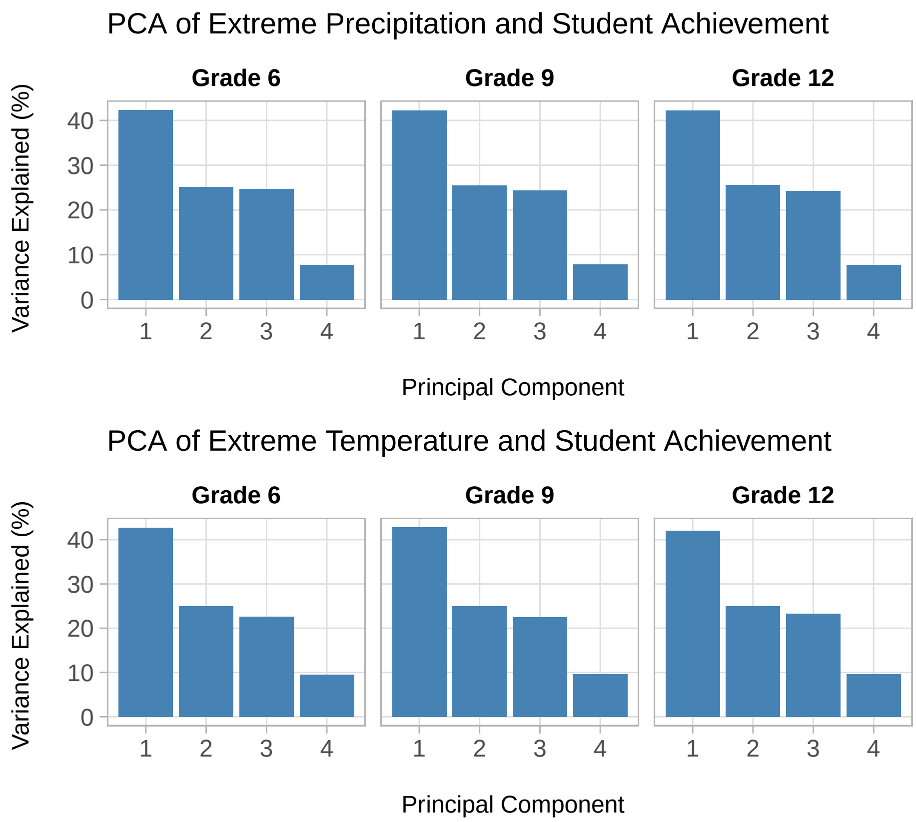

Figure 6: Percentage of Variance Explained by Principal Components of Extreme Climate and Student Achievement

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.

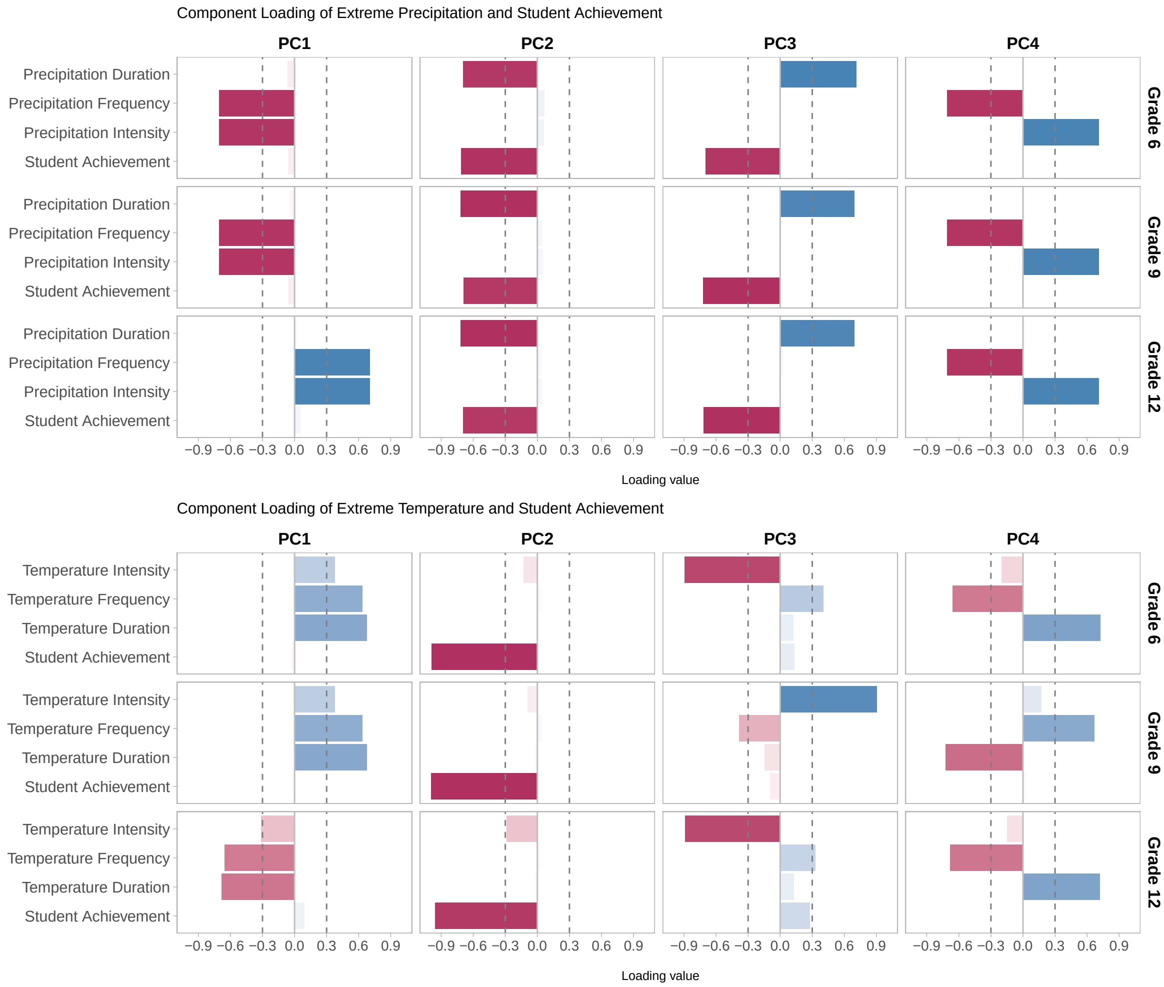

Figure 7: Component Loading of Extreme Precipitaion, and Student Achievement

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

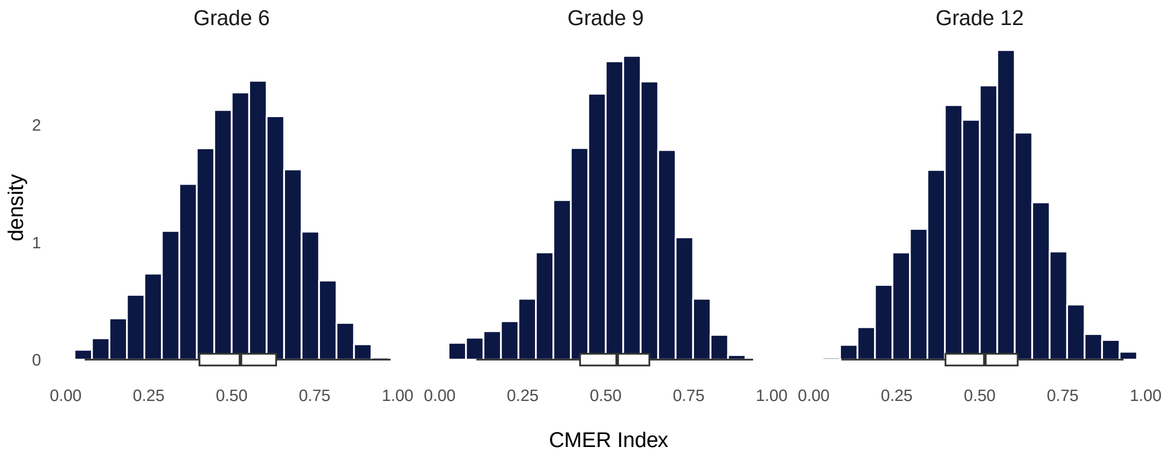

Figure 8: Histogram of School CMER Index categorized by student level

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.

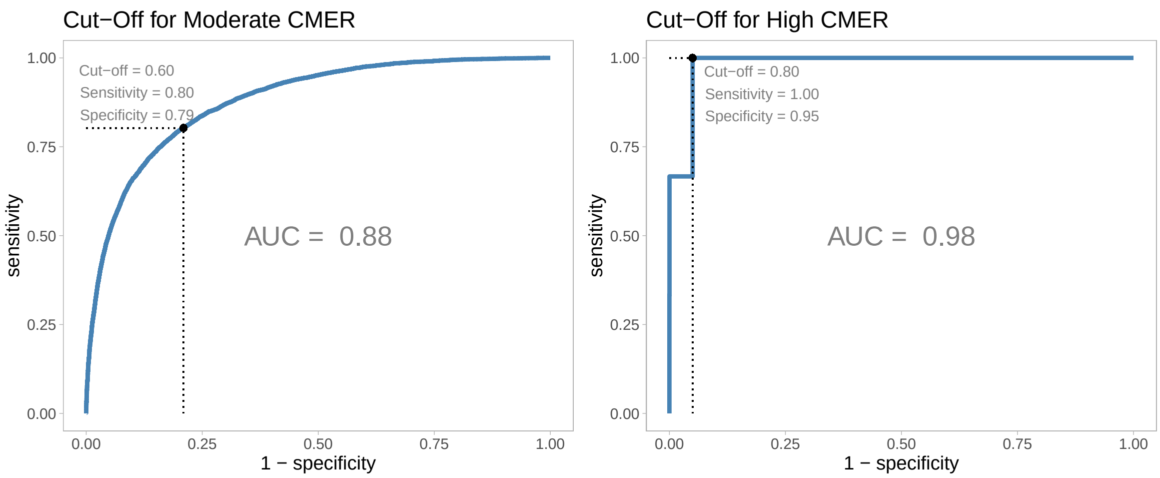

Figure 9: ROC Curve for Determining the Cut-off of the CMER Index

Distribution of CMER Index Categorized by Risk Level

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	N	M	SD	Min	Max
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

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%).
- 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.

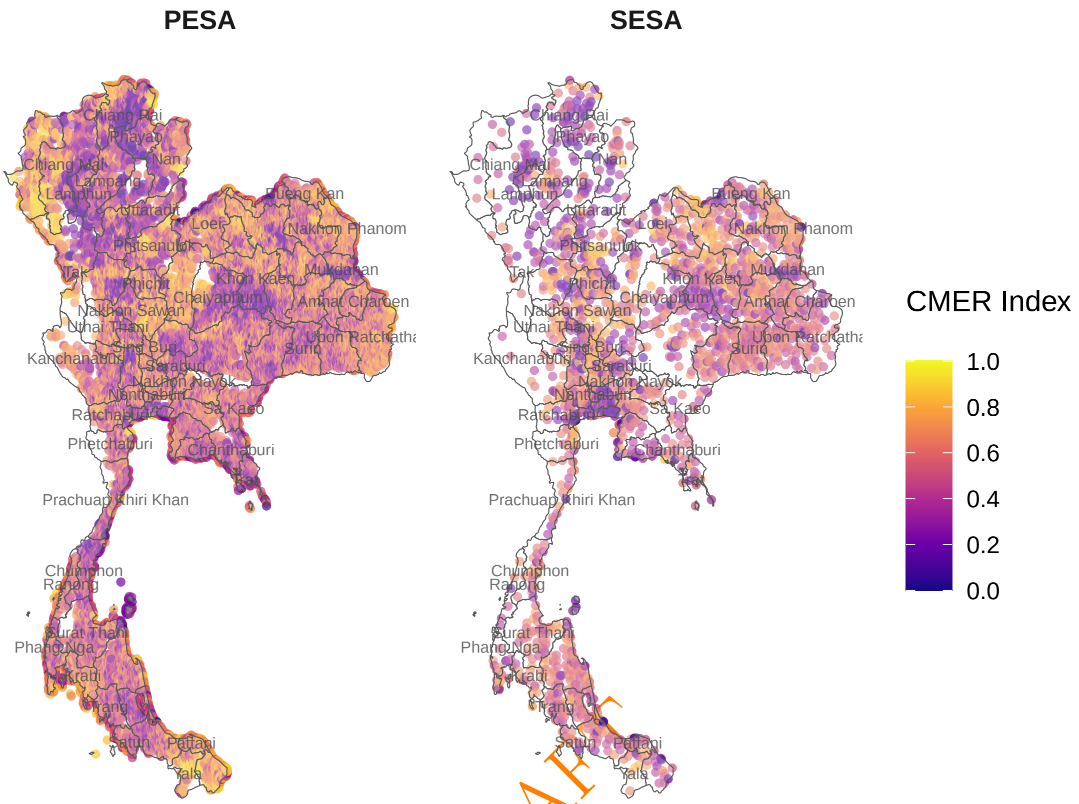

Figure 10: Geospatial Distribution of School CMER Index Categorized by Student Level (2017-2021)

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.

