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Title: The Association between Adverse Temperature Shocks and Schooling Outcomes in India: Impact Quantification and Mitigation Potentials

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The Association between Adverse Temperature Shocks and Schooling Outcomes in India: Impact Quantification and Mitigation Potentials

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Abstract

Does extreme heat adversely affect educational outcomes in India? We link results from the Indian Upper Primary Level Examination to local weather, air pollution, and vegetation data derived from remote sensing. Our four-year panel tracks student performance within the same schools while accounting for time-invariant characteristics. Both cumulative heat during the school year and higher temperatures during exams significantly reduce performance. Even under the most optimistic RCP scenario, a constant temperature increase would, *ceteris paribus*, lower pass rates by 3%, implying substantial human capital losses. Effect sizes peak when maximum temperatures exceed 40°C and are similar for general measures of thermal comfort combining heat and humidity. Students in poorer areas, especially the urban poor, are most vulnerable, and newer or non-centrally managed schools may require retrofitting. Vegetation near schools mitigates heat impacts but not sufficiently to offset future risks.

Keywords: Education, Climate Change, Heat Stress, Inequality, India
JEL codes: Q54, I24, I25

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"India will have the highest population of young people in the world over the next decade, and our ability to provide high-quality educational opportunities to them will determine the future of our country."

Indian National Education Policy 2020[1]

1 Introduction

In India, significant warming trends have been observed in recent decades, accompanied by a marked increase in the frequency of warm-extreme events. Moreover, the frequency and intensity of warm days and nights are projected to continue rising, while the occurrence of cold days and nights is expected to decline (Sanjay et al., 2020). UNICEF's *Children's Climate Risk Index* (CCRI), a composite measure linking child vulnerability to climate and environmental hazards, reflects these developments. In line with these projected trends, India ranks as low as 26th out of 163 countries, primarily due to a poor score in the category *"Climate and environmental shocks."* Debnath et al. (2023) show that extreme heat and prolonged heatwaves pose particular risks to India's development trajectory and have the potential to slow down – or even reverse – the country's progress towards achieving the *Sustainable Development Goals (SDGs)*.

The present study aims to contribute nuanced evidence on India's educational system by quantifying the consequences of exposure to extreme heat on early schooling success. We do so in the spirit of Dell et al. (2014), combining two types of panel data that measure exam results on a fine spatial grid. First, we draw on the official *District Information System for Education (DISE)* dataset, which provides longitudinal school- and class-level information on exam results, along with basic demographic data and descriptive information on schools' infrastructure and local conditions. Second, we retrieve longitudinal data on meteorological conditions and land use for fine-grained spatial grid cells from satellite observations (see Donaldson and Storeygard, 2016, for a review of the use of remote sensing data in economics). We match these datasets by time and location using geo-coded school addresses.

Using the matched data, we estimate logistic panel regression models to analyse the log-odds of passing the exam, or passing with distinction, as a function of observed temperature, humidity, and other local weather conditions measured during both the school year preceding the exam and the immediate exam period, while controlling for school fixed-effects.

We find that elevated temperatures exceeding long-term, location-specific averages significantly decrease the odds of students passing the exam as well as the odds of passing with distinction.

[1]See `https://www.education.gov.in/sites/upload_files/mhrd/files/NEP_Final_English_0.pdf` for details, last accessed in June 2024.

These effects are robust to the inclusion of various meteorological and remote-sensing variables as controls as well as alternative temperature and temperature-humidity metrics, such as the full temperature distribution observed at a location, wet-bulb temperatures, the heat index, and the count of tropical nights. The negative effect of heat becomes even more pronounced when high temperatures coincide with elevated humidity. We also find evidence that vegetation in the proximity of schools may mitigate the negative effects of heat on cognitive performance, suggesting a potential adaptation strategy. However, the estimated effect sizes indicate that this measure alone is insufficient to adequately shield students from heat exposure.

To illustrate the magnitude of the heat effect, we translate our estimates into the number of students affected. We compare the predicted number of students who fail or miss a distinction under observed temperatures with simulated results based on official *Representative Concentration Pathways (RCP)* climate change scenarios. Our estimates predict that an increase in average temperature of merely 0.64°C (an optimistic scenario) would lead to a 3.0% decline in the number of students passing the exam. Given India's large youth population – the largest in the world – this potentially translates into hundreds of thousands of children achieving less favourable results every year and, consequently, being less likely to reach their full potential.

A heterogeneity analysis further reveals several vulnerabilities that point to the need for targeted policy interventions. Schools located in rural areas are more severely affected than those in urban areas, potentially due to uneven access to coping strategies and income differences. This notion is supported by a heterogeneity test of the heat effect on exam results across regions with varying socio-economic capacities: the wealthier a region, the less students are affected by heat. After controlling for pre-existing disparities, we find that the urban heat island effect places students in poorer urban areas at greater risk than students in comparably poor rural regions. Furthermore, schools run or aided by the government are substantially less affected than other types of schools, suggesting a need for enhanced oversight of non-government schools. Schools built before 1970 are also systematically less affected, potentially due to superior construction quality. This finding may encourage policymakers to improve the quality of school infrastructure in the future. Gender disparities are relatively unimportant in this context, as rising temperatures do not differentially affect boys and girls.

To explore low-cost mitigation strategies, we further examine how natural green areas affect heat exposure and its impact on educational outcomes by exploiting information on tree cover density in the vicinity of schools, thereby leveraging the cooling effects of vegetation (Han et al., 2024). Our findings point to a potential adaptation strategy: students attending schools located in areas with greater vegetation – and thus experiencing a cooler microclimate – are significantly more likely to pass the exam and to do so with distinction. However, the estimated effect sizes remain too small to fully offset the adverse effects of heat, indicating that additional measures are needed.

This study contributes to broader literatures on the socio-economic consequences of climate change as well as the economics of education, development, and inequality. Excess heat has been shown to negatively affect health: for example, Agarwal et al. (2021) find that elevated temperatures are associated with increased hospitalisations and higher public and private health expenditures in China, and a meta-analysis by Pan et al. (2023) concludes that heatwaves are clearly associated with increased mortality in the Chinese population. While studies on China are becoming increasingly common, evidence on the effects of heat on economic outcomes in India remains scarce. To our knowledge, Garg et al. (2020) provide the only existing evidence of the adverse effects of heat on educational outcomes in India. Using self-reported survey data, they show that exposure to heat negatively affects math and reading scores for children in primary and secondary schools, arguing that reduced agricultural productivity during hot periods is a key mechanism.

Related studies find that increased air pollution can lead to worse student performance and higher absenteeism (e.g., Currie et al., 2009; Ebenstein et al., 2016). Palacios et al. (2022) conduct a field experiment among primary schools in the Netherlands and show that insufficient classroom ventilation negatively affects children's cognitive performance and, consequently, decreases standardised test results. Previous research has also demonstrated the negative impact of high temperatures on cognitive performance and learning. Cho (2017) and Graff Zivin et al. (2020) study the effects of temperature on short-run cognitive performance during college entrance examinations in South Korea and China, respectively. Similarly, Akesaka and Shigeoka (2025) provide evidence that elevated temperatures negatively affect exam performance in Japan, with the strongest effects observed among lower-performing students, thereby exacerbating existing educational inequalities. Furthermore, Park et al. (2020, 2021) and McCormack (2023) investigate how cumulative heat exposure – partly compounded by the lack of air conditioning – directly affects education in the United States by increasing absenteeism and hindering learning both at home and at school. Conte Keivabu (2024) focuses on hot and cold extremes in England and documents a link between hot days and increased absences in primary and secondary schools.

Even short-term exposure to heat has been shown to negatively affect student performance in cognitive tasks in various classroom intervention studies. Turunen et al. (2014) examine the relationship between indoor environmental quality in schools and student performance in the United States, finding significantly lower performance among students in classrooms with above-average temperatures and below-average ventilation rates. Haverinen-Shaughnessy and Shaughnessy (2015) compare student performance across classroom conditions and document that significantly more students score satisfactorily in mathematics and reading tests in classrooms with lower temperatures and higher ventilation rates than in those with higher temperatures and lower ventilation rates. However, the temperature ranges measured in these studies are far below those experienced by students in India. In this regard, we are aware of only one study conducted in a tropical context: Porras-Salazar et al. (2018) carry out a field intervention among elementary school students in Costa Rica, comparing student performance in artificially cooled classrooms (26°C) to that in classrooms without cooling, where indoor temperatures ranged from 29.5 to 30.1°C. In cooled classrooms, task performance speed increased, as did some (though not all) indicators of accuracy. Large-scale evidence on such effects across substantial variations in observed temperatures, including exposure to extreme heat, is currently lacking.

While evidence of the adverse effects of heat on educational outcomes is steadily growing, such a study is still missing for the world's most populous country: India. However, the detrimental impact of excessive air pollution on child development and academic performance has been documented for India by Balietti et al. (2022) and Balakrishnan and Tsaneva (2021), which is why we include such measures as control variables.

In sum, although systematic studies on the effects of heat exposure on performance in high-stakes examinations in a hot country are currently lacking, the existing evidence suggests that elevated average temperatures and extreme heat events may jeopardise a country's educational objectives. This is particularly concerning because we measure the adverse effects for an examination marking the completion of primary education, which may serve as an early negative signal of performance, influencing future educational outcomes and potentially overall success in life.