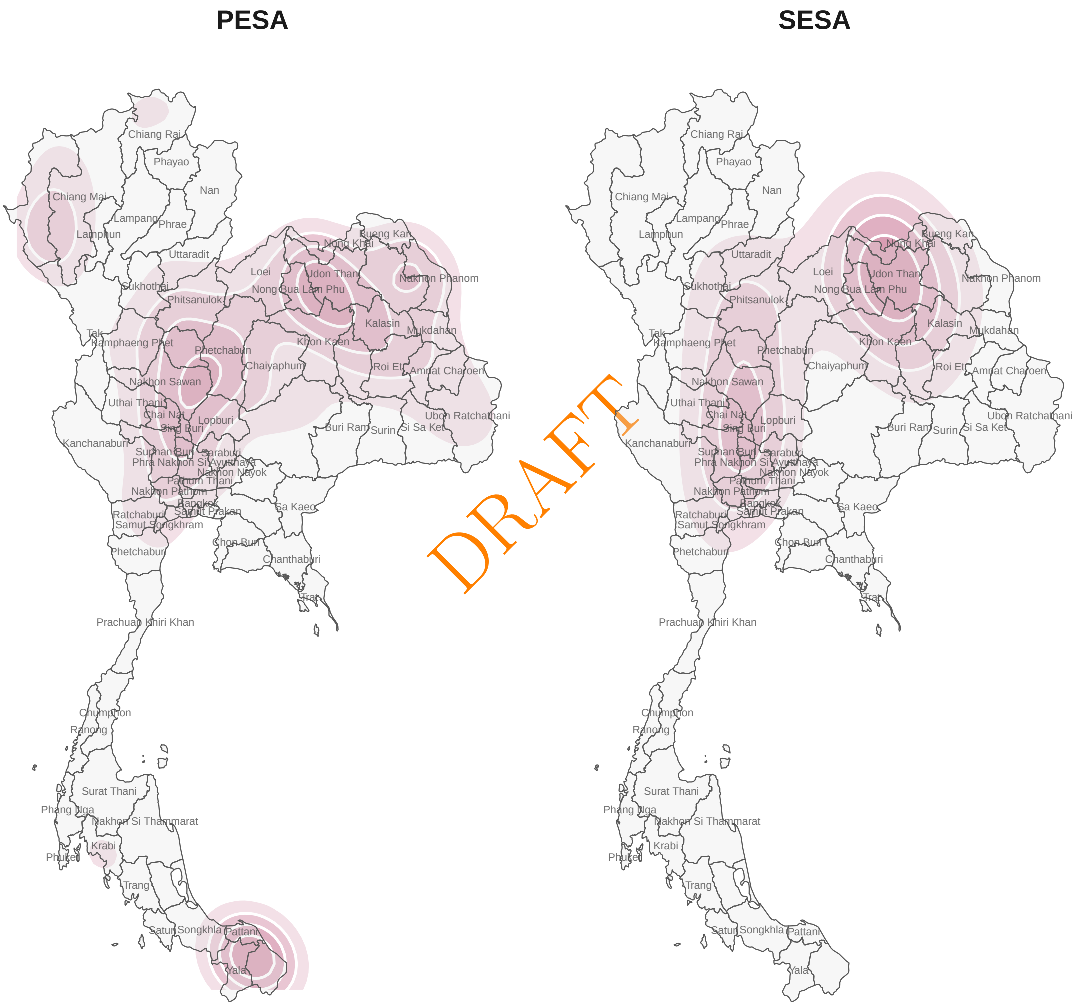

Figure 11: Contour Map of School with High Level of CMER (CMER > 0.8) Categorized by Educational Service Area (2017-2021)

6.1.3 Provincial Descriptive Analysis of CMER Risk

The contour map in Figure 11 visualizes school-level CMER risk, revealing that elevated risks are not uniformly distributed but are concentrated in certain regions. While this provides granular detail about the distribution of risk, it may not clearly represent the boundaries or the extent of risk at the provincial level.

To gain a more comprehensive understanding, a broader analysis at the provincial level is necessary to identify overarching patterns and trends in CMER risk across different regions, 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) illustrating the trends in educational risk across provinces over the study period from 2017 to 2021, and (1) presenting the overall risk levels and the number of high-risk schools in each province. The details are as follows:

Trends in Provincial CMER Risk Over Time

In the Figure 12, 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.

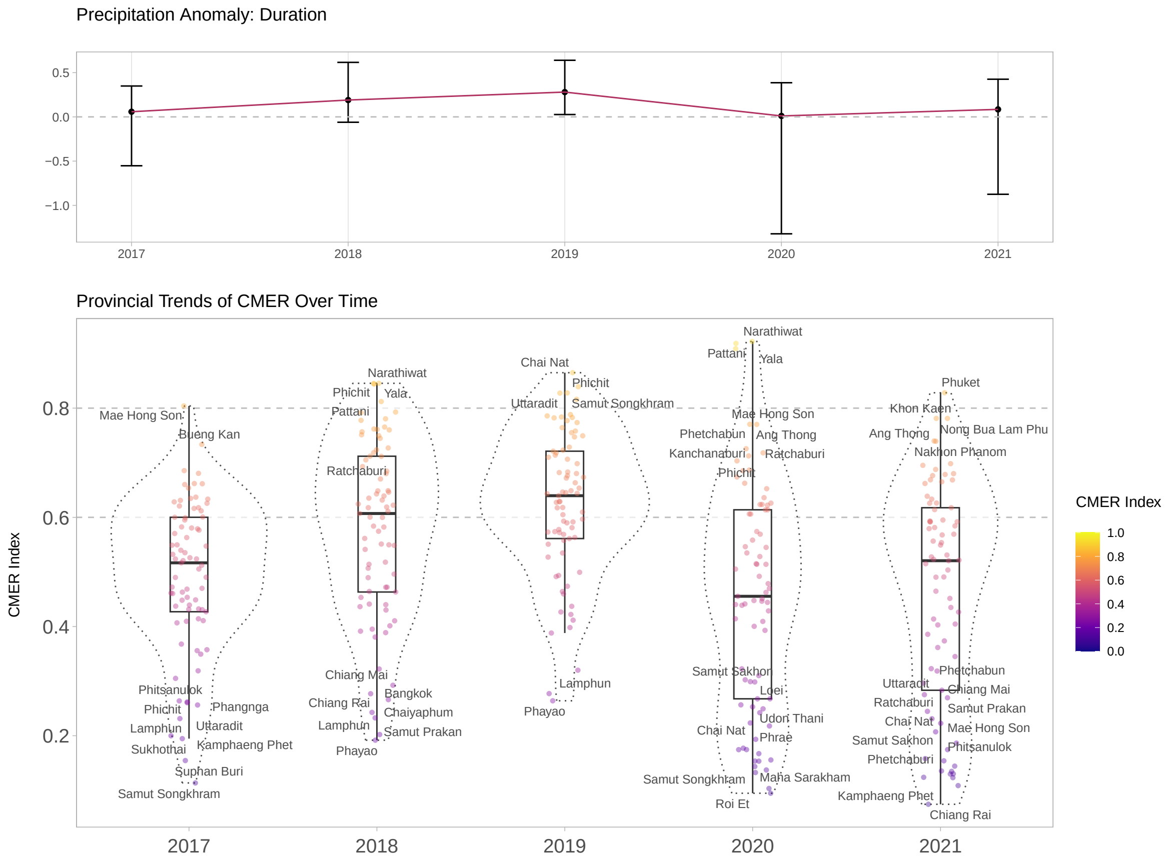

Figure 12: Provincial Trends of Precipitation Anomaly and CMER Over Time

The contour map presented in Figure 13 illustrates areas in Thailand with schools identified as having high educational risk, categorized by the study years from 2017 to 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.

CMER Risk Levels and High-Risk School Distribution Across Provinces

The Figure 14 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.

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 15 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

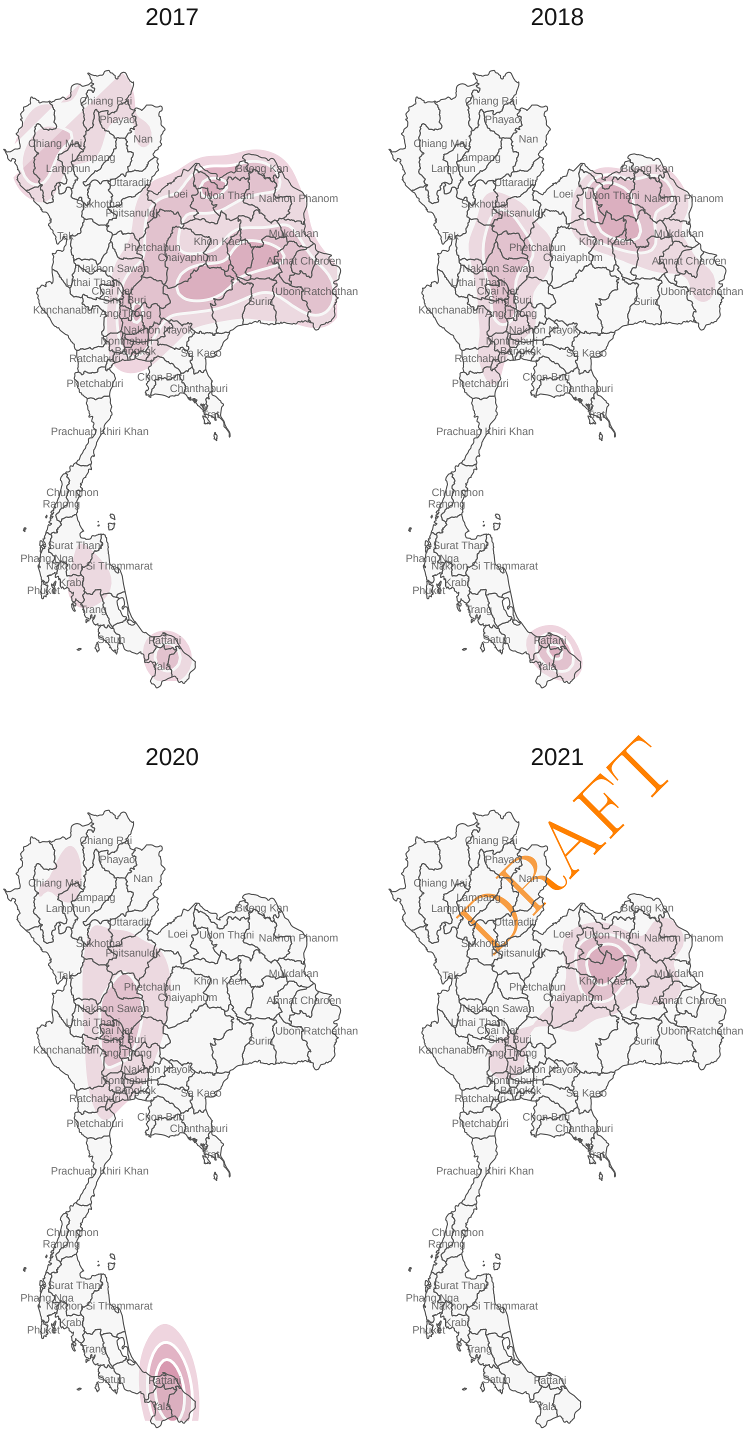

Figure 13: Temporal Contour Map of High CMER School (2017-2021)

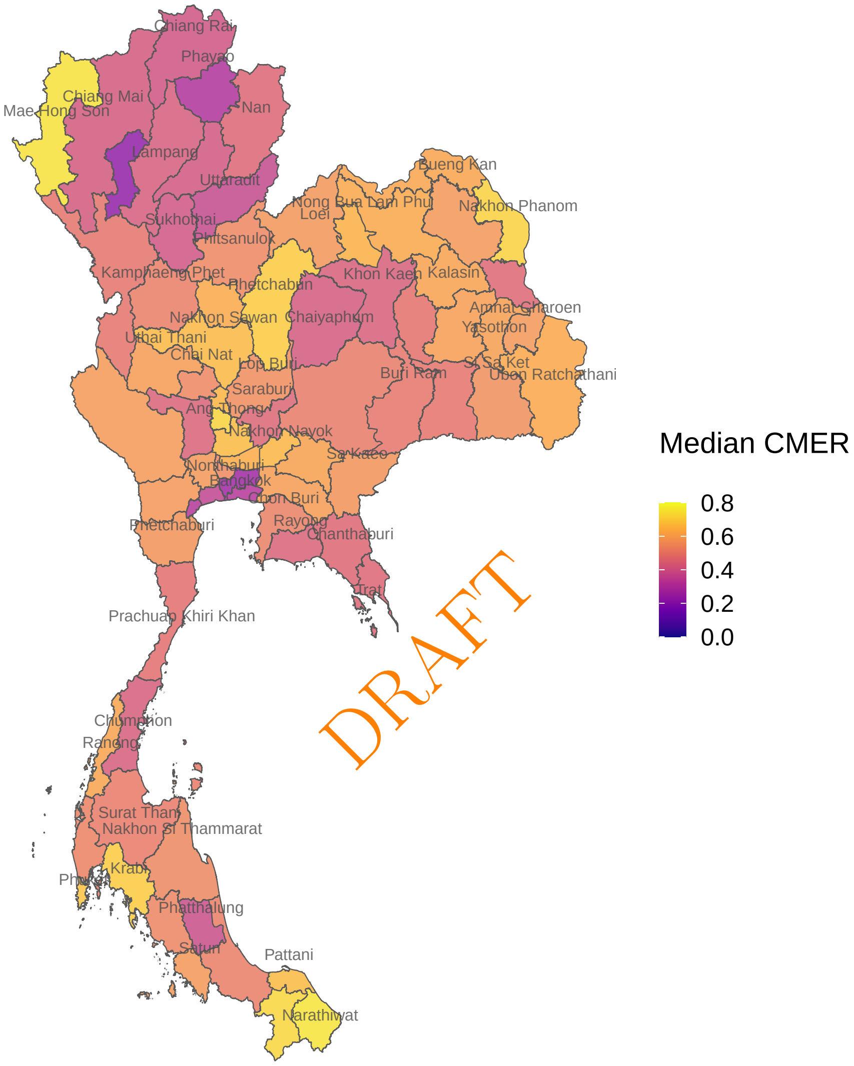

Figure 14: CMER Index Categorized by Province

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.