The remainder of this article is structured as follows: section 2 introduces the Indian primary education system, discusses the consequences of failing, the mechanism we aim to model and derives measurement concepts. Thereafter, section 3 assesses the effect of heat exposure on educational outcomes and section 4 discusses adaptation and mitigation measures. Finally, section 5 concludes. A comprehensive appendix provides additional details.

2 Context, Mechanisms and Measurement Concepts

2.1 Schooling in India

Education in India is a fundamental right of every child and thus is generally free and compulsory according to the 2009 *Right of Children to Free and Compulsory Education Act* (see Srivastava and Noronha, 2014, for details). Precisely, Article 45 of the Indian Constitution states:

> **Provision for free and compulsory education for children.** *The State shall endeavor to provide, within a period of ten years from the commencement of this Constitution, for free and compulsory education for all children until they complete the age of fourteen years.*

The Indian education system hence commences with two cycles of *compulsory* primary education: Primary school (Class I to V) and upper primary school (Class VI to VIII), which is followed by largely non-compulsory secondary education or vocational training (see Hill and Chalaux, 2011, Figure 1).

Each primary education cycle concludes with a country-wide exam: the *Primary Level (Class IV/V) Examination (PLE)* and the *Upper Primary Level (Class VII/VIII) Examination (UPLE)*. The necessary condition to pass these exams is to score at least 35%, while scoring at least 60% results in a distinction.

Following primary education, school continues to be free yet is non-compulsory. Secondary education lasts for four years and is split into two cycles each lasting for two years (General/Lower Secondary School and Upper/Senior Secondary School).

Overall, UDISE+ data[2] shows that there have been significant improvements in access to primary education. The share of students enrolled in upper primary (Class VI-VIII) education has increased from 67.77% for girls and 64.47% for boys in 2012-13 to 71.66% for girls and 71.00% for boys in 2021-2022. These shares still remain low for higher grades: the enrollment share for higher secondary education (Class XI-XII) increased from 24.71% for girls and 25.18% for boys in 2012-13 to only 34.95% and 33.54%, respectively, in 2021-22.

2.2 Consequences of Failing, Mechanisms and Measurement Concepts

As per the *2009 Right to Free and Compulsory Education Act*, students in India cannot, in principle, be detained even if they fail their examinations, as the Act "prohibits holding back and expulsion of a child from school till the attainment of elementary education."[3] Since its enactment, debate has continued over whether students who fail should repeat a grade. A 2019 amendment allowed states to conduct examinations in Classes V and VIII and to require failing students to repeat, effectively overturning the "no-detention policy." Under the revised provisions, students may retake examinations, and repeated failure may permit states to detain them. States have implemented this amendment differently.

We analyze data from the intermediate period (2014–2018), when exam failure had no immediate consequences, which facilitates simulation exercises using publicly available school-level data.

Even without mandatory grade repetition, failure can have significant long-term consequences. Papay et al. (2010) use a regression discontinuity design to study students near the pass/fail threshold of Massachusetts' high school exit exam. While average effects are small, low-income urban students who narrowly fail face reduced graduation rates in comparison to students just passing. Machin et al. (2020) similarly show that students in England just missing a grade C in the General Certificate of Secondary Education (GCSE) exam are more likely to drop out and become 'not in education, employment, or training' by age 18. Ebenstein et al. (2016) find that temporary shocks, such as pollution, negatively affect exit exam results in Israeli high schools with long-term impacts.

These studies suggest that exam outcomes matter beyond formal progression rules. They act

[2]See subsubsection 2.3.1 and `https://udiseplus.gov.in/#/home` for details, last accessed in May 2024.

[3]See the Clarification on Provisions of the 2009 Act: `https://www.education.gov.in/sites/upload_files/mhrd/files/upload_document/RTE_Section_wise_rationale_rev_0.pdf`, last accessed June 2024.

as signals to employers, creating stigma, and reflect latent educational attainment—both of which influence future opportunities.

Thus, we assume that the observable outcome of the *UPLE* examination reflects two latent continuous variables: cumulative learning over the school year (long-term) and exam performance (short-term). Our aim is to estimate the total effect of heat exposure on these variables. Rather than modeling complex mechanisms directly, we estimate a reduced-form relationship between thermal conditions and exam outcomes.

Research shows that both acute and cumulative exposure to high temperatures impairs cognition. In a meta-study, Seppanen et al. (2006) find that mental performance related to typical office tasks increases with temperature up to 21–22°C but declines above 23–24°C. Yin et al. (2024) link extreme heat to cognitive decline in China, though the effect is weaker in hotter regions. Akesaka and Shigeoka (2025) show a similar hump-shaped pattern of temperature on compulsory nationwide exam results in Japan. While cumulative exposure to colder and hotter temperatures are both associated with lower test scores, hot extremes are more important yet muted for schools equipped with air conditioning facilities. Costa and Goldemberg (2025) assess Brazilian public schools and find that a rise in the number of hot days significantly increases dropouts. Generally lower-performing students are more strongly affected by heat thus exacerbating pre-existing inequalities. Prolonged heat exposure also reduces teaching quality (Park et al., 2020), further disadvantaging students. Hence, heat affects both cumulative learning and short-term exam performance *directly*. Deviations from local temperature norms, not just absolute levels, appear crucial, and mitigating factors must be taken into account.

Additionally, heat can *indirectly* affect learning by increasing absenteeism. Conte Keivabu (2024) show that cumulative exposure to extreme heat or cold increases school absences through four channels: health, behavior, institutions, and energy poverty. Heat-related illness and parental decisions significantly raise authorized absences, while institutional closures reduce learning time. Limited access to cooling technologies exacerbates these effects.

Overall, the previously documented mechanisms suggest that it is crucial to consider both the impact of cumulative and immediate heat exposure to fully capture potential systematic adverse effects of heat on student's exam results, as well as the amplifying and mitigating impacts of other conditions and heat prevention measures. The former include air pollution (Halliday et al., 2025) and humidity (Raymond et al., 2020) as potential intensifying effects, while the latter suggests assessing mitigating measures in the form of air conditioning facilities (Akesaka and Shigeoka, 2025) or natural cooling. To clearly separate the temperature effect from other time-varying conditions students are exposed to, we control for a wide range of meteorological and environmental measures. By that we are able to holistically model students' exposure to ambient conditions. These considerations lead to a series of measurement concepts and data needs introduced next.

2.3 Measurement Concepts and Data

2.3.1 Measuring Schooling Outcomes

The *Upper Primary Level Examination (UPLE)*, also called *Class VIII* exam concludes primary education. Exam results are collected within the *District Information System for Education (DISE)*, a government database created by the Indian *Ministry of Education* and administered by the National University of Educational Planning and Administration (NUEPA). DISE data cover all registered primary and secondary schools. Due to its broadly applicable information content, DISE has been used by researchers for several purposes, e.g., for studying the effect of schools organized by NGOs on general access to education (Blum, 2009), private education (Kingdon, 2020), as well as the link between the provision of sanitary pads and girls' school attendance (Agarwal et al., 2024).

DISE reports results in the categories 'failed', 'passed' or 'passed with distinction.' We focus on an exam taking place early in students' school career. The loss of knowledge and skills at this stage will have life-long consequences. Moreover, failing may be perceived as a negative signal of performance and, by that, negatively impacting students' remaining educational career and hence also future success in life as concluded from administrative data and longitudinal cohort studies tracking groups of children from birth to old-age (see Machin et al., 2020, for an overview of this literature).

We assess exam results for public schools in seven Indian states (Andhra Pradesh, Arunachal Pradesh, Gujarat, Kerala, Madhya Pradesh, Maharashtra, and Tamil Nadu) between the school years 2014-15 and 2017-18. The exact selection procedure is explained in Appendix A.1 and aimed to ensure a high degree of comparability with regards to the principle type of school and the structure of the academic year. The latter is crucial to consistently link exposure to heat during the same phase of the school year and, thus, also the rough learning schedule.

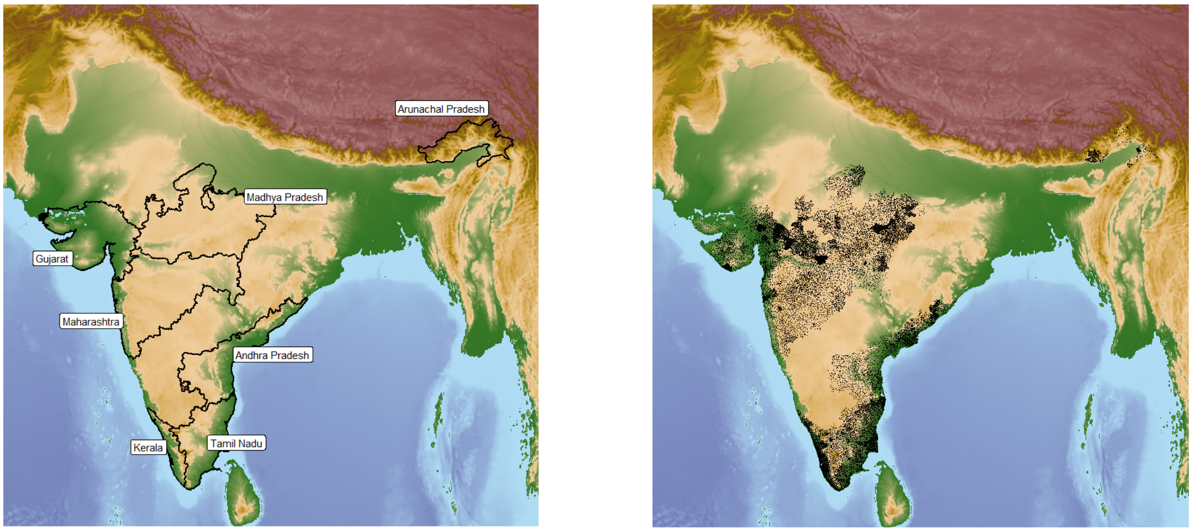
Ultimately, 134,985 schools enter the analysis: Panel (a) of Figure 1 shows the states assessed and Panel (b) the exact location of individual schools part of our analyses.

We use school addresses to proxy all local weather conditions relevant for affecting the learning process, that comprises learning at school *and* learning at home. This approximation is supported by Rekha et al. (2020) assessing travel distances of students in Tiruchirappalli City (Tamil Nadu). They find that 39% of people need to travel less than 2km, 25% between 2 and 5 km, 33% between 5 and 10 km and only 3% travel larger distances (10–20 km) for school trips. This indicates that our approximation is expected to cover both locations where learning takes place.

The data is available at grade-level, i.e., for each grade in each school characteristics of the student and teacher population as well as students' exam results are reported in the form of shares of the total number of students at this grade. For our models, we change the data format by projecting this wide table into a long table yielding information per student i, year t and

Figure 1: Schools' Location.

(a) (b)



Notes: Topographic map of the subcontintent. Panel (a) highlights Indian states included in this study and Panel (b) the location of individual schools.

school s.

To account for all unobserved factors related to time or space, we adopt a panel model approach by including school address ('school') fixed-effects as well as school year ('time') fixed-effects to our final generic model presented in subsection 3.1. We cluster standard errors for district-year combinations, since meteorological conditions are likely to be similar within close proximity, and because unobservable local shocks of various kinds may induce correlation in the error term.

It is important to note that the vast majority of students pass these early exams. Failing is indeed rare yet we are interested in the increase in these rare events and their link with elevated temperature. We assume that underlying the observable outcome of the exam, there exists an unobservable continuous variable measuring the amount of learning by each student, and we are precisely interested in the variations in this latent variable.

Because of the school fixed-effects, only schools with reported variation in the outcome variable contribute to the estimation. For this reason, we have to rely on a sub-sample of students (about 13%), who are enrolled in schools where at least one student failed the exam over our period of observation. The same applies to the models predicting the odds of passing with distinction, but the selection criteria is only binding in less than 10% of schools: for this model, we are able to retain about 92% of the observations corresponding to all schools that do not pass all its students with distinction in all years of observation.

Descriptive statistics are reported as part of Table 1. The first column summaries the whole sample, the second for the sub-sample of students enrolled in schools where somebody fails the exam, and the third column for the sub-sample of students enrolled in schools where somebody fails to get a distinction. Naturally, pass rates are higher in the full sample as it also includes schools where all students passed (with distinction) in all the four school years assessed. Figure 5 in Appendix D reports the distribution of the average maximum temperature during the entire school year for the whole sample and the two sub-samples.

Table 1: Summary Statistics.

	All schools		**Only schools with variation in outcome**			
			Outcome: Pass		Outcome: Distinction	
	Mean/Share	St. Dev.	Mean/Share	St. Dev.	Mean/Share	St. Dev.
Exam Results						
Pass [%]	0.988	0.110	0.909	0.287	-	-
Pass with Distinction [%]	0.711	0.453	-	-	0.692	0.462
Weather Data						
Temperature Overall [°C]	30.694	1.455	30.523	1.426	30.687	1.458
Temperature Mar [°C]	32.854	1.850	32.852	1.858	32.848	1.768
Temperature Jun-Feb [°C]	30.303	1.478	30.121	1.427	30.300	1.477
Temperature Brackets						
Days < 10°C [count]	0.011	0.673	0.012	0.655	0.011	0.614
Days 10-15°C [count]	0.056	1.637	0.070	1.821	0.056	1.628
Days 15-20°C [count]	0.937	4.344	1.210	4.840	0.983	4.413
Days 20-25°C [count]	9.401	14.193	11.015	14.550	9.599	14.261
Days 25-30°C [count]	87.220	33.885	88.910	32.717	87.074	33.641
Days 30-35°C [count]	93.471	29.978	91.696	30.442	93.287	29.785
Days 35-40°C [count]	24.320	17.754	22.232	15.490	24.362	17.807
Days > 40°C [count]	2.354	3.384	2.621	3.488	2.404	3.419
IMD Temperature [°C]	32.084	1.199	31.983	1.134	32.068	1.207
Wet Bulb Temperature [°C]	21.907	1.600	21.697	1.559	21.903	1.598
Heat Index [°C]	32.057	1.903	31.789	1.874	32.054	1.894
Avg. Diurnal Temp. Variation [°C]	9.513	1.449	9.633	1.366	9.520	1.451
Tropical Nights [count]	201.136	53.846	192.963	51.157	200.951	54.110
Heat Wave Days [count]	3.430	5.192	3.679	5.374	3.458	5.207
Relative Humidity [%pt]	57.995	7.411	57.654	6.989	58.005	7.440
Wind Speed [m/s]	2.654	0.650	2.631	0.622	2.649	0.652
Precipitation [mm]	2.018	0.997	2.037	0.987	2.026	1.003
Air Pollution						
PM 2.5 [μg/m^3]	38.063	9.971	39.697	9.773	38.215	10.076
Carbon Monoxide	90.752	5.268	90.370	5.255	90.698	5.263
Nitrogen Dioxide	189.953	74.549	197.979	77.739	190.823	75.017
Locational Attributes						
Rural vs. Urban [%]	0.671	0.470	0.637	0.481	0.672	0.470
Local Relative Wealth Index	0.254	0.509	0.267	0.526	0.256	0.513
Forrest Density Close to Schools						
1.00 km radius [ha]	22.776	54.068	19.757	47.987	23.010	54.656
0.50 km radius [ha]	5.356	13.209	4.601	11.655	5.413	13.344
0.25 km radius [ha]	1.239	3.175	1.069	2.797	1.252	3.203
No. of Students	20,176,051		2,603,717		18,619,735	
No. of Schools	134,985		13,659		113,048	

Notes: Summary statistics refer to the intersection of all data used as described in detail in subsection 2.3. Meteorological data refer to the entire school year (from June to March), unless stated otherwise.

2.3.2 Temperature

As we know the geolocation of each school, we can precisely link students' exposure to adverse conditions, described through a wide set of meteorological indicators, tracked either over the entire school year or during the exam period only (see Appendix A.2 for details). We obtain these meteorological data from several sources, with the main source being the *Copernicus Climate Change Service*. Specifically, we use the ERA5-Land dataset (Muñoz Sabater et al., 2021), which provides hourly values for various climate- and weather-related variables from 1950 to the present. The data have a spatial resolution of $0.1° \times 0.1°$ (approximately 100 km^2 at the equator).

We operationalize temperature exposure in several ways. Our main approach relies on the average maximum temperature during school days[4] (see Figure 6 in Appendix D). The corresponding results are presented in Table 2. Results from alternative measures of thermal comfort are reported as robustness checks in Table 6 in the Appendix. Concretely, these measures are relative humidity, wet-bulb temperature and the heat index, a full temperature distribution measured in small bins, as well as concept of tropical nights and Diurnal temperature range (DTR).

To identify the effect of adverse temperature shocks on learning, we regress exam results on a temperature measured at the schools' locations during the academic year preceding the exam ('cumulative heat exposure'). Each school year begins in late May or early June, and ends at the end of March, or beginning of April.

Moreover, we test for the effect of heat exposure during the last month of each school year (March). By that we measure temperature shortly before and during the exam period ('immediate heat exposure'), because hot temperatures likely also affect studying success and adequately preparing for the exam.

2.3.3 Supplemental Concepts and Data

We rely on a variety of additional meteorological data as controls as other conditions both can mitigate or intensify the consequences of heat, as discussed in section 3 and section 4.

Additionally, we assess heterogeneity in effects by several school and location characteristics reported within the DISE data, as well as regional indicators we match with school locations. The latter includes the Relative Wealth Index (RWI) developed by Chi et al. (2022) as a measure of regional inequalities (see subsection B.7).

[4]All days between June and March, excluding Saturdays, Sundays, and all state-specific and federal public holidays.

3 The Effect of Heat Exposure on Test Results

3.1 Empirical Strategy

Exam results are reported in the broad categories of ‘fail’, ‘pass’ and ‘pass with distinction.’ A large majority of students does indeed pass the exam. We therefore estimate two separate logit models that distinguish ‘fail’ versus ‘pass’ and ‘fail/pass’ versus ‘pass with distinction’.