- Certain provinces, despite having a median CMER below 0.6, have over 10% of their schools classified as high-risk. These include Uthai Thani, Ratchaburi, Loei, Phitsanulok, Chainat, Kamphaeng Phet, Chiang Mai, and Chiang Rai, indicating that educational inequalities in these areas may be linked to extreme climate factors. Additionally, nearly all provinces contain schools falling into the high-risk category. These findings emphasize the widespread nature of educational vulnerabilities across Thailand, highlighting the need to address climate-related educational risks both provincially and nationally to promote more equitable outcomes.

6.1.4 Descriptive Analysis of CMER Index by Educational Service Area

This section presents an analysis of educational risks associated with climate change, categorized by Thailand's educational service areas, which are divided into Primary Educational Service Areas (PESA) and Secondary Educational Service Areas (SESA). The analysis aims to understand the differences in educational risks within each administrative region and to provide a clearer picture of the distribution and concentration of these risks at the educational service area level. The data reveals that there are a total of 244 educational service areas in Thailand, with 183 classified as PESA and 61 as SESA. This distinction highlights the larger number of administrative regions dedicated to primary education compared to secondary education, an important consideration when assessing the distribution and analysis of educational risks across the country.

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

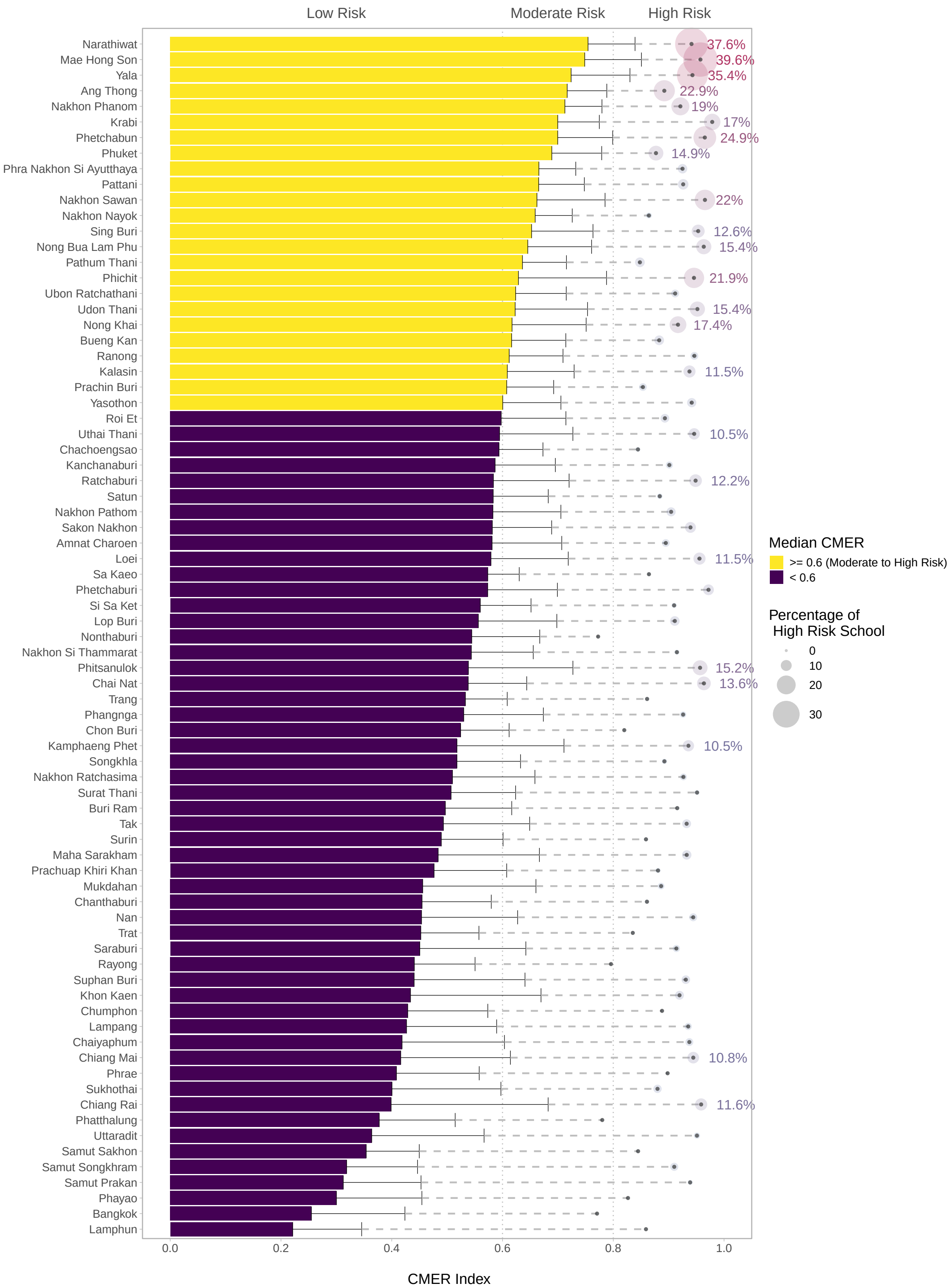

Figure 15: Provincial Distribution of CMER Index and Percentage of High-Risk Schools

(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	N	M	Med	SD	Min	Max
PESA						
Low Risk	16280	0.42	0.45	0.13	0.01	0.60
Moderate Risk	7084	0.68	0.67	0.05	0.60	0.80
High Risk	762	0.84	0.83	0.04	0.80	0.98
SESA						
Low Risk	1674	0.43	0.46	0.13	0.04	0.60

Moderate Risk	501	0.66	0.65	0.05	0.60	0.80
High Risk	10	0.83	0.82	0.02	0.80	0.85

Figure 16 visualizes the relationship between the median CMER (Climate-Mapped Educational Risk) score and the percentage of high-risk schools across different educational service areas in Thailand. The y-axis represents the median CMER score, reflecting the typical risk level in each area, while the x-axis shows the percentage of schools classified as high risk.

The size of the dots corresponds to the third quartile (Q3) of the CMER scores, where larger dots indicate areas with a Q3 score greater than or equal to 0.6, suggesting a higher concentration of high-risk schools. The dot colors differentiate between Primary Educational Service Areas (PESA, in orange) and Secondary Educational Service Areas (SESA, in green). Labels on the plot highlight specific service areas for further context.

Overall, the plot effectively reveals the variation in both the median risk and the proportion of high-risk schools across different regions, pinpointing areas with pronounced educational inequalities and climate-related vulnerabilities.

- The analysis of the scatter plot reveals that PESA Yala Area 2 stands out as an educational service area with both a high median CMER score and a notably high percentage of schools classified as high risk, exceeding 50%. This indicates that the majority of schools in this area face significant educational risks related to climate conditions.
- Additionally, there are 19 other areas with a median CMER above 0.6 and more than 10% of schools classified as high risk. These areas are predominantly Primary Educational Service Areas (PESA), including Narathiwat Area 1, Mae Hong Son Area 2, Nakhon Phanom Area 1, Phra Nakhon Si Ayutthaya Area 2, Chiang Mai Area 5, Krabi Area, Nakhon Sawan Area 3, Yala Area 3, Sakon Nakhon Area 3, Udon Thani Area 4, Ang Thong, Phetchaburi Area 1, and Phetchabun Areas 1, 2, and 3. Meanwhile, the three Secondary Educational Service Areas (SESA) that also fall into this high-risk category include Yala, Sing Buri-Ang Thong, and Nong Khai. Among these top 20 areas, the distribution between PESA and SESA is markedly uneven, with 17 areas classified as PESA and only 3 as SESA. This pattern underscores the regional disparities in educational vulnerability, particularly in primary education service areas where both the level of risk and the concentration of high-risk schools are considerable.
- Additionally, several educational service areas demonstrate a high degree of resilience to extreme climate conditions, as indicated by their low median CMER scores across all or nearly all schools. These areas reflect a strong capacity to

withstand climate anomalies without facing significant educational risks. Notable among these are Secondary Educational Service Areas (SESA) like Nonthaburi, Chiang Rai, and Bangkok Area 1. The Primary Educational Service Areas (PESA) include Phatthalung Areas 1 and 2, Tak Area 1, Rayong Area 2, several areas within Chiang Rai (Areas 1, 2, and 4), Chiang Mai Areas 1 and 4, Phayao Areas 1 and 2, Khon Kaen Areas 2 and 3, Lamphun Areas 1 and 2, and Samut Prakan Area 2. These regions exhibit robust educational systems capable of maintaining stability and avoiding high-risk classifications, despite potential climate challenges.

To complement the information presented in Figure 15, Figure 17 provides a visualization of the median CMER values across Thailand, categorized by educational service areas. This map offers a geographical perspective on the distribution of educational risks, highlighting the variations in risk levels across different regions and their respective service areas. By examining the median CMER, the map aims to offer insights into regional disparities in educational vulnerability to climate anomalies, providing a clearer understanding of how risks are spread throughout the country.

Figure 16: CMER Index and Percentage High-Risk Schools Categorized by Affiliation

6.2 Results for Research Objective 2:

The results for Research Objective 2 aim to explore and identify the specific characteristics of schools, provinces, and areas in which educational outcomes are particularly

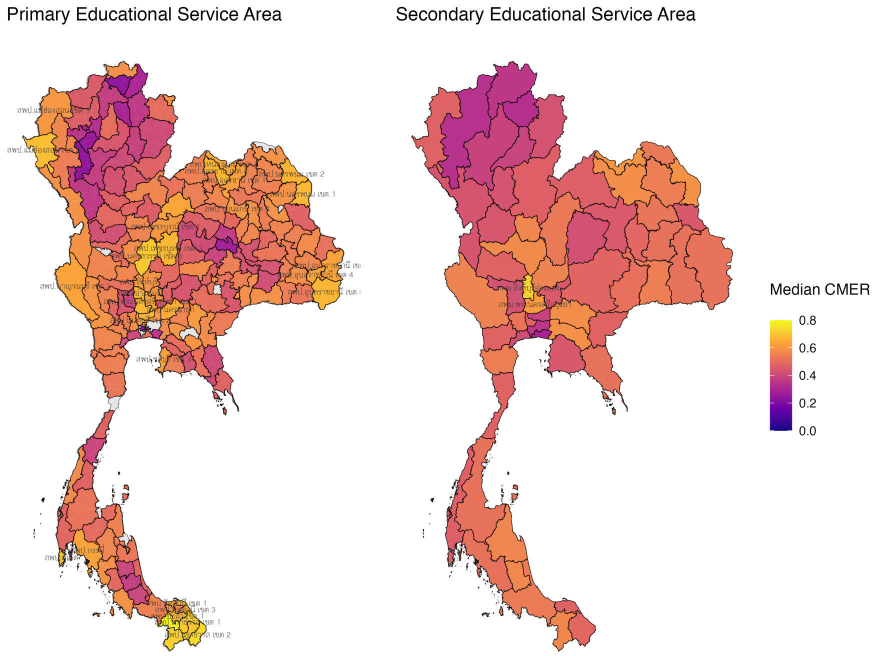

Figure 17: Median of CMER Categorized by Educational Service Area

susceptible to climate-related risks. The analysis focuses on uncovering patterns and vulnerabilities based on various dimensions, such as regional disparities, urban vs. rural settings, socio-economic conditions, the presence of age groups, and the categorization of schools based on hardship locations. By examining these characteristics, the study seeks to provide a comprehensive understanding of the factors that contribute to educational vulnerabilities within different geographic and social contexts, thereby informing targeted interventions and policies to mitigate these risks.

The analysis framework for Research Objective 2 is designed to explore how various school-related factors contribute to the Climate-Mapped Educational Risk Index (CMER Index). The framework categorizes factors into four key dimensions: (1) School Characteristics—focusing on school size (small, medium, large, and extra-large) to assess resource distribution and capacity in managing climate risks; (2) School Location & Accessibility—including the distance from the district center and the degree of accessibility difficulty, which indicate geographical remoteness and the challenges of school access, especially during extreme weather events; (3) School Infrastructure & Connectivity—evaluating the Infrastructure Readiness Score, covering electricity, water, and internet access, to understand how equipped schools are to handle climate disruptions; and (4) Student Profile—examining the percentage of low-income students (particularly in PESA) and student levels (Grades 6, 9, and 12) to identify how risks vary across age groups and socioeconomic backgrounds.

Regression Analysis is applied, and the analysis is conducted separately for Primary Educational Service Areas (PESA) and Secondary Educational Service Areas (SESA) to reflect the diverse regional educational contexts. This comprehensive approach aims to provide a nuanced understanding of educational vulnerabilities linked to climate hazards.

6.2.1 Summary of Key Factors Influencing Educational Risk

The first part of the analysis explores the overall relationships between non-climate variables across four dimensions and the CMER Index using a regularized regression model. This section provides a broad view, followed by a more detailed breakdown across different educational service areas. The results are presented for each of the 244 educational service areas, assessing the strength and significance of these relationships using two main metrics: the regression coefficients and the Variable Importance Plot (VIP).

The regression coefficients indicate the effect size or the rate of change in the CMER Index as the non-climate variables change. A positive coefficient suggests an increase in educational risk with a rise in that variable, while a negative coefficient implies a mitigating effect on the CMER Index. By interpreting these coefficients, we gain insight into how various factors impact educational vulnerabilities related to climate hazards.

The Variable Importance Plot (VIP) ranks and visualizes the importance of predictors in the model. In this analysis, the VIP score is derived from the absolute value of the corresponding t-statistics (Bring, 1994), which can be used to test the significance of the influence of each variable. A higher VIP score indicates that a variable plays a significant role in predicting the CMER Index, whereas lower scores suggest less influence. By examining the VIP scores, the key contributors to educational risks can be identified both at an overall level and within specific educational service areas.

The analysis presented in the Table 6, and Figure 18 illustrates the impact of non-climate factors on the CMER (Climate-Mapped Educational Risk) index, broken down by the two types of educational service areas in Thailand: Primary Educational Service Areas (PESA) and Secondary Educational Service Areas (SESA). Each non-climate factor is represented by its estimated effect size on the CMER index, with boxplots showing the distribution of these effects across different educational areas.

This table presents the analysis results for various non-climate factors impacting the Climate-Mapped Educational Risk (CMER) Index, categorized into two groups: Primary Educational Service Areas (PESA) and Secondary Educational Service Areas (SESA). Each factor is assessed based on its effect size, measured by the mean change in the CMER Index, along with additional statistics such as standard deviation (SD), quartiles (Q1, Median, Q3), maximum value (Max), and the percentage of significance (%Sig). For the PESA regions,

- The "Small School" factor, which reflects the constraints on resources for school administration, was analyzed in 181 regions. The mean impact on educational risk (CMER) was 0.11 (SD = 0.15), with a median of 0.10, indicating a moderate positive correlation with educational risk. The maximum observed impact was 0.49, and approximately 30.4% of these regions showed statistical significance, suggesting that small schools with limited resources are likely associated with a higher educational risk.
- The "Hard to Reach" factor, reflecting the remoteness and inaccessibility of school locations, was analyzed in 33 regions. The mean impact on CMER was 0.07 (SD = 0.12), and the median was 0.07. Although the overall impact is moderate, the maximum value observed was 0.30, indicating a higher impact in certain areas. Approximately 39.4% of these regions showed statistical significance, suggesting that difficult access is associated with higher educational risk in these regions.
- The "School Distance" factor, representing the distance between the school and the community, was analyzed in 183 regions. The mean impact on CMER was 0.06 (SD = 0.10), with a median of 0.05. Although the overall impact is relatively low, the maximum observed value was 0.42, implying that in some areas, greater school distance is linked to higher educational risk. About 27.9% of these regions showed statistical significance, indicating the challenges of traveling to school that may affect educational risk.
- The "Lack of Infrastructure" factor was analyzed in 176 regions, with a mean impact on CMER of 0.03 (SD = 0.07) and a median of 0.02. The overall impact on educational risk is relatively small, but the maximum value reached 0.23, with 15.9% of regions showing statistical significance. This suggests that in some areas, inadequate infrastructure may be associated with increased educational risk.
- The "Younger Student" factor was analyzed in 183 regions, with a mean impact on CMER of 0.02 (SD = 0.05) and a median of 0.02. Although the effect is low, the maximum observed value was 0.37, and 16.4% of the regions showed statistical significance, indicating that younger students may have higher educational risks in certain areas.
- Finally, the "Poor Family" factor was analyzed in 176 regions, with a mean impact on CMER of 0.02 (SD = 0.04) and a median of 0.01. The effect on educational risk is minimal overall, but the maximum value reached 0.31, and 14.2% of regions showed statistical significance. This highlights that economic status may be associated with increased educational risk.

For the SESA regions, the top-ranked non-climate factor is “Small School,” similar to the PESA regions. The details are as follows:

- the “Small School” factor, reflecting the constraints on resources for school administration, was analyzed in 61 regions. The mean impact on CMER was 0.18 (SD = 0.10), and the median was 0.18, indicating a substantial positive effect on educational risk. The maximum observed value was 0.61, and 77.0% of these regions showed statistical significance, suggesting a strong correlation between limited resources in small schools and increased educational risk.
- The “School Distance” factor, reflecting the distance from school, was analyzed in 61 regions. The mean impact on CMER was 0.06 (SD = 0.15), with a median of 0.06. While the overall impact is moderate, the maximum observed value was 0.61, and 19.7% of the regions showed statistical significance, indicating that school distance may be linked to higher educational risk.
- The “Lack of Infrastructure” factor was analyzed in 61 regions, with a mean impact of 0.02 (SD = 0.09) and a median of 0.03. The overall effect is relatively low, but the maximum observed value was 0.27, and 18.0% of regions showed statistical significance. This suggests that inadequate infrastructure may be associated with educational risk in certain areas.
- The “Hard to Reach” factor, which reflects the remoteness of the school, was analyzed in 5 regions. The mean impact on CMER was -0.01 (SD = 0.16), and the median was 0.09, with no statistical significance observed (0.0%).
- Lastly, the “Younger Student” factor was analyzed in 61 regions, with a mean impact of -0.03 (SD = 0.08) and a median of -0.02. Although the effect is slightly negative, the maximum value reached 0.16, and 24.6% of the regions showed statistical significance. This indicates that younger students may have a higher educational risk in certain regions.

Overall, both PESA and SESA regions show that the “Small School” factor, which reflects constraints in resources for school management, has a prominent positive impact on educational risk (CMER), particularly in SESA regions where its influence is higher and more statistically significant (77.0%) compared to PESA (30.4%). The “School Distance” factor, representing the remoteness of the school, also consistently affects educational risk in both PESA and SESA, though its impact is moderate. “Lack of Infrastructure” shows a relatively low influence on CMER in both regions but still exhibits some statistical significance. The “Hard to Reach” factor appears to have a moderate effect on educational risk in PESA, while in SESA, it does not show a significant influence. Lastly, the “Younger Student” factor has a minimal effect on CMER in both PESA and SESA regions, indicating a slight risk associated with younger student populations, particularly in PESA where it shows slightly higher significance. Overall, while both regions share similar factors affecting educational risk, the extent and significance of these influences vary, with SESA regions showing a stronger association between small school size and increased CMER.

Table 7: Summary of Effect Sizes for Non-Climate Factors Influencing CMER

term	N	Mean	SD	Q1	Median	Q3	Max	%Sig.
PESA								
Small School	181	0.14	0.12	0.04	0.12	0.20	0.49	30.4%
Hard to Reach	33	0.11	0.08	0.06	0.08	0.19	0.30	39.4%
School Distance	183	0.09	0.08	0.04	0.07	0.13	0.42	27.9%
Lack of Infrastructure	176	0.06	0.05	0.02	0.05	0.08	0.23	15.9%
Younger Student	183	0.04	0.04	0.01	0.02	0.05	0.37	16.4%
Poor Family	176	0.03	0.03	0.01	0.02	0.04	0.31	14.2%
SESA								
Small School	61	0.18	0.10	0.12	0.18	0.22	0.61	77.0%
Hard to Reach	5	0.13	0.07	0.09	0.11	0.11	0.26	0.0%
School Distance	61	0.11	0.12	0.04	0.09	0.12	0.61	19.7%
Lack of Infrastructure	61	0.07	0.06	0.03	0.07	0.10	0.27	18.0%
Younger Student	61	0.06	0.06	0.02	0.04	0.08	0.32	24.6%

The maps in Figure 19 depict the non-climate factor most associated with the CMER risk in each educational service area, distinguishing between PESA and SESA regions. The analysis reveals that PESA regions exhibit a variety of dominant factors. In the northern region, the main factors include “Lack of Infrastructure,” “Hard to Reach,” and “Small School.” In the northeastern and central regions, “School Distance,” “Small School,” and “Lack of Infrastructure” are prevalent. In the southern region, “Younger Student” emerges as the most significant factor.

For the SESA regions, “Small School” is the predominant factor across a large portion of the country, particularly in the central and southern regions, indicating that the educational risk in these areas is most closely related to the challenges faced by small schools. Meanwhile, in the northern regions, other factors such as “Hard to Reach” and “School Distance” are more prevalent, reflecting regional differences in the drivers of educational risk. A notable observation is that the factor “Younger Student” is also found in the southern SESA regions, similar to the pattern seen in PESA, indicating a commonality in the southern region where the age of students plays a key role in educational risk.

In summary, while PESA regions show diverse influential factors, SESA regions are primarily characterized by the influence of “Small School.” However, the impact of “Younger Student” in the southern areas is evident in both PESA and SESA, highlighting a regional trend in the influence of student age on educational risk.

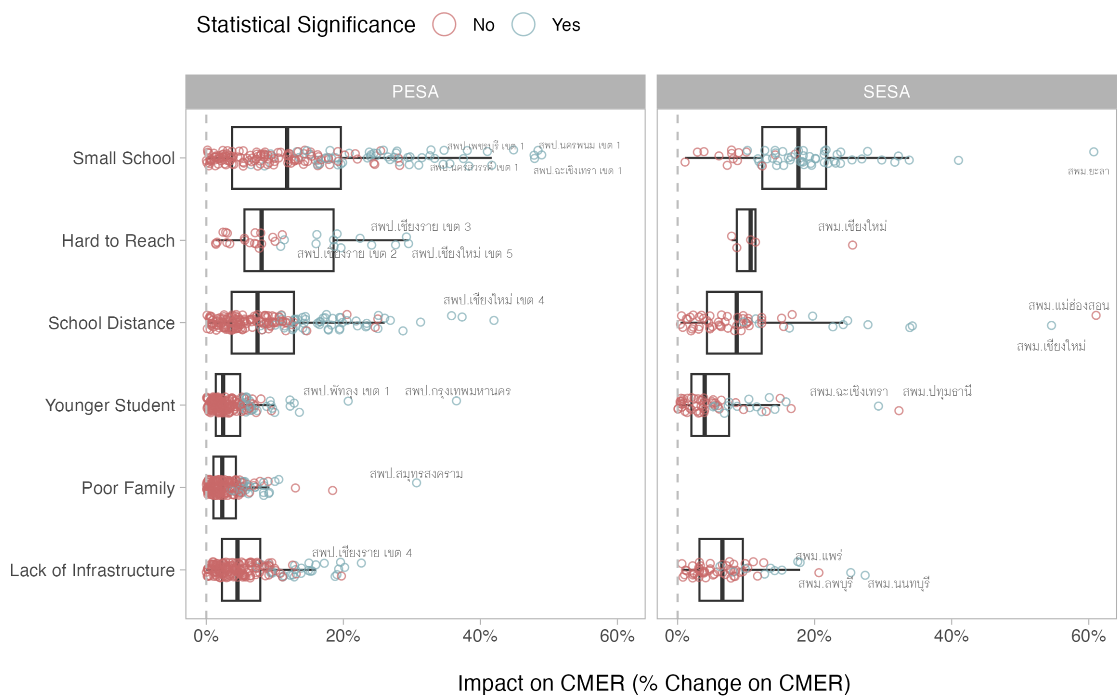

Figure 18: Distribution of Effect Sizes for Non-Climate Factors Influencing CMER

6.2.2 Risk-Importance Matrix

The researcher developed the Risk-Importance Matrix (RIM) as a tool to assess climate-mapped educational risk and classify educational service areas into subgroups to enhance planning and policy-making. The RIM provides a systematic approach to identify priority areas for intervention by evaluating both the CMER Index and the relative importance of contributing factors in each district. The matrix is designed with two key axes: the Y-axis and the X-axis. **The Y-axis displays the CMER Index**, representing educational risk derived from academic achievement and extreme rainfall conditions, where higher values indicate increased levels of risk that require urgent attention. **The X-axis represents the relative importance score (RI Score) of six factors** influencing educational risk, measured through Variable Importance (VIP). This axis highlights the significance of each factor in contributing to the overall risk in different districts.