To ensure clean measurement, we account for any time-invariant school-, or more generally speaking, location-specific aspects by estimating a fixed-effects model. Thus, we rely on temperature variation within each school-location over four academic-years (2014-15 to 2017-18).

This general set-up yields two logit regressions modeling the outcome of passing the exam y^p and passing the exam with distinction y^{pd}, respectively. For both outcomes $y \in \{p, pd\}$ following form:

$$Pr\{y_{ist} = 1 | \text{temperature}_{st}, X_{ist}, \alpha_s, \lambda_t, \beta, \gamma\} = \textbf{logit}(\beta \text{ temperature}_{st} + X_{ist}\gamma + \alpha_s + \lambda_t), \quad (1)$$

whereby y^p_{ist} is equal to 1 if student i in school s, year t passes the exam and 0 otherwise, and accordingly y^{pd}_{ist} for the outcome “pass with distinction.” The matrix X_{ist} contains an optional set of further meteorological controls with associated parameters γ. The models include fixed-effects α_s to account for any school-specific (and by that also location-specific) effects as well as time fixed-effects λ_t relating to school years. Robust standard errors are clustered for district-year combinations.[5]

In both cases, the identifying assumption is

$$E(\varepsilon_{ist} | \text{temperature}_{st}, X_{ist}, \alpha_s, \lambda_t) = 0,$$

i.e., the error term is conditionally independent of our respective temperature measure, the controls, and the fixed effects.

3.2 Cumulative Heat Exposure

We start by assessing the impact of elevated heat during the school year (‘cumulative heat exposure’) on test results at the end of the year. For that, we measure the deviation from the long-term location- and season-specific average temperature during the entire school year as detailed in subsubsection 2.3.2.

Table 2 reports results. Overall, we find that with cumulative exposure to higher average temperatures at the school location, the odds of students passing the exam as well as the odds of passing with distinction decreases significantly. In a model neglecting any other meteorological conditions, the decrease in log odds is -0.176 for passing and -0.459 for passing with

[5] Statistical analyses were conducted in R using the `fixest` package (Bergé, 2018).

distinction.

We add the battery of supplemental meteorological indicators discussed in subsubsection 2.3.3 as controls. As expected, the likelihood of passing the exam (with distinction) decreases with increasing humidity. Wind speed is negatively correlated with the likelihood of passing (with distinction), while the effect of precipitation and air pollution are not unambiguously clear.

Our preferred models (3) and (6) include all basic control variables that may correlate with temperature and affect learning. By accounting for relative humidity, wind, precipitation and air pollution, the effect size of temperature remains negative, large in magnitude, and highly statistically significant: the log ratios are -0.642 for passing and -1.104 for passing with distinction, respectively. This means that a 1°C increase in temperature is predicted to decrease the odds of passing by 47.3%, and the odds of getting a distinction by 66.8%.

Table 2: Cumulative Heat Exposure.

	Pass			Pass with Distinction		
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	-0.176*	-0.570**	-0.642***	-0.459****	-1.134****	-1.104****
	(0.101)	(0.225)	(0.239)	(0.066)	(0.145)	(0.143)
Humidity		-0.081*	-0.099**		-0.160****	-0.160****
		(0.042)	(0.043)		(0.024)	(0.024)
Wind		-1.004**	-0.748		-1.400****	-1.407****
		(0.486)	(0.499)		(0.217)	(0.223)
Precipitation		-0.258****	-0.249****		0.038	0.073
		(0.074)	(0.074)		(0.048)	(0.046)
PM 2.5			-0.013			-0.036***
			(0.019)			(0.012)
Carbon Monoxide			0.031**			0.0002
			(0.016)			(0.007)
Nitrogen Dioxide			-0.005**			-0.002
			(0.002)			(0.001)
School FE	Y	Y	Y	Y	Y	Y
School year FE	Y	Y	Y	Y	Y	Y
Observations	2,603,717	2,603,717	2,602,815	18,619,735	18,619,735	18,606,807
BIC	1,281,754	1,279,879	1,278,043	20,506,904	20,469,396	20,446,566
Adj. Pseudo R^2	0.302	0.303	0.304	0.180	0.182	0.182

Note: The table reports estimation results for Logit model with fixed effects expressed as log odds. Cluster-robust standard errors are reported in parentheses. Statistical significance is coded following the standard notation: *p<0.1; **p<0.05; ***p<0.01; ****p<0.001

We validate these results with a series of robustness checks, reported in Appendix C. We test whether our results are sensitive to technical choices and specifications. We alter the model class used and rely on various alternative ways to proxy heat exposure and more generally thermal comfort. Specifically, we rely on temperature measured by weather stations, allow for non-linear effects of temperature by making use of temperature brackets, we rely on three established measures combining temperature with humidity, a measure capturing the variation of temperature between days and night to capture the concept of nocturnal cooling potential, the concept of "tropical nights," i.e., the absence of cooling over night, as well as the concept of heat waves, i.e., prolonged excessive heat. These checks confirm our main results and interpretations: the likelihood to pass the exam or receive a distinction decreased with increasing temperature, prolonged and intensified heat exposure, and when paired with humidity. Only the interaction between temperature and DTR has unexpectedly no significant positive effect.

To better understand the severity of the impact of elevated temperatures on educational outcomes, we express this effect in absolute numbers of students affected. Note that we hypothetically increase the average temperature over an extended period of time; therefore, even small changes represent a substantial increase in actual temperature. The simulated temperature increases are in-line with several global warming projections for the region and hence mimic a future scenario in the case of no adaptation measures related to school year and exam schedules as well as school-buildings.

Concretely, we compute the number of students that are expected to fail due to adverse temperature conditions via a counterfactual analysis. Therefore, we test changes in aggregate exam results for an increase in current location-specific temperature (temperature_{st}) during the academic year by θ_{js} degrees, i.e.,

$$T_{st} = \text{temperature}_{st} + \theta_{js},$$

where s identifies a school-location, and j indexes climate change scenarios. We choose θ_{js} reflecting a long-term temperature anomaly consistent with three *Representative Concentration Pathways* (IPCC, 2014): a stringent mitigation scenario (RCP2.6), an intermediate scenario (RCP4.5), and a scenario with high green-house gas emissions (RCP8.5).

> "The increase of global mean surface temperature by the end of the 21st century (2081–2100) relative to 1986–2005 is likely to be 0.3°C to 1.7°C under RCP2.6, 1.1°C to 2.6°C under RCP4.5, [...] and 2.6°C to 4.8°C under RCP8.5" (IPCC, 2014, p. 10).

We use multi-model projections of temperature change between June and March in the South Asia region, from the CORDEX experiment.[6] We obtain θ_{js} by matching each school s to each scenario j's raster data on the expected change in mean maximum daily temperature by 2081-2100, relative to 1995-2014 (see Figure 9 in Appendix D). Thereby, we focus on the marginal

[6] The data was downloaded from the IPCC Interactive Atlas in December 2024 (IPCC, 2023; Iturbide et al., 2022): `https://interactive-atlas.ipcc.ch/`.

Table 3: Counterfactual Analysis: Increased Temperature

Scenario	$\overline{\theta}$	Empirical Probability of Passing $\mathbb{P}(p)$	# Not Passing $(\neg p)$	Absolute Change $\Delta^p(\theta)$	Relative Change $\Delta^p(\theta)$
baseline	-	0.909	236,315	-	-
RCP2.6	+0.64°C	0.882	306,656	-70,341	-3.0%
RCP4.5	+1.58°C	0.832	437,479	-201,164	-8.5%
RCP8.5	+3.48°C	0.692	802,710	-566,395	-23.9%

Notes: The table reports the simulated excess number of students not passing in case of an increase in the typical school-specific temperature by θ_{js} degrees. Here, we report the average ($\overline{\theta}$) for the total sample. Shares relate to the total student populations of $N^p = 2,602,815$.

effect of rising temperature, refraining from simulating any further potential changes (e.g., a change in precipitation).

To construct a benchmark, we make use of the estimated coefficients from model (3), and predict numbers of students $\hat{y}_{ist}$ that fail for the observed temperature via plug-in estimators. Similarly, we use the same model yet hypothetically increased temperatures to compute counterfactual numbers $\hat{y}_{ist}^{\theta}$ for a specific increase θ.

Overall, we observe outcomes for $N^p = 2,602,815$ students over the four school years under consideration.We compute the excess numbers of students failing $\Delta^{\neg p}(\theta_{js})$ given an increase in temperature of θ_{js} degrees via

$$\Delta^{\neg p}(\theta_{js}) = \sum_{i=1}^{N^p} \left(\hat{y}_{ist} - \hat{y}_{ist}^{\theta}\right). \tag{2}$$

Table 3 reports results for $j \in \{$*baseline*, RCP2.6, RCP4.5, RCP8.5$\}$. An increase in temperature under the stringent mitigation and hence most optimistic scenario (RCP2.6) means a drop in the number of students passing the exam by -3.0%. In absolute numbers, 70,341 would achieve less favorable results and thus likely not live up to their full potential. Under the most pessimistic scenario, this number increases in magnitude to -23.9%. Even though such a linear extrapolation likely overstates numbers (particularly for more severe scenarios), the direction of results is clear: no matter which scenario may realize, any projected increase in temperature means – without appropriate adaptations – a severely negative impact on students' learning and cognitive performance.