It is important to note that the relative importance of each factor is not only measured within each district but also compared across all districts. Therefore, a district that exhibits a high relative importance for a specific factor suggests that this factor has a prominent and unique relationship with the CMER Index within that district. This allows the RIM to effectively pinpoint areas where particular factors—such as "School Distance," "Small School," or "Lack of Infrastructure"—stand out as strong contrib-

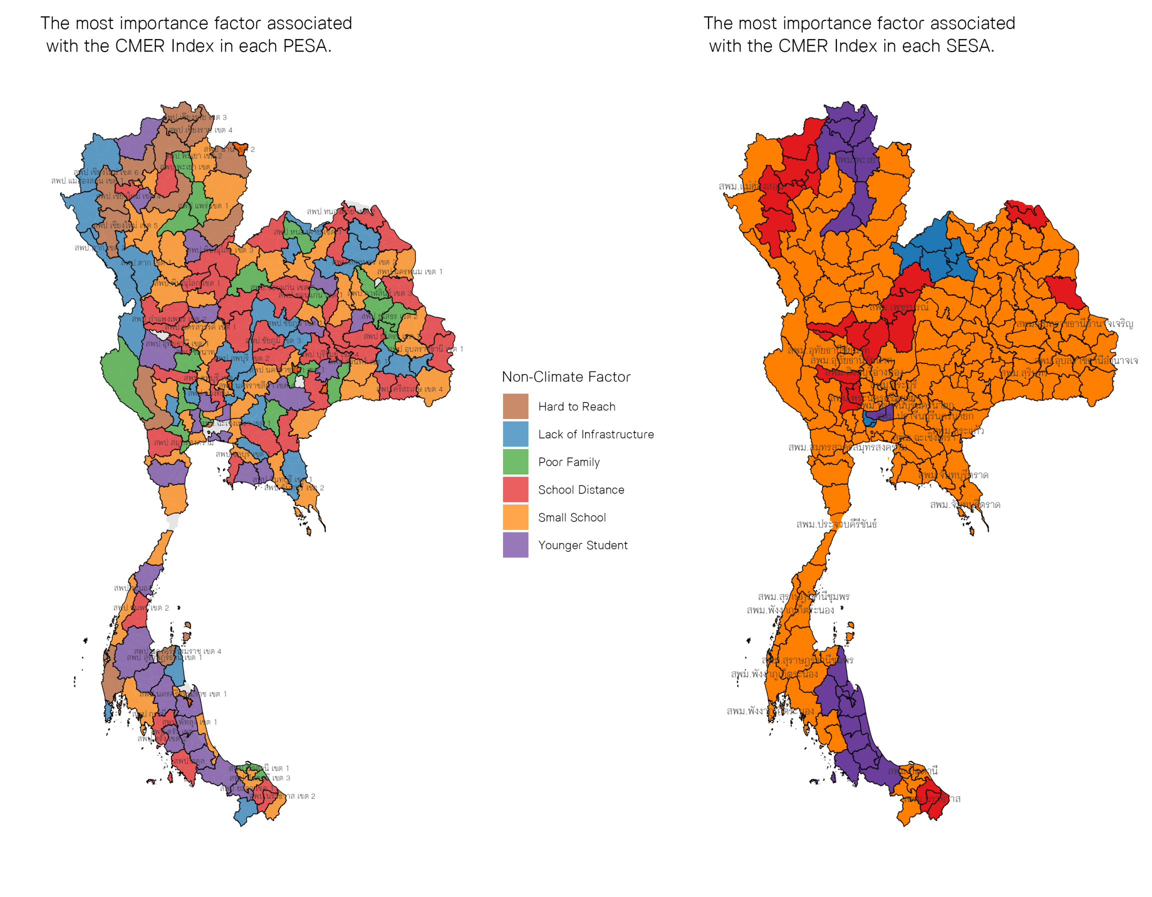

Figure 19: The Most Important Non-Climate Factors Categorized by Educational Service Area

utors to educational risk. By distinguishing these influential factors, the RIM guides policymakers in prioritizing targeted interventions and resource allocation to address the most impactful determinants of educational vulnerability in each district.

Points situated higher on the Y-axis correspond to districts with greater educational risk, suggesting a need for more immediate intervention. In contrast, points located further to the right on the X-axis indicate that certain factors have a greater impact on driving risk within those districts. The matrix categorizes regions into key groups based on their position along these axes.

The "Strategic Focus" Group includes areas characterized by both high CMER (Climate-Mapped Educational Risk) scores and high relative importance (RI) of non-climate factors, making them prime targets for immediate policy intervention. This classification is designed to guide resource allocation effectively, ensuring that districts where the interplay between educational risk and non-climate factors is most pronounced receive the necessary support.

The criteria for defining this group are based on two main thresholds:

- Y-axis thresholds for the CMER Index: These are set to reflect varying levels of educational risk, with higher CMER values indicating a critical need for urgent action. The thresholds have been carefully chosen to include regions slightly below a CMER score of 0.60, thereby capturing districts with moderate risk that are significantly influenced by important non-climate factors. This ensures that regions where these factors have a particularly strong impact on educational outcomes are not overlooked.
- X-axis thresholds for RI scores: A minimum RI score of 40% is used to highlight the significance of non-climate factors in contributing to educational risk. A higher RI score suggests a more substantial influence of these factors on the CMER Index, ensuring that regions with pronounced non-climate challenges are appropriately prioritized for policy measures and interventions.

By combining these thresholds, the Strategic Focus group is tailored to identify districts where immediate, targeted action can have the most impact on mitigating educational risk. This classification aims to maximize the effectiveness of policy interventions by focusing on areas with both significant risk and substantial contributing non-climate factors.

To effectively classify regions within the RIM, a diagonal boundary is established to differentiate between **the Development Priority and Monitoring groups**. This boundary separates districts based on both the CMER Index and the relative importance (RI) of non-climate factors, with CMER values ranging from 0.6 to 0.2.

The upper threshold of 0.6 is set as the minimum boundary for moderate risk, ensuring that the Development Priority group includes regions with CMER values in the moderate to higher range. These areas might not exhibit extreme risk but show a significant and clear association with one or more contributing non-climate factors. The boundary then extends down to a CMER value of 0.2, encompassing regions that may have moderate or relatively lower risk but still display a strong link to identifiable non-climate factors affecting educational risk.

Regions that fall below this diagonal boundary, yet have a CMER Index above 0.2 or show a strong association with non-climate factors, are classified under the Monitoring group. This ensures that even areas with moderate or lower levels of educational risk are still considered for ongoing observation, particularly if a clear non-climate factor can be identified as influencing the risk.

By using this approach, the matrix allows for a nuanced classification. The Development Priority group includes not only regions with clear associations between factors and moderate or higher risk but also districts where the risk is moderate to low yet the contributing non-climate factors are clearly influential. This ensures that interventions are focused not only on areas of urgent risk but also on regions where targeted action on key factors can significantly mitigate educational vulnerabilities.

The remaining group within the RIM classification is the **Low-Risk group**. This category includes districts that have very low CMER Index values, indicating minimal educational risk. Additionally, these regions do not show any strong or clear associations between non-climate factors and the observed risk, meaning that the contributing factors do not significantly elevate the educational risk in these areas.

The Low-Risk classification serves to highlight districts where the overall vulnerability is minimal and where non-climate influences do not play a major role in affecting educational outcomes. These regions require the least immediate intervention, as their low-risk status suggests a stable environment with respect to both climate-related and non-climate-related factors. However, they are still important to monitor over time to ensure that their low-risk status is maintained and to quickly identify any emerging factors that might alter their risk profile in the future.

PESA Risk-Importance Matrix

The Risk-Importance Matrix (RIM) analysis, presented in Figure 20 and Table 8, identifies "Strategic Focus" areas within the PESA regions, categorizing these areas based on the factors that significantly contribute to educational risk. The integration of CMER (Climate-Mapped Educational Risk) scores and the Relative Importance (RI) of various non-climate factors helps in highlighting specific issues that elevate educational vulnerabilities in these areas.

The Strategic Focus group within PESA consists of 19 districts that are identified as high-priority areas due to their combination of high CMER Index values and significant RI scores across various non-climate factors. The CMER Index for these areas ranges from 0.52 to 0.73, indicating varying but consistently elevated levels of educational risk, which require urgent policy attention. The RI scores vary between 43.88% and 100%, showing that certain non-climate factors play a critical role in driving the educational risk within these regions.

These districts are dispersed across several geographic regions of Thailand, highlighting a widespread influence of educational risks throughout the country. For example, the southern region includes districts such as Narathiwat, Yala, and Pattani; the northern region is represented by areas like Mae Hong Son and Chiang Mai; and northeastern areas such as Nakhon Phanom, Nong Khai, and Kalasin are also present. Additionally, there are central provinces like Chachoengsao and Chainat. This distribution reflects the complexity and diverse challenges of educational risk across Thailand's various regions.

The influential factors contributing to the CMER Index across various districts include "Poor Family," "School Distance," "Small School," and "Lack of Infrastructure," each playing a significant role in elevating educational risk. These factors reflect a combination of socioeconomic challenges, geographical accessibility, school size (which in turn indicates the level of budget and resource allocation from central administration), and infrastructure readiness. Together, they shape the capacity of schools to provide quality education and highlight critical areas where interventions can help mitigate educational vulnerabilities. For instance, while some areas face compounded effects from multiple factors, others are driven predominantly by one influential element that significantly contributes to their educational risk profile.

The analysis underscores the multifaceted nature of educational risk across these districts, with some areas being impacted by multiple factors simultaneously, while others are dominated by a single influential non-climate factor. This broad geographical spread and variety of contributing factors emphasize the need for targeted, region-specific interventions to effectively mitigate educational vulnerabilities in these Strategic Focus districts.

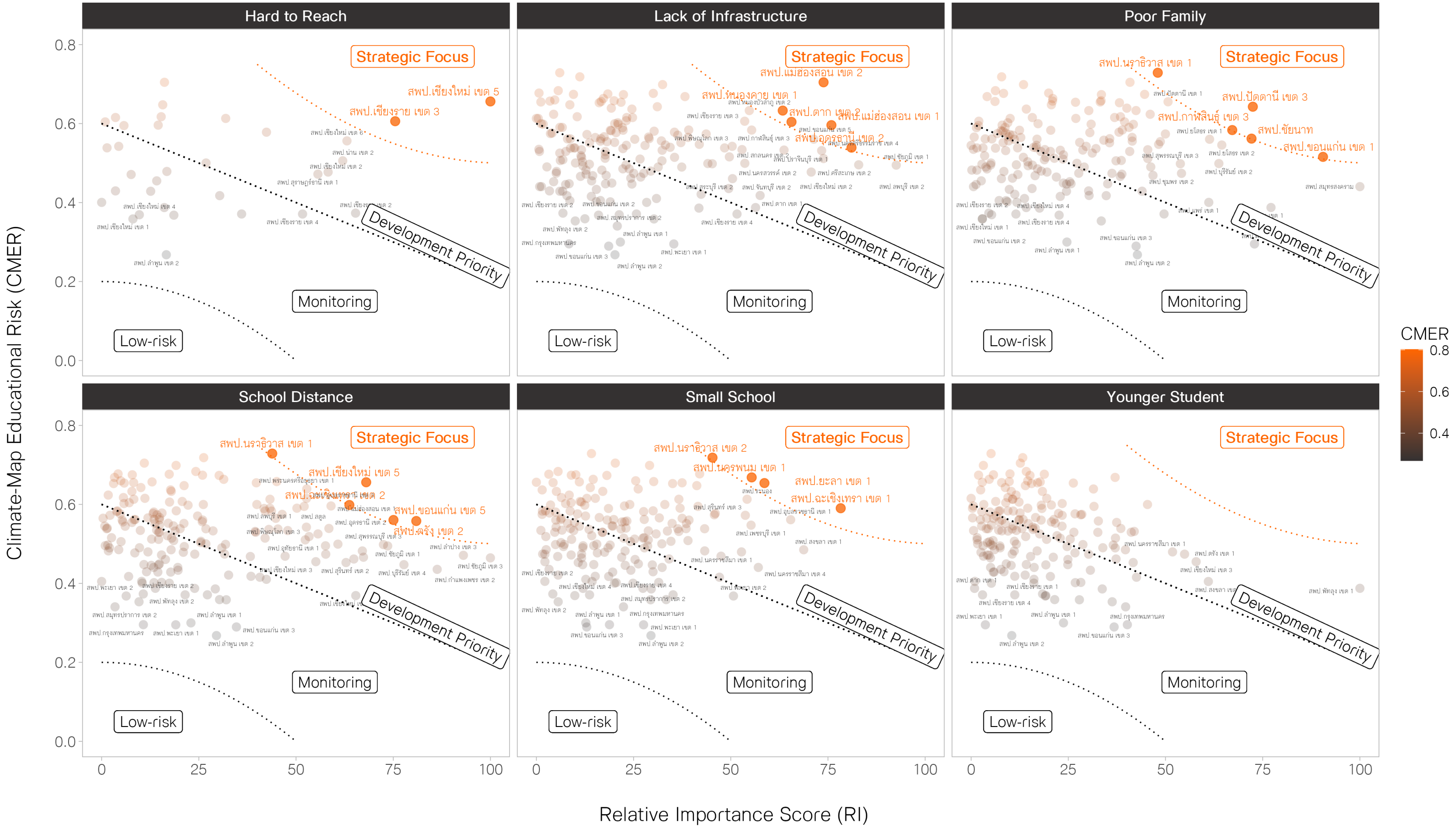

Figure 20: Risk-Importance matrix (RIM) of PESA

Table 8: Strategic Focus PESA

PESA	CMER	Factor	RI score
Narathiwat Area 1	0.73	Poor Family	48.01
Narathiwat Area 1	0.73	School Distance	43.88
Narathiwat Area 2	0.72	Small School	45.30
Mae Hong Son Area 2	0.70	Lack of Infrastructure	73.87
Nakhon Phanom Area 1	0.67	Small School	55.38
Chiang Mai Area 5	0.66	Hard to Reach	100.00
Chiang Mai Area 5	0.66	School Distance	68.05
Yala Area 1	0.65	Small School	58.66
Pattani Area 3	0.64	Poor Family	72.46
Nong Khai Area 1	0.63	Lack of Infrastructure	63.36
Chiang Rai Area 3	0.61	Hard to Reach	75.50
Mae Hong Son Area 1	0.60	Lack of Infrastructure	75.89
Tak Area 2	0.60	Lack of Infrastructure	65.62
Chachoengsao Area 2	0.60	School Distance	63.72
Chachoengsao Area 1	0.59	Small School	78.28
Kalasin Area 3	0.58	Poor Family	67.16
Trang Area 2	0.56	School Distance	80.93
Khon Kaen Area 5	0.56	School Distance	75.06
Chainat	0.56	Poor Family	72.12
Udon Thani Area 2	0.54	Lack of Infrastructure	81.05
Khon Kaen Area 1	0.52	Poor Family	90.51

Regions with Multiple Influential Factors

Several PESA regions are influenced by more than one key non-climate factor, suggesting complex educational challenges:

- Narathiwat Area 1 faces significant challenges from both "Poor Family" and "School Distance," indicating that socioeconomic difficulties and geographic accessibility combine to elevate educational risks in this area.
- Chiang Mai Area 5 is affected by a combination of "Hard to Reach" and "School Distance." These factors emphasize how remote locations and travel distance contribute significantly to educational risk, making accessibility a major concern in this region.

For regions with multiple influential factors, the presence of more than one factor related to the CMER Index suggests the possibility of interactions between these factors. Therefore, an analysis in Figure 21 was conducted to examine these potential interactions. The analysis in the plot provides insights into the relationship between non-climate factors and the CMER Index across two distinct areas, Narathiwat Area 1 and Chiang Mai Area 5, categorized by different conditions:

Narathiwat Area 1

The plot compares the average CMER Index between urban and suburban schools, further categorized by the proportion of poor students (majority or minority). Key observations include:

- Urban schools generally have a lower CMER Index compared to suburban schools. However, when the proportion of poor students is high, the CMER Index in urban schools increases, indicating that poverty amplifies the risk regardless of the location.
- Suburban schools, where educational risk is already higher, show even further elevated CMER Index values if they have a majority of poor students. This suggests that the effects of location and poverty are compounded, intensifying the educational risk more than either factor would individually.

The analysis reveals that poverty is a more critical factor in influencing educational risk than distance or location alone. Even urban schools, which typically have lower educational risk, face heightened CMER Index values when the majority of students are poor—comparable to or even higher than suburban schools with fewer poor students. This underscores the significant impact of poverty on educational risk, suggesting that targeted interventions addressing socioeconomic disparities may be more effective than focusing solely on geographical factors.

Chiang Mai Area 5

This plot compares the CMER Index based on how “hard to reach” a school is, as well as the distance from the district center (whether it is within or greater than 10 km). The 10 km threshold is set based on the median distance of all schools in the area. The relationship between accessibility and the distance from the district center indicates a strong interaction effect:

- Distance from District Center: Schools that are more than 10 km away from the district center show significantly higher average CMER Index values, indicating a greater educational risk associated with remoteness.
- Schools categorized as “Hard to reach” and those that are more than 10 km away show significantly elevated CMER Index values. While distance from the district center independently contributes to risk, this risk is exacerbated when schools are also harder to reach.

- Conversely, for schools classified as "Not Hard," the CMER Index remains moderate if they are within 10 km of the district center but increases if they are located further away. This suggests that distance magnifies the effect of accessibility challenges.

The interplay between non-climate factors in both Narathiwat Area 1 and Chiang Mai Area 5 reveals how these factors do not act in isolation but rather interact to elevate educational risks. In Narathiwat Area 1, the combination of suburban location and a higher proportion of poor students significantly increases risk. In Chiang Mai Area 5, the risk is amplified when schools are both remote (over 10 km) and difficult to access. These interaction effects suggest that interventions in these regions should prioritize support for remote and hard-to-reach schools, as these institutions face compounded educational risks due to both accessibility challenges and remoteness.

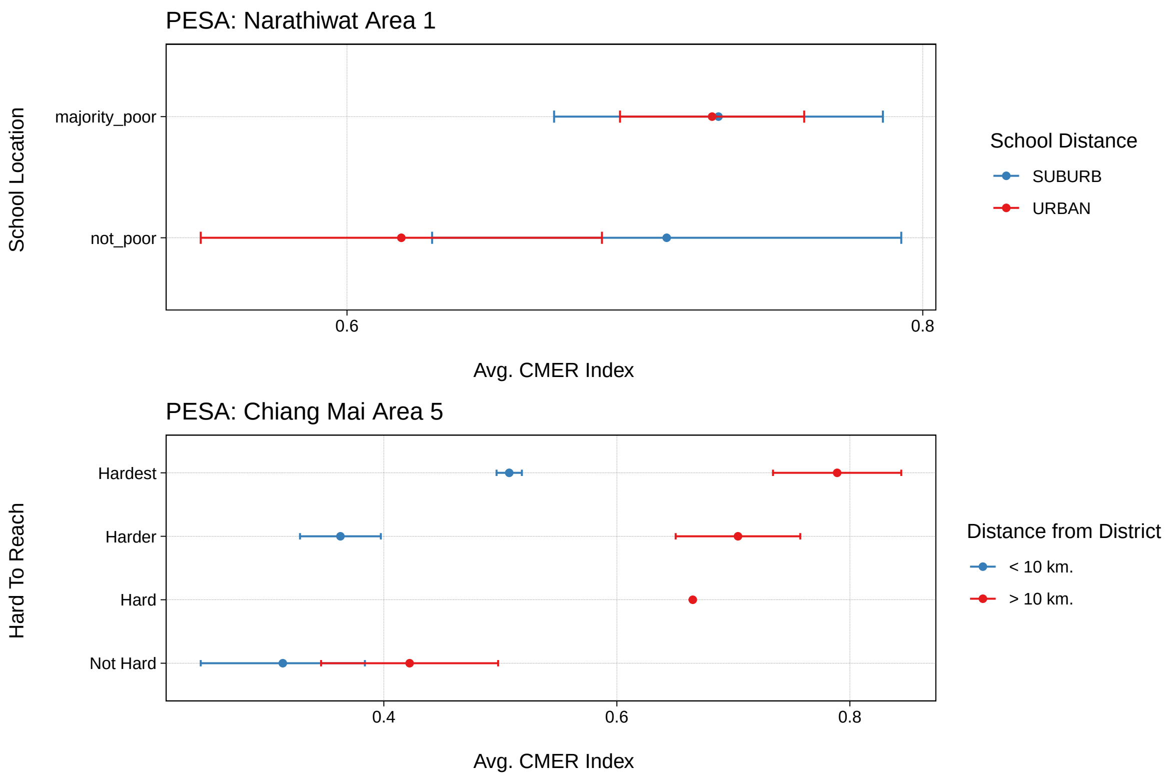

Figure 21: Interaction Analysis: PESA Regions with Multiple Influential Factors

Regions Dominated by a Single Factor

Some PESA regions are predominantly impacted by one non-climate factor that drives the educational risk:

- **"Small School"** is a leading factor in areas like **Narathiwat Area 2, Yala Area 1, Nakhon Phanom Area 1, and Chachoengsao Area 1.** In these regions, the presence of smaller schools, often with limited resources and support, emerges as a crucial driver of the CMER.
- **"Poor Family"** is a critical single-factor influence in **Pattani Area 3, Kalasin Area 3, Chainat, and Khon Kaen Area 1.** The socioeconomic challenges associated with poverty directly correlate with higher educational risks in these regions.
- **"Lack of Infrastructure"** is the dominant concern in regions such as **Mae Hong Son Area 2, Nong Khai Area 1, Udon Thani Area 2, and Tak Area 2**, emphasizing the role of basic service deficiencies—like limited access to electricity, water, and internet—in shaping educational risks.
- **"School Distance"** is a dominant issue in **Trang Area 2, Chachoengsao Area 2, and Khon Kaen Area 5**, where the physical distance between schools and the main community areas significantly impacts educational access and outcomes.

SESA Risk-Importance Matrix

The Risk-Importance Matrix (RIM) analysis for secondary educational service area (SESA), as shown in Figure 23 and Table 9, identifies key "Strategic Focus" regions where educational risk is notably impacted by various non-climate factors. The SESA "Strategic Focus" group comprises several regions with notable educational risks as measured by the CMER Index. The CMER values in these regions range from 0.50 to 0.69, with corresponding high RI scores indicating that non-climate factors significantly contribute to educational vulnerability. The dominant factor across most regions is "Small School," highlighting how school size, linked to resource limitations and support from central administration, plays a crucial role in influencing educational risk.

However, Sing Buri & Ang Thong is an exception, being influenced by two significant factors: "Small School" (RI = 84.76) and "Lack of Infrastructure" (RI = 70.72). This combination suggests that both limited school size and infrastructural challenges together elevate educational risk in this region.

Overall, while "Small School" is a key driver of risk across most SESA regions, Sing Buri & Ang Thong's situation underscores the potential for multiple factors to compound and intensify educational challenges, indicating a need for targeted multi-faceted interventions.

Regions with Multiple Influential Factors

One region is influenced by more than one significant non-climate factor:

- Sing Buri & Ang Thong: This region is impacted by both "Small School" and "Lack of Infrastructure," with RI scores of 84.76 and 70.72, respectively. This combination suggests that limited school size and infrastructure challenges together contribute significantly to educational risk.

In a similar manner, the finding that a region is influenced by more than one significant non-climate factor suggests a potential interaction effect between these factors on the CMER Index. The analysis, as shown in Figure 22, indicates how the interplay between school size and infrastructure readiness influences educational risk:

- Small Schools: Regardless of their infrastructure readiness (whether equipped with necessary infrastructure or not), small schools have consistently high CMER Index values, with averages around 0.737. This suggests that the size of the school itself poses a significant risk, independent of the presence of infrastructure.
- Medium Schools: There is a noticeable difference in CMER Index based on infrastructure readiness. Medium-sized schools with adequate infrastructure have an average CMER of 0.717, while those lacking proper infrastructure have a lower average CMER of 0.586. This indicates that infrastructure availability has a substantial effect on medium-sized schools, with better-equipped schools showing higher educational risk.
- Large and Extra-Large Schools: The CMER Index is much lower for larger schools, particularly for extra-large schools with an average CMER of 0.211, regardless of their infrastructure status. Large schools with adequate infrastructure have a moderate risk (0.558). This suggests that larger school size generally correlates with lower educational risk.

The results highlight the interaction between school size and infrastructure readiness. While small schools show high risk regardless of their infrastructure, medium schools are more vulnerable when infrastructure is lacking. The reduced risk observed in large and extra-large schools, particularly those with better infrastructure, underscores the role of school size and resource availability in mitigating educational risks.

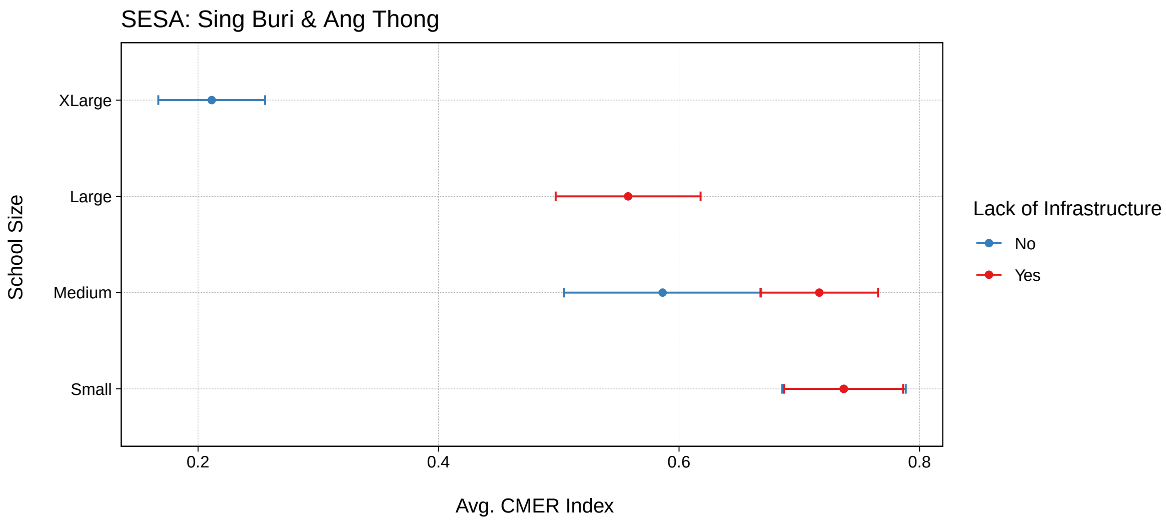

Figure 22: Interaction Analysis: SESA Regions with Multiple Influential Factors

Regions Dominated by a Single Factor

Several regions demonstrate educational risk driven primarily by one non-climate factor:

- **"Small School"** is a common factor influencing educational risk across many SESA regions, such as **Phra Nakhon Si Ayutthaya, Yala, Nakhon Phanom, Udon Thani, Prachinburi & Nakhon Nayok, Chachoengsao, Surin, Chanthaburi & Trat, and Ubon Ratchathani & Amnat Charoen**. The dominance of "Small School" in these regions, with RI scores ranging from 62.93 to 100.00, underscores how school size and its associated challenges, like limited resources and facilities, are critical contributors to educational vulnerabilities.
- **"Younger Student"** stands out as a key factor in **Nakhon Si Thammarat**, with an RI score of 90.00. This indicates that educational risk is particularly high for younger students in this area, which may reflect specific challenges faced by this age group in the educational context.
- **"Lack of Infrastructure"** is the primary factor influencing educational risk in **Sisaket & Yasothon**, with an RI score of 100.00. This suggests that deficiencies in basic services like electricity, water, and internet access are major contributors to educational risk in these regions.