3.3 Heterogeneity Analysis

While these overall results are remarkable, we next examine whether specific groups are disproportionately at risk of being negatively affected by exogenous adverse shocks during their educational trajectories. We do so by splitting the sample or adding interactions between specific student or school characteristics, and temperature. Assessed characteristics include school management boards, students' gender, year of school establishment, school location (urban versus rural), and prosperity of the region the school is located in.[7]

First, we assess heterogeneous impacts of heat across school types differentiating them by school management (see Panel (a) in Figure 2). While about one quarter of schools are managed by the Department of Education (26% of schools in our sample), schools are also run by local bodies (30%), privately (aided or unaided, 17% and 18%, respectively) or by the Social Welfare Department (Tribal Schools, 9%). Private aided schools ("Semi-Government Schools") are partly funded by the government and partly by private organizations. As described in Appendix A, private schools appearing in the DISE data are low-fee institutions and overall quality is heterogeneous, which is also reflected by our results. While the negative impact of heat is close to zero in school centrally managed by the Department of Education or co-funded by private and public bodies, the other types reveal important negative heat effects. This may suggest closer supervision of schools not managed centrally.

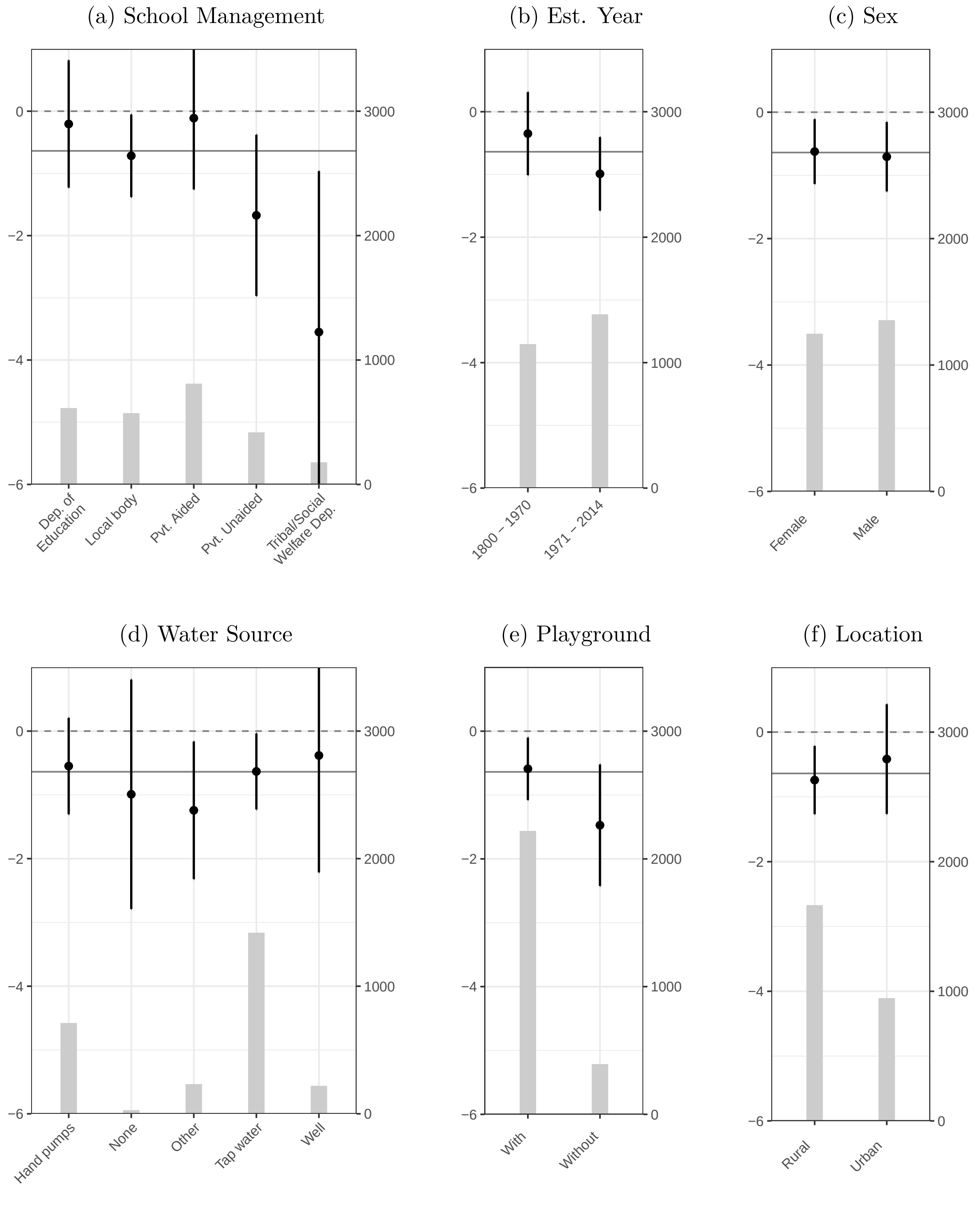
Panel (b) distinguishes effects by the year of school establishment: as highlighted by Srivastava et al. (2013), schools established before 1970 were predominantly attended by children of richer families, and the schools established back then were constructed in a more solid way than in later decades. In-line with this notion, we detect a larger effect for students attending schools established since 1970 as shown in Figure 2. In fact, the heat effect is statistically zero for older schools.

Next, Panel (c) reports results by students' sex: the average effect of -0.642 we found in the main model (see model (3) in Table 2) appears to affect boys slightly less strongly yet the difference is very small in magnitude: an increase in temperature by 1°C is predicted to decrease the odds of passing for boys by 46.9% and for girls by 47.5%, meaning no statistically significant difference. As evident by the barplots, however, much fewer girls overall enroll in and pass the exam. Interacting the sex variable with the wealth index indicates that in general girls in less wealthy areas perform worse than boys, only in the wealthiest areas girls outperform boys. Boys and girls have an equal probability of passing for RWI=1.33. For areas with a lower RWI, boys are more likely to pass, and for a larger RWI girls are more likely to pass. However, only 0.8% of all students attend a school in such a prosperous district.

Lower investment in girls is consistent with evidence of unequal intra-household resource allocation biased against girls in India, particularly in less wealthy areas, as documented by Kaul

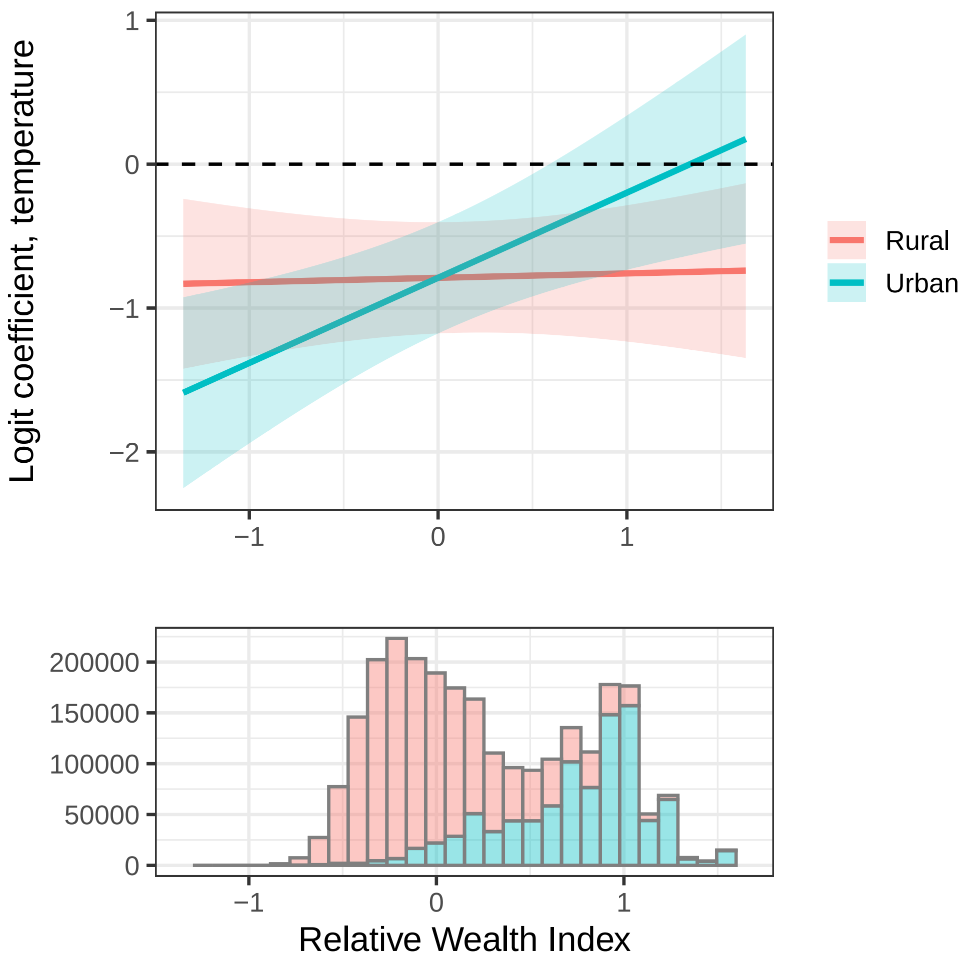
[7]Further tests along the dimensions of schools' student-teacher ratios, schools' official share of disadvantaged students enrolled, and across climate zones did not reveal clearly consistent heterogeneities.