In summary, the SESA regions identified as "Strategic Focus" are primarily affected by the "Small School" factor, which is prevalent across a wide range of regions. In some cases, such as Sing Buri & Ang Thong, the educational risk is influenced by both "Small School" and "Lack of Infrastructure," indicating complex challenges. On the other hand, regions like Nakhon Si Thammarat and Sisaket & Yasothon have a single dominant factor—"Younger Student" and "Lack of Infrastructure," respectively—that significantly drives educational risk. This distinction between regions with multiple influential factors and those with a single dominant factor provides a targeted approach for intervention and policy development.

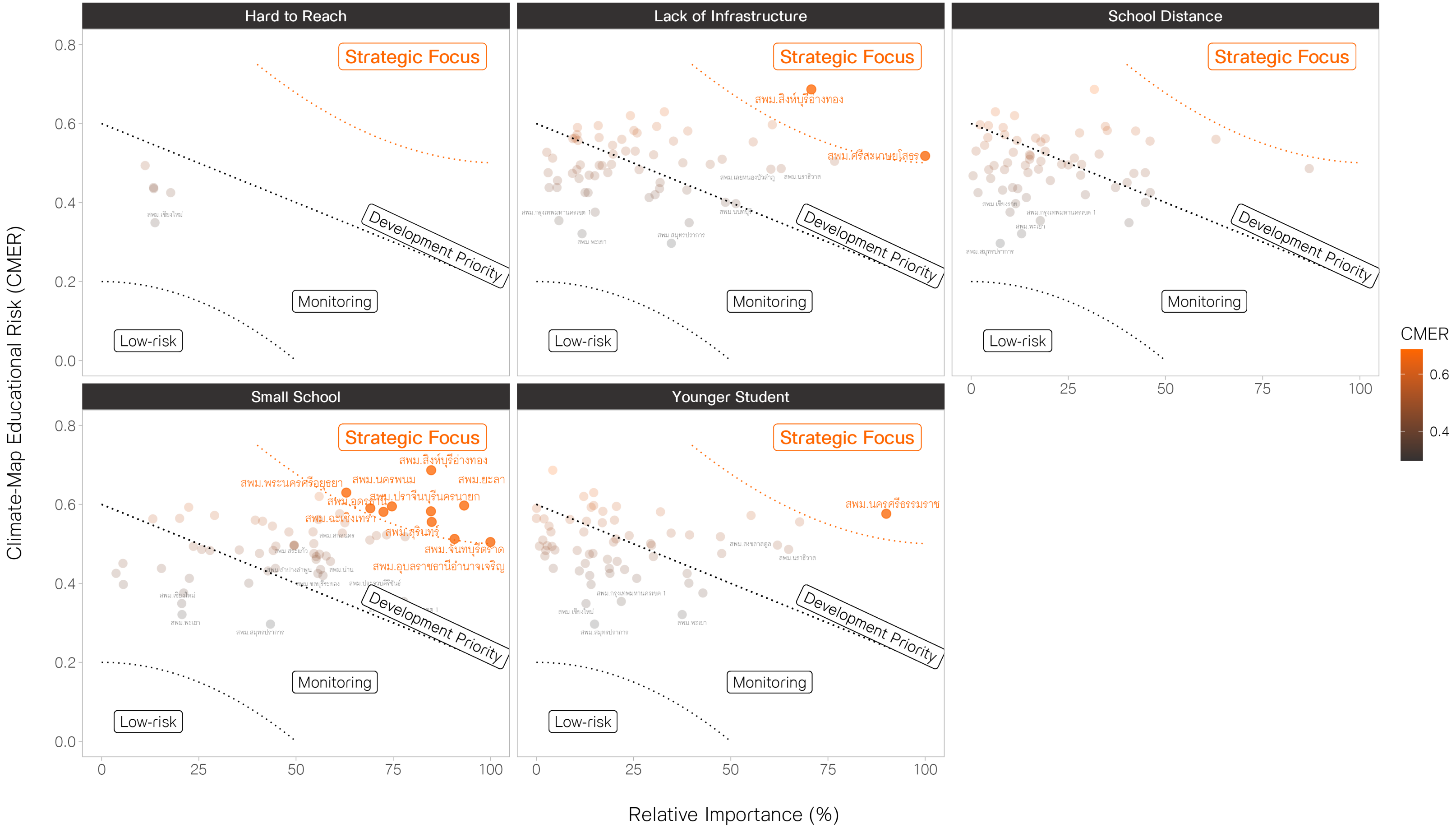

Figure 23: Risk-Importance matrix (RIM) of SESA

Table 9: Strategic Focus SESA

SESA	CMER	Factor	RI score
Sing Buri & Ang Thong	0.69	Small School	84.76
Sing Buri & Ang Thong	0.69	Lack of Infrastructure	70.72
Phra Nakhon Si Ayutthaya	0.63	Small School	62.93
Yala	0.60	Small School	93.24
Nakhon Phanom	0.59	Small School	74.66
Udon Thani	0.59	Small School	69.11
Nakhon Si Thammarat	0.58	Younger Student	90.00
Prachinburi & Nakhon Nayok	0.58	Small School	84.70
Chachoengsao	0.58	Small School	72.49
Surin	0.56	Small School	84.88
Sisaket & Yasothon	0.52	Lack of Infrastructure	100.00
Chanthaburi & Trat	0.51	Small School	90.77
Ubon Ratchathani & Amnat Charoen	0.50	Small School	100.00

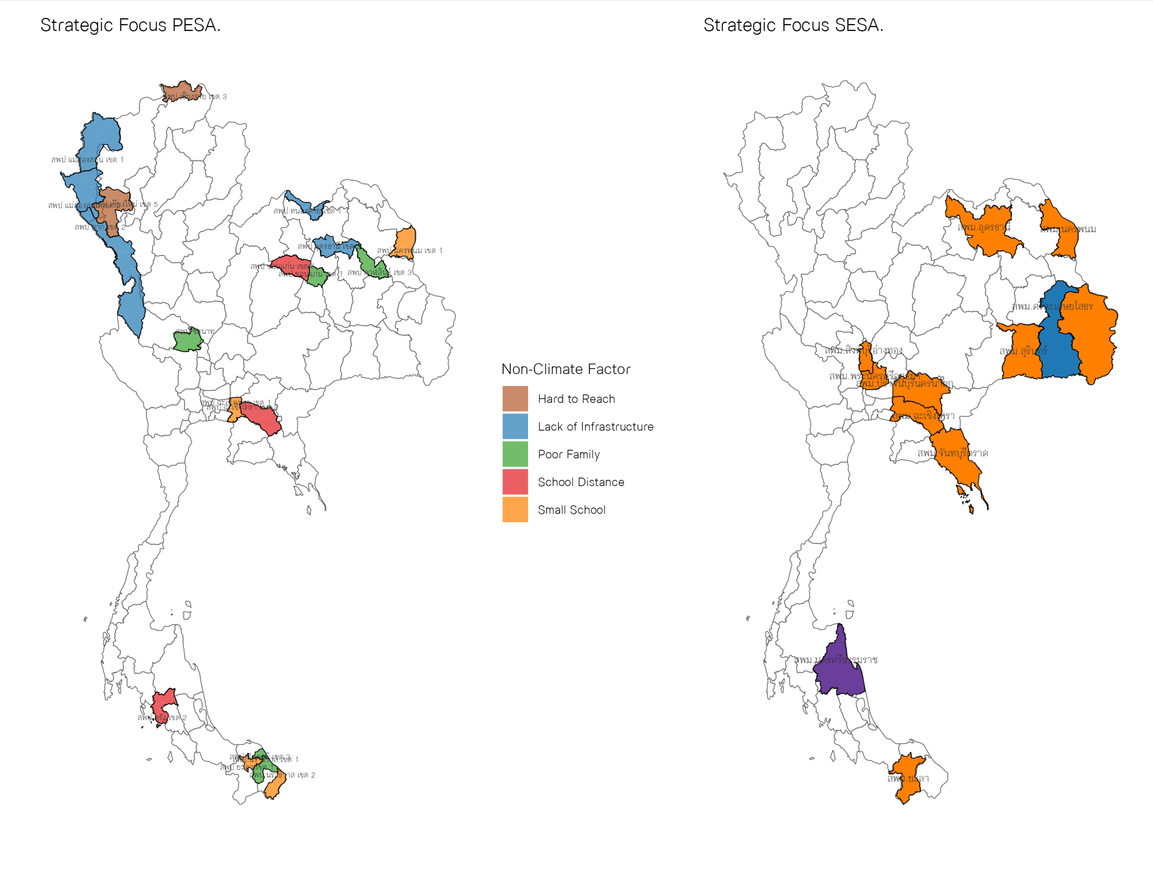

Figure 24: Strategic Focus of PESA & SESA.

7 Recommendation

The following recommendations are proposed based on the findings of the CMER analysis, highlighting key areas for targeted policy interventions and strategic planning. These recommendations aim to support educational resilience against climate anomalies by identifying both high-risk areas and best practices from well-prepared schools. By addressing a range of factors, from resource allocation in small schools to enhancing infrastructure and accessibility, policymakers can develop comprehensive strategies to mitigate educational risks and improve outcomes for students across various regions. The five key recommendations are as follows:

7.1 Recommendation 1: Utilizing the CMER Index for Comprehensive, Targeted Identification and Management Climate-Related Educational Risk.

The CMER Index, developed in this research, provides a new and more comprehensive approach to understanding educational risks associated with climate anomalies, surpassing traditional secondary data such as flood-prone maps (Geo-Informatics and Space Technology Development Agency (GISTDA), 2024). While flood-prone maps primarily identify regions frequently affected by flooding, the CMER Index not only aligns with these areas but also expands its scope by assessing the impact of prolonged heavy rainfall on educational outcomes. The CMER Index is specifically designed to pinpoint schools and areas where climate anomalies affect students' learning outcomes, enabling a broader and more nuanced identification of educational risks. This includes not only direct flooding impacts but also indirect effects, such as landslides and transportation challenges, which hinder educational access and continuity. As a result, the CMER Index provides a more holistic view of educational vulnerabilities, covering both alignment with flood-prone regions and a wider range of climate-induced factors impacting student performance. Consequently, the CMER Index allows for a more accurate identification of schools or areas that are truly affected, compared to conventional indices that aggregate scores without considering the direct impact on education.

The strategic use of the CMER Index allows policymakers to accurately pinpoint schools and regions highly vulnerable to various climate-related factors, ensuring that interventions are not limited to flood-prone zones alone. By offering a holistic view, the CMER Index supports more effective policy action and resource allocation, targeting regions that face a wide range of climate-induced challenges.

In applying the CMER Index, **policymakers and relevant stakeholders can prioritize areas requiring urgent intervention to mitigate educational risks related to climate anomalies through the following approaches:**

1. Identifying Regions for Urgent Intervention: The CMER Index facilitates the identification of regions facing significant educational risks influenced by climate factors, enabling policymakers to make targeted and timely decisions for assistance and support.
2. Proactive Planning and Preparedness: The CMER Index can be utilized for proactive planning to enhance educational resilience by monitoring risks and responding promptly to climate irregularities. Moreover, conducting in-depth analysis within high-risk areas identified by CMER can help develop policies or allocate resources that are more targeted and tailored to the specific needs of each region.

This approach will ensure that interventions effectively reduce educational vulnerabilities in areas most impacted by climate anomalies.

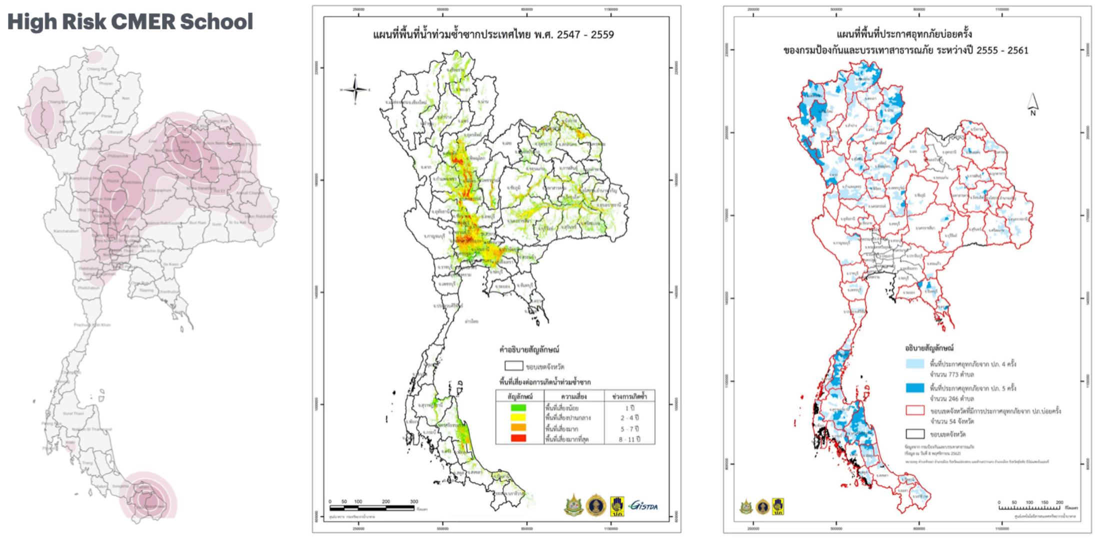

Figure 25: Comparison of High-Risk CMER Schools with Flood-Prone Areas in Thailand

7.2 Recommendation 2: Leveraging Resilient Schools as Models for Climate-Adapted Education Management

The analysis reveals that some schools, despite being located in areas prone to extreme climate conditions, exhibit a relatively low CMER risk. This suggests that these schools possess resilience to climate-related risks, effectively mitigating potential educational disruptions. Preliminary findings identify 26 such schools across 22 provinces in Thailand, including Bangkok, Kalasin, Kamphaeng Phet, Nakhon

Pathom, Nakhon Si Thammarat, Nonthaburi, Nan, Phitsanulok, Phuket, Lopburi, Songkhla, Udon Thani, and Phrae. These schools vary in size, from small to very large, and are distributed across both urban and suburban areas, with some schools having a majority of students from low-income backgrounds.

Interestingly, none of these schools are located in remote areas, suggesting that their capacity to manage climate risks may not solely depend on their geographic location or level of accessibility. Some of these schools are situated outside district centers, and despite being in high-risk areas for extreme weather, they demonstrate a level of resilience that allows them to maintain stable educational outcomes.

This resilience presents a valuable opportunity for policy development and educational planning. The practices, strategies, and policies implemented by these schools to handle climate anomalies may offer insights into creating more climate-resilient educational systems. By examining the management and operational practices of these schools, particularly in how they ensure continuity of learning and protect students from climate-related disruptions, policymakers can identify key factors that contribute to educational resilience.

Actionable Recommendation for Policymakers and Stakeholders

Policymakers and educational stakeholders should consider conducting in-depth case studies of these resilient schools to understand their specific practices in managing climate-related challenges. Key areas of investigation may include:

1. School Management and Preparedness: Assess the strategic planning and preparedness measures these schools implement to manage extreme weather events, including infrastructural improvements, emergency protocols, and coordination with local authorities.

2. Support Systems for Students: Explore how these schools support their students during periods of climate anomalies, such as providing mental health resources, flexible learning arrangements, or additional academic support to ensure students' learning continues uninterrupted.

3. Community Engagement and Resources: Investigate how these schools engage with their surrounding communities to access resources, build support networks, and create a community-driven approach to managing climate-related risks.

By understanding these practices, policymakers can develop adaptable strategies to bolster the climate resilience of schools across Thailand, especially those currently identified as vulnerable to extreme weather conditions. Incorporating successful approaches from these resilient schools can help build more robust and sustainable educational systems, safeguarding student achievement in the face of climate change.

7.3 Recommendation 3: Addressing the Vulnerabilities of Small Schools to Enhance Educational Resilience

The analysis of non-climate factors influencing the CMER Index reveals that the status of being a "Small School" is a significant contributor to educational risk across multiple districts. In some regions, this factor holds substantial weight in determining the CMER score, indicating that small schools are particularly vulnerable to climate-related educational risks. This correlation may point to a shortage of budgetary and resource support from central administration for the management and learning processes in these schools.

Actionable Strategies for Policymakers

1. Increase Targeted Funding and Resource Allocation: Policymakers should consider providing increased financial and resource support to small schools, ensuring that they have adequate materials, infrastructure, and human resources to build educational resilience. This includes funding for school facilities, access to digital learning tools, and the recruitment of sufficient teaching staff.
2. Capacity Building for School Leaders and Teachers: Initiate professional development programs tailored to small school contexts, focusing on enhancing school leaders' and teachers' capacity to manage educational risks. Training in climate preparedness, adaptive teaching strategies, and efficient resource utilization can empower small schools to better navigate challenges linked to both climate-related and educational factors.
3. Foster Collaborative Networks Among Schools: Create opportunities for small schools to collaborate and share best practices with larger or more resource-equipped institutions. Building networks or partnerships can help small schools gain access to shared resources, mentorship, and support, thereby mitigating the limitations that come with their size.
4. Localized Support Mechanisms: Develop support mechanisms at the local level to ensure small schools receive timely assistance and resources during climate anomalies or other disruptions. Localized support can include emergency funds, flexible policy arrangements for school operations, and local community engagement to address immediate needs.

By addressing the vulnerabilities faced by small schools, policymakers can significantly reduce educational risks and enhance the overall resilience of the educational system in regions where size-related factors pose a challenge. Ensuring that small schools are equipped with the necessary support will help mitigate the adverse effects of climate-related factors on student learning outcomes, contributing to a more equitable and robust educational landscape.

7.4 Recommendation 4: Tailored Interventions for Regions with Multiple Influential Factors

The findings indicate that regions with more than one influential non-climate factor require a customized approach to effectively address their educational risks. Specifically, in Narathiwat Area 1, Chiang Mai Area 5, and Sing Buri & Ang Thong, the compounded effects of factors like poverty, remoteness, school size, and lack of infrastructure significantly influence the CMER Index. These insights can guide policymakers in formulating precise interventions.

Narathiwat Area 1: Prioritizing Socioeconomic Support

For Narathiwat Area 1, the CMER Index is predominantly influenced by poverty and school location. The recommended strategy is to focus primarily on addressing the needs of poor students:

- Support for Schools with High Proportions of Poor Students: Implement targeted financial support programs such as scholarships, nutritional assistance, and after-school programs to alleviate socioeconomic barriers for students from poor families. This ensures that these students have the resources necessary for consistent educational engagement and achievement.
- Accessibility for Non-Poor, Suburban Schools: For schools that are not primarily poor but are located in suburban areas, interventions should aim to improve access and transportation to educational resources. This may involve enhancing transportation networks, providing school transportation services, and improving access to remote learning resources for students who live further from urban centers.

Chiang Mai Area 5: Enhancing Access to Remote and Hard-to-Reach Schools

Chiang Mai Area 5 is characterized by its "Hard to Reach" status and distance from district centers. The recommendation is to specifically support schools that are both remote and more than 10 km away from the district center:

- Focusing on Hard-to-Reach, Distant Schools: Schools that are more than 10 km away from the district center and are categorized as "Hard to Reach" face compounded educational risks. Enhancing access through improved transportation infrastructure, reliable internet connectivity for distance learning, and community-based support for remote teaching can address these challenges.
- Supporting Teacher Resources for Remote Education: Invest in professional development and training for teachers who work in these challenging, remote environments. Providing resources and support for both in-person and distance teaching can help bridge the gap caused by accessibility issues.

Sing Buri & Ang Thong: Addressing Infrastructure Gaps

In Sing Buri & Ang Thong, the combined effect of "Small School" and "Lack of Infrastructure" requires a dual-focused strategy. The analysis shows that infrastructure readiness plays a significant role, especially in small and medium-sized schools:

- Targeting Infrastructure Improvements for Medium Schools: Enhance basic infrastructure in medium-sized schools, which are more vulnerable when lacking proper facilities. Investing in utilities like electricity, internet access, and sufficient learning materials can reduce their educational risk significantly.
- Resource Allocation for Small Schools: For small schools, which show high educational risks regardless of their infrastructure readiness, additional funding and resource support are essential. Providing financial resources, educational materials, and flexible support services can mitigate the risks associated with their small size.

General Recommendations for Regions with Multiple Influential Factors

From the analysis, it is recommended that policymakers implement the following actions:

1. Socioeconomic Support and Access to Resources: Provide direct support to poor students and schools in areas with high poverty levels. Ensure equitable access to educational resources and transportation for schools located in suburban or remote areas.
2. Targeted Infrastructure Improvements: Focus on enhancing infrastructure for small and medium-sized schools, particularly in regions where a lack of infrastructure is identified as a significant factor. Improved facilities will support more effective teaching and learning.
3. Monitoring and Evaluation: Establish a monitoring system to track the progress of interventions. Regular assessments of educational outcomes and adjustments to policies based on emerging data will ensure that interventions remain effective and relevant to the regions' evolving needs.

By adopting these tailored strategies, interventions can more effectively address the interplay between socioeconomic status, school size, infrastructure, and remoteness, ultimately reducing educational risks and enhancing resilience across these vulnerable regions.

7.5 Recommendation 5: Tailored Interventions for Regions Dominated by a Single Factor

The Risk-Importance Matrix (RIM) analysis reveals that several regions are predominantly impacted by a single non-climate factor contributing to educational risk. These factors include “Small School,” “Poor Family,” “Lack of Infrastructure,” and “School Distance.” Each of these factors, individually, has a significant influence on the CMER Index, pointing to clear challenges within these regions that can be effectively addressed through targeted interventions. By focusing on the primary drivers of risk in each area, it becomes possible to implement strategic solutions that address the most pressing needs of these regions and improve educational outcomes.

1. Addressing “Small School” Challenges

For regions where the “Small School” factor is dominant—such as Narathiwat Area 2, Yala Area 1, Nakhon Phanom Area 1, Chachoengsao Area 1, and various SESA regions (Phra Nakhon Si Ayutthaya, Udon Thani, Surin, etc.)—the primary focus should be on addressing the limitations faced by smaller schools. Such schools often struggle with inadequate resources, teaching staff, and facilities. Policy recommendations include:

- Resource Allocation and Support: Ensure that small schools receive sufficient funding and support to provide quality education. This includes hiring qualified teachers, improving school facilities, and providing adequate educational materials.

- Capacity Building and Network Support: Establish networks between small and larger schools to share resources, support joint activities, and enable mentoring among teaching staff. Cluster-based approaches to resource sharing can help reduce disparities caused by school size.

2. Mitigating Socioeconomic Challenges

For regions where “Poor Family” is the driving factor, such as Pattani Area 3, Kalasin Area 3, Chainat, Khon Kaen Area 1, and SESA regions, targeted interventions should focus on alleviating the socioeconomic challenges faced by students:

- Targeted Social Programs and Financial Assistance: Implement financial support programs for students from low-income families, including scholarships, food assistance, and after-school programs that promote academic achievement.

- Community Development Initiatives: Collaborate with local communities to enhance support networks for families, promote community-based learning opportunities, and ensure that schools are connected to other social support services aimed at reducing educational disparities caused by poverty.

3. Improving Infrastructure and Access

In regions where "Lack of Infrastructure" is the predominant issue—such as Mae Hong Son Area 2, Nong Khai Area 1, Udon Thani Area 2, Tak Area 2, and Sisaket & Yasothon—the focus should be on improving access to basic services:

- Invest in Essential Infrastructure: Ensure that all schools have access to electricity, clean water, sanitation, and internet connectivity. This may involve governmental and private partnerships to improve service delivery, especially in rural and underserved areas.
- Technology-Enhanced Learning: Use technology to bridge gaps in education caused by inadequate infrastructure, particularly for remote or hard-to-reach schools. Providing schools with digital devices and internet access can enhance learning opportunities and reduce disparities.

4. Enhancing Accessibility for Schools with Distance Challenges

In areas where "School Distance" significantly impacts educational access—like Trang Area 2, Chachoengsao Area 2, Khon Kaen Area 5—the geographical isolation of schools poses a major barrier to education:

- Improve Transportation and Accessibility: Develop transportation solutions to reduce travel time for students, such as providing school buses or improving roads to make remote schools more accessible.
- Support for Distance and Remote Learning: For students who live far from schools, consider implementing distance learning programs, either through online education or community-based teaching centers, to ensure that they have consistent access to educational resources.

5. Addressing Needs of Younger Primary Students

In regions like Nakhon Si Thammarat, where the factor "Younger Student" significantly contributes to educational risk, policies should focus on enhancing support for primary school-aged students:

- Strengthen Primary Education: Invest in teacher training, curriculum development, and classroom resources specifically designed for younger students in primary education. Providing a robust educational experience for this age group can help establish a strong foundation for further academic achievement.
- Parental and Community Involvement: Encourage the active involvement of parents and local communities in supporting primary education. This can be achieved through programs that promote parental engagement in learning and collaboration with community organizations to create a supportive environment for students' educational development.

General Recommendations for Regions with a Single Influential Factor

- Targeted Resource Allocation: Allocate resources based on the primary factor driving educational risk in each region, ensuring that interventions are both strategic and tailored to local needs.
- Data-Driven Policy Development: Utilize data from the CMER Index to continuously monitor the impact of interventions, making data-informed decisions for policy adjustments and improvements as needed.
- Collaborative Stakeholder Engagement: Engage local communities, schools, and relevant organizations in the policy-making process to ensure that solutions are comprehensive, locally relevant, and sustainable.

By implementing targeted, factor-specific interventions, policymakers can effectively reduce educational vulnerabilities in regions dominated by a single influential non-climate factor. This approach enables a more efficient allocation of resources and a more profound impact on the educational outcomes of the affected regions.

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