Figure 2: Heterogeneity Analysis.



Notes: The figure shows the heterogeneous (cumulative) effect of temperature on the probability of passing. The solid horizontal line represents the total effect from the baseline model (Table 2, model 3). The left y-axes refer to point estimates (and 95% confidence intervals) and the right axes to bar plots indicating the absolute numbers of students concerned (in thousands).

Figure 3: Wealth Index and the Urban-Rural Divide.



Notes: The histogram reports the number of observations by relative wealth index bin and confirms a general disparity across students in rural and urban schools. However, the effect of heat on pass rates is most negative among schools in poorer locations in urban agglomerations indicated by the top panel. Numerical results are reported in Table 8.

(2018). Hence, while there is some indication that girls may be in a slightly more advantageous position with respect to the negative effects of heat on schooling success, they appear to be overall less successful in school in all but the wealthiest parts of the country.

Furthermore, we assess the relevance of resources provided by the school, which we interpret as a proxy for the quality of the school premises. Panel (d) decomposes the effect by water-source available at a school and Panel (e) by the availability of a playground. While effects are more negative for schools with lower quality water sources, there appears to be no significant difference with respect to schools being resourced with a hand pump, tap water or a well. Similarly, students having access to a playground at their school are less affected by the negative impact of heat. Both may suggest that amenities-rich schools are overall less affected by the negative impact of heat.

Finally, we check for differences by school location as we hypothesize that the UHI effect could be a major driver of the adverse heat effect on educational outcomes. Therefore, we make use of an identifier provided by schools themselves that classifies their location as either 'rural' or 'urban.' This hypothesis is not confirmed, as shown in Panel (f) and Model (1) in Table 8: in fact, the effect of temperature on the probability of passing is stronger in rural areas. Thus, these differences cannot be directly explained by the UHI effect but may instead point to a more general heterogeneous impact associated with spatial inequalities. To test this refined hypothesis, we assess again the relative wealth index. Descriptive results indeed reveal substantial regional disparities: separately evaluating this index for schools classified as rural and urban, respectively, yields an average score of -0.074 for rural and 0.642 for urban schools (weighted by students enrolled in the exam, rural schools score on average 0.035 and urban schools 0.738). Further, Stainier et al. (2025) show that rural households are strongly affected by adverse *economic consequences* of heat due to the high prevalence of small family farms in rural India. To test whether these pre-existing economic disadvantages may contribute to the larger negative effect for students in rural schools, we interact temperature with the relative wreath index. Models (2) and (5) in Table 8 indeed find that schools located in wealthier areas are significantly less adversely affected by heat. This confirms that pre-existing socio-economic disadvantages dominate a potential UHI effect. In a similar manner, Halliday et al. (2025) showed that disadvantaged students were also more affected by an exogenous pollution event: air pollution caused by volcanic eruptions in Hawaii appear to systematically stronger impact students with lower socio-economic status.

Figure 3 introduces a targeted interaction of temperature with the rural-urban indicator and the relative wealth index.[8] The triple-interaction reveals more nuanced dynamics: rural areas are indeed generally poorer than urban agglomerations (as shown by the histograms) and, hence, overall more negatively affected by heat as already confirmed by model (1) in Table 8. Yet, the top panel in Figure 3 also shows that schools in poor-urban areas are much more negatively affected by heat than schools in poor-rural regions in terms of pass rates (yet not distinctions)

[8] Numerical results are reported in Model (3), Table 8.

– supporting the particular vulnerability of students in poorer urban areas to a negative heat effect on their educational outcomes. Schools situated in wealthier urban areas appear to be the least affected by heat, potentially because of their enhanced access to resources for adaptation. Poor urban schools may require the greatest attention in efforts to mitigate the impact of heat on learning. This conclusion is similar to findings by Costa and Goldemberg (2025) documenting that students attending urban public schools are most affected by drop-outs associated with heat, while such a pattern is not detected for private schools.

3.4 Cumulative vs. Immediate Heat Exposure

So far, we have focused on cumulative exposure to heat over a school year modeling effects of heat on learning. However, as discussed in subsection 2.2 there might also be a negative effect of acute heat exposure during the exam period in March. We thus split the school year preceding the exam into two distinct periods: the immediate exam period and the preceding "learning period."

Table 4[9] thus reports effects separately for the two phases as well as for March only. We find again that with higher measured temperature during the immediate period before and during the exam, the odds of students passing (column 1) and passing with distinction (column 3) decrease, although the effect is only statistically significant for the latter. If temperature increases by one standard deviation in March only (i.e., around +1.8°C), the odds of passing decrease by 28% and the odds of a distinction decrease by 43%.

When assessing both the learning and exam periods in the same models, reported in Models (2) and (4), we find that both explanations are relevant: immediate heat exposure as well as cumulative exposure over the preceding school year are negatively associated with both passing and passing with distinction, yet they differ in importance.

Considering both an increase of one standard deviation in temperature in March and an increase of one standard deviation in temperature during the school year except March (i.e., +1.5°C) suggests that elevated temperatures in March decrease the likelihood of passing by 7%, while hotter average temperatures between June and February mean a decrease of 62%. Moreover, for passing, the importance of heat in March is not statistically significant.

Repeating the same assessment for passing with distinction, we find qualitatively similar results yet effect sizes are larger in magnitude and the temperature in March remains statistically significant. Elevated temperatures in March are associated with a reduced likelihood to pass with distinction by 29%, and elevated temperatures during June and February mean a by 77% lower likelihood of a distinction.

Thus, exposure to elevated heat over an extended period appears to be even more detrimental than above-average temperatures during the exam period itself, particularly with regard to pass

[9]While Table 4 reports results for models including all meteorological control variables, the findings are very similar when dropping these controls.

rates. Therefore, simply rescheduling exams to a different time of year would not be sufficient to mitigate the adverse effects of heat on exam results.

Table 4: Cumulative vs. Immediate Heat Exposure.

	Pass		Pass with Distinction	
	(1)	(2)	(3)	(4)
Temperature Mar	-0.179*	-0.042	-0.309****	-0.194****
	(0.095)	(0.067)	(0.056)	(0.030)
Temperature Jun-Feb		-0.646***		-0.968****
		(0.215)		(0.125)
Humidity	-0.052***	-0.103**	-0.006	-0.173****
	(0.019)	(0.047)	(0.011)	(0.025)
Wind	0.072	-0.698	-0.170****	-1.426****
	(0.088)	(0.496)	(0.047)	(0.224)
Precipitation	0.050	-0.263***	-0.352****	0.107**
	(0.076)	(0.081)	(0.049)	(0.050)
Air pollution	Y	Y	Y	Y
School FE	Y	Y	Y	Y
School year FE	Y	Y	Y	Y
Observations	2,596,363	2,602,815	18,579,638	18,606,807
BIC	1,275,739	1,277,775	20,449,475	20,447,168
Adj. Pseudo R^2	0.303	0.304	0.180	0.182

Note: The table reports estimation results for Logit model with fixed effects expressed as log odds. Cluster-robust standard errors are reported in parentheses. Humidity, wind, precipitation and air pollution are averaged over March in columns (1) and (3), and over each full school year in columns (2) and (4). Statistical significance is coded following the standard notation: *p<0.1; **p<0.05; ***p<0.01; ****p<0.001

4 Adaptation and Mitigation

4.1 The Role of Vegetation

As we have documented an adverse impact of heat on exam results, we now turn to discussing and evaluating the effectiveness of a potential mitigation strategy. Previous research has highlighted the importance of air conditioning in reducing the negative effects of heat on learning (Park et al., 2020). However, in India, air-conditioning equipment in residential units remains rare – installed in only about 7-9% of the residential housing stock, according to the governmental *India Cooling Action Plan* (Cell, 2019). Thus, the effectiveness of low-cost complementary measures is of particular interest in the first instance. We, therefore, investigate the potential impact of a "natural" cooling strategy based on vegetation in the vicinity of schools, which could help mitigate the negative effects of heat on learning.

4.2 Technical Implementation

Up to this point, our analysis has relied on relatively low-resolution temperature data. Because the meteorological data have a spatial resolution of $0.1° \times 0.1°$, each grid cell covers an area of approximately 100 km^2. While this resolution is sufficient to capture the overall effect of heat exposure, it averages out variation in highly localized conditions and thus introduces noise into the temperature actually experienced at each specific school location. We refine this measure by incorporating high-resolution land-use data, which allows us to account for the well-established fact that artificial surfaces tend to absorb and reflect more heat than natural landscapes, and that temperatures in urban areas can be significantly higher than in their immediate rural surroundings. This approach enables us to explicitly consider how vegetation and tree cover density systematically influence the microclimate (Knight et al., 2021).

To incorporate this dimension, we add variation in tree cover to the analysis and use time-varying Global Forest Change (GFC) data to measure forest loss, as described in Appendix B.6. Only a relatively small share of schools in our sample experienced any change in tree cover in their surroundings during the study period: when measuring tree loss within a 1 km radius of each school, only about 5% of schools experienced any variation. We consider three radii: 0.25km, 0.5km, or 1km.

4.3 The Mitigating Effect of Vegetation

Before directly testing for the mitigating effect of vegetation within our regression framework, we present some descriptive evidence already hinting towards a positive effect of natural cooling through vegetation on exam pass-rates. Specifically, the summary statistics reported in Table 1 an average forest cover of schools within 1km (0.5km, 0.25km), for the full sample is 22.8ha (5.3ha, 1.2ha). This includes also schools with a pass-rate of 100% in all school years. For the sample of schools where there is variation in passing (i.e., where the probability of passing is lower), the average amount of forest is 19.8ha (4.6ha, 1.1ha). This indicates that schools exhibiting variation in pass rates – that is, schools where not all students consistently pass – tend to have, on average, less vegetation in their surroundings. For distinctions, forest density is almost the same for the full sample and the subsample of schools not awarding distinctions to all students. Hence, this first descriptive analysis suggests that the forest effect may be more important for passing than for distinctions.

Next, we test for this association within our main regression set-up: Table 5 reports the results for the 0.25 km radius.[10] We add tree cover density ('Forest') as an additional covariate to the main model. Indeed, models (1) and (3) indicate a statistically significant positive effect of forest cover on pass rates and distinctions. An additional hectare of forest increases the probability of passing by 0.5 percentage points on average (improving the odds by 92%), and the probability of getting a distinction by 3.1 pp. on average (improving the odds by 23%). Results hold also for a 0.5km and 1km radius as reported in Table 7 in the Appendix, although they tend to be less precisely estimated as the radius grows.

A back-of-the-envelope calculation based on the average partial effects from models (1) and (3) reveals that one additional hectare of forest over an area of 19.6 hectares would offset the impact of an increase in temperature by 1°C, on the probability of passing the exam.[11] Analogously, 5.4 hectares of forest would be needed to offset the impact of the same temperature change on the probability of achieving a distinction.

Further, we test whether the positive effect of tree cover becomes more important for higher temperatures, i.e., we interact the Forest effect with temperature. We use the "double-demeaned" within estimator for the interaction proposed by Giesselmann and Schmidt-Catran (2022). Estimates of the interacted effects should therefore be interpreted as referring to the mean of their moderator. As reported in models (2) and (4), these interactions are mostly – while consistently positive – insignificant for pass rates. For distinctions, also these interactions are significant – even for the larger radii. This suggests that a higher extend of tree cover may have only a systematically larger effect for higher temperatures when assessing the harder-to-achieve distinctions, yet for pass rates the effect appears to not differ significantly across the temperature distribution. This may suggest that tree cover has a general positive impact on student's well-being or systematically proxies also other quality measures related to school buildings or ambient amenities.

These findings suggest that more vegetation in the proximity of schools may have a certain positive effect on heat mitigation and hence somewhat alter students' achievements in the Upper Primary Level Examination. Thus, ensuring that schools currently strongly exposed to heat could make more use of vegetation for natural cooling purposes. However, this measure alone will likely not be sufficient to lean against the totality of adverse heat effects and more investment in structures and an adaptation of exam scheduling may be needed.

5 Conclusions

We empirically assess the link between exposure to heat and schooling success in India. Precisely, we link results in the exam concluding compulsory education reported in the categories 'Fail', 'Pass' and 'Pass with Distinction' to temperatures measured during the preceding school year or the month of the exam at the school location. To isolate this association, we make

[10]The results for the 1 km and the 0.5 km radii are similar and reported in Table 7 in Appendix C.3.

[11]I.e. on average, offsetting the +0.64°C increase in temperature projected under RCP2.6 would require an additional forest area equal in size to a standard football (soccer) pitch, within 250 meters from the school.

Table 5: Tree Cover Effect, 0.25 km radius.

	Pass		Pass with Distinction	
	(1)	(2)	(3)	(4)
Temperature	-0.613**	-0.614***	-1.103****	-1.104****
	(0.238)	(0.238)	(0.143)	(0.143)
	[-0.0047]	[-0.0047]	[-0.1687]	[-0.1688]
Forest 0.25km	0.652***	0.523	0.205*	0.130
	(0.242)	(0.339)	(0.108)	(0.143)
	[0.0050]	[0.0040]	[0.0314]	[0.0198]
Temperature*Forest 0.25km		0.871		1.323*
		(1.410)		(0.700)
		[0.0067]		[0.2022]
Humidity/Wind/Precipitation	Y	Y	Y	Y
Air pollution	Y	Y	Y	Y
School FE	Y	Y	Y	Y
School year FE	Y	Y	Y	Y
Observations	2,602,815	2,602,815	18,606,807	18,606,807
BIC	1,277,847	1,277,856	20,446,476	20,446,301
Adj. Pseudo R^2	0.304	0.304	0.182	0.182

Note: Average partial effects are reported in square brackets. Cluster-robust standard errors are reported in round bracket. Statistical significance is coded following the standard notation: *p<0.1; **p<0.05; ***p<0.01; ****p<0.001.

use of the vast variation in weather conditions observed across India and over our period of study (2014 to 2018). Our identification strategy hence relies on the repeated observation of the same school (and thus the same location) over time. As high temperatures are particularly dangerous when combined with high levels of humidity and in the absence of cooling factors such as wind speed or precipitation, we add further meteorological information, which leads to effects pointing in the same direction yet being even larger in magnitude.

Students exposed to elevated temperatures are less likely to both, passing the exam and passing the exam with distinction. Students attending not centrally managed schools, more recently established schools, and without outdoor facilities are more strongly affected. While rural schools are generally more affected, schools in poor urban areas experience the largest negative heat effect.

We separate the school year preceding the exam into two periods to differentiate between an effect of heat on learning over the year and an effect on immediate cognitive performance during the exam period. We find that both channels are important, yet extended periods of elevated temperatures appear to be more harmful.

We use our estimation results to simulate the impact of hypothetical future increases in temperature on the excess number of students obtaining poorer test results due to this change. Simulated scenarios are based on climate change projections for the region. Even small rises in temperature are associated with substantial increases in the number of students who fail. Such dramatic growth in low-performing students at this early stage of formal education is likely to have adverse consequences for their subsequent academic trajectories and future life outcomes.

Furthermore, we investigate the impact of a possible mitigation strategy relying on increased vegetation surrounding schools. For that, we quantify the effect of the current level of vegetation (measured via tree cover density in the direct neighborhood of a school) on the likelihood of passing or passing with distinction. We detect that relying on natural cooling in the form of increased vegetation can mitigate some of the adverse heat effects yet is not able to fully offset it.

These findings challenge whether the official Indian *National Education Policy 2020* can be achieved without addressing the challenge of heat negatively affecting students' learning, as it envisions "an education system rooted in Indian ethos that contributes directly to transforming India, that is Bharat, sustainably into an equitable and vibrant knowledge society, by providing high-quality education <u>to all</u>, and thereby making India a global knowledge superpower" [National Education Policy[1] 2020, paragraph 1.6].

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Appendix

A School Data

A.1 School Selection Procedure

The *DISE* database covers all registered primary and secondary schools in in 23 states and territories.[12] We use this database as the starting point, which then undergoes a step-wise selection process to ensure comparability and ultimately clean estimation. The step-wise selection procedure can be summarized as follows:

- Include public schools if managed by
  + the Department of Education,
  + the Tribal/Social Welfare Department,
  + a local body, or
  + the central government.
- Include private schools if managed by
  + a private institution, or
  + a private institution, yet aided by the government ("Semi-Government Schools").
- Exclude schools
  - not starting the school year in June,
  - classified as Madrasa,
  - classified as unrecognized,
  - classified as 'other,' or
  - schools with inconsistent classification over time.

The rationales driving decisions to drop schools are the following: First, we exclusively keep schools that roughly follow the same academic year. This is important to precisely link meteorological data to the academic year and compare like with like. The majority of schools start in June, and ends in March or early April. These are schools located in the states Andhra Pradesh, Arunachal Pradesh, Gujarat, Kerala, Madhya Pradesh, Maharashtra, and Tamil Nadu. We thus exclude schools in other states. Further, schools located in these states yet reporting (at least in some years) a different beginning of the academic year.

[12] Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Chandigarh, Chhattisgarh, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, West Bengal.

We rely on both, public and recognized private schools. The latter are under private management and usually depend on school fees. However, these fees are usually low (see also Singh and Bangay, 2014, for more information on private schools in the DISE data set). We keep recognized private schools as they generally meet infrastructure, curricular, and teaching norms as discussed by Srivastava et al. (2013). There are mixed perceptions on whether private schools are on average of higher or lower quality than public schools. Qualitative expert interviews conducted by Singh and Bangay (2014) reveal mixed perceptions in terms of quality differences between the public and low-fee private sector. While many experts highlight the general positive contribution of this privately run school-type in terms of access and quality, some experts warn about generalizations and emphasize the varying nature in quality due to a lack of systematic evaluation of several quality indicators including teaching materials used, pedagogical soundness, and teacher quality in general.

Next, we exclude institutions classified as Madrasa (Islamic education) and drop schools that we cannot unambiguously classify as either managed by the government, or managed by a private institution with the aid or consensus of the government. Similarly, we exclude schools that over the observed period (2014-2018) are not consistently classified as either a private or a public institution. We exclude schools that are not consistently classified as either rural or urban schools, as "boys-only", "girls-only" or "co-educational", whose stated main language of instruction changes, or that change affiliation to the board administering the secondary school examinations. We drop schools that are not reported in the data every year of the panel.

This selection process yields ultimately a set of 134,985 well comparable schools, which means a drop from 1,567,741 in the original DISE database. Figure 1 shows the geographic distribution of schools entering our analysis.

A.2 School Geo-location

To match school locations with meteorological data, we rely on geolocations (longitudes and latitudes). Hence, we merge schools' addresses reported in the DISE dataset with official geolocations reported by the *Department of School Education and Literacy* (Indian Ministry of Education) and accessible via their website: `https://schoolgis.nic.in`.

B Description of Supplementary Data

We use a bulk of supplementary concepts that potentially mitigate or intensify the consequences of heat exposure as discussed in section 3 and section 4.

B.1 Relative Humidity

It has been well-studied that heat in combination with humidity can have even larger impacts on human's health and performance. Extreme heat in combination with humidity means elevated risks and discomfort. As Raymond et al. (2020) put it: "A normal internal human body temperature of 36.8°C ± 0.5°C requires skin temperatures of around 35°C to maintain a gradient directing heat outward from the core. [...] Once the air (dry-bulb) temperature (T) rises above this threshold, metabolic heat can only be shed via sweat-based latent cooling, and at WBT [wet-bulb temperature] exceeding about 35°C, this cooling mechanism loses its effectiveness altogether." They assess WBT hotspots between 1997 and 2017 globally and find that all measures of WBT occurrences show a clear upward trend over time. However, even lower temperatures can have – in combination with humidity – strong adverse effects particularly when adaptive measures are not taken. India is adversely affected by this dangerous combination (see for instance Wehner et al., 2016).

As heat is particularly dangerous in combination with humidity, we additionally make use of the concept of *relative humidity* measuring water vapor relative to air temperature. Therefore, we source temperature and dew point data from the ERA5-Land data set, and calculate relative humidity using the August-Roche-Magnus approximation yielding an easy algebraic relationship between relative humidity [%], the dew point Dp [°C] and temperature T [°C]. Using the coefficients suggested by Alduchov and Eskridge (1996) implies

$$\text{Relative Humidity} = 100 * \frac{\exp\left(\frac{17.625\, Dp}{243.04 + Dp}\right)}{\exp\left(\frac{17.625\, T}{243.04 + T}\right)}.$$

Again, we link each school's location to daily relative humidity, and average over all school days in each academic year.

B.2 Wet-Bulb Temperature and Heat Index

Next to measuring temperature and humidity separately, we can also draw on the concept of *wet bulb temperature* (WBT) that merges dry air temperature with humidity into a single measure as mentioned in subsection B.1. This is achieved by measuring the temperature of a surface from which water has evaporated. Thus, it can be interpreted as the minimum temperature necessary for sweating being able to cool the body given current air temperature and humidity.

Physiologists have theorized a wet-bulb temperature of 35°C to be the limit to human adaptability to extreme heat for young and fit subjects (Sherwood and Huber, 2010; Raymond et al., 2020) and thus the threshold for survivability. While empirical work argues that thresholds need to be adjusted downwards and more heterogeneity needs to be accounted for (see, for instance, Vecellio et al., 2022), we take from this line of research that negative effects are already to be expected for WBT way below the extreme threshold of 35°C.

Furthermore, we use the simplified version of the index suggested by Steadman (1979) that relies only on air temperature and moisture, generally known as the "heat index". Steadman's index translates air temperature and air moisture into the temperature that humans would perceive if dew point temperature were 14°C. The heat index has become a widely used measure of thermal comfort in environmental health research (see Anderson et al., 2013), and it is used by the U.S. National Weather Service to indicate the level of threat to human health: "heat indices meeting or exceeding 103°F (39.4°C) [in the shade] can lead to dangerous heat disorders with prolonged exposure and/or physical activity in the heat".[13]

We compute the maximum daily heat index using hourly air temperature and relative humidity of each school day, then average over the school year.[14]

B.3 Wind Speed

Wind causes heat loss and thus helps to mitigate the adverse effects of heat on the micro climate and human thermal comfort. The mitigating effect of wind on heat has been particularly highlighted for urban areas where the loss of vegetation has led to higher level of air and surface temperature in comparison to rural areas. This leads to UHI as increased ambient temperature of urban areas due to warmer surfaces (see Synnefa et al., 2007). Previous research has empirically shown that particularly for tropical regions, wind does play an important role: For instance, Erell et al. (2012) measure that in Singapore a wind velocity of 1–1.5 m/s creates cooling effect equivalent to a 2°C decrease in measured temperature. Thus, we match our school data with daily wind speed from the ERA5-Land data set, and average over school days.

B.4 Precipitation

Precipitation (from ERA5-Land) is calculated as cumulative precipitation over each school day, then averaged over all school days. Precipitation is considered as a relevant climatic factor for assessing the impact of heat in hot climates such as India. This is due to its "potential to naturally mitigate heat excess in buildings and cities by evaporative cooling; and as a primary source of water to artificially reproduce this cooling mechanism, particularly in the humid tropics and subtropics" (Diaz et al., 2015).

B.5 Air Pollution

As air pollution may correlate with temperature and other meteorological variables, we control for the average level of air quality. We obtain grid data on particle pollution from fine particulates (PM 2.5) from Van Donkelaar et al. (2021), and grid data on Carbon Monoxide and Nitrogen Dioxide from the NASA Earth Observations database.[15]

B.6 Tree Cover

The spatial resolution at which we measure temperature variation is rather low ($\approx$ 100 km^2). However, there could be significant unobserved variation within each cell of the grid, driven by, for example, land use. This creates concerns as differences in vegetation and canopy height may systematically impact the micro-climate in the surrounding of schools.

[13]See `https://www.weather.gov/ama/heatindex`, last accessed in May 2024.
[14]We use the algorithm provided by Anderson et al. (2013) in the R package *weathermetics*.
[15]See `https://neo.gsfc.nasa.gov`, last accessed in October 2023.

The height and amount of the vegetation above ground level is a key component of the impact of temperature on the ground: forests function as a thermal insulator and thus, when ambient temperatures are hot, forests and in general trees cool the understory (see De Frenne et al., 2019). Furthermore, in urban areas tree canopy shading has been shown to alleviate the UHI effect and to increase thermal comfort (Iungman et al., 2023; Knight et al., 2021).

It is possible that the presence and extent of vegetation correlates with unobserved school characteristics that contribute to heat mitigation, or that influence cognitive performance. To address this threat to identification, we use data on *Global Forest Change (GFC)* from the *Global Land Analysis and Discovery Laboratory* (Hansen et al., 2013), to track variations in trees' density over time. The data, based on images from the Landsat satellite program, covers yearly gross forest cover loss since 2001, with a spatial resolution of 1 arc-second (about 30×30 meters at the equator).

India has the tenth largest forest area in the world FAO (2010) (see Figure 8), mostly concentrated in the Eastern and North-Eastern regions (mostly tropical moist and tropical dry forests) and in the Southern regions (tropical moist forest and rain forest) (FAO, 2012).

These forests mean a rich natural resource of global importance. The *Global Forest Watch (GFW)* platform[16] monitors various changes in forests globally and also uses, inter alia, GFC data as input. According to these data, India has lost a sizable amount of its forest (2.29 Mha between 2001 to 2023 whereas only 38.1 kha thereof were lost due to fires but the vast majority due to any other reason including deforestation). This rate had been larger over the past 10 years as compared to the preceding decade. At the same time, however, India has also gained substantial amounts of forest over the same period. Overall, the net effect of changes in forest cover is positive between 2000 to 2020: 874 kha (1.3%) in tree cover.

Although the GFC data has been extensively used to study deforestation (see, for instance, Li et al., 2016; Lui and Coomes, 2016), this is not the main concern in India as discussed above. Thus, we are not interested in measuring the implications of large-scale, fast-paced forest loss, yet we focus on heterogeneity within the country. The high spatial resolution of the data allows us to measure small-scale fluctuations in the extent of tree coverage in the proximity of schools.

As the GFC data is only available on a solar year basis, we cannot perfectly overlap the school years to the yearly changes in tree cover. We use the forest loss from the solar year that mostly overlaps with the school year, and that precedes the end of the school year: we match tree cover loss from 2014 with observations in the school year 2014-15, and so on.

We measure the extent of tree cover, in hectares, within a circle of 0.25 km (0.5 km; 1 km) centered around each school. We use the forest cover of 2012 as the benchmark, and compute yearly values for each school by subtracting the yearly loss of forest in the relevant area. Hansen et al. (2013) codify forest loss as binary, and they define it as a “stand-replacement disturbance, or a change from a forest to non-forest state.”

[16] See `https://www.globalforestwatch.org` for details; last accessed in May 2024,

B.7 Relative Wealth Index

The *Relative Wealth Index (RIF)* introduced by Chi et al. (2022) is a measure of wealth and poverty for low- and middle-income countries available for grid cells with a 2.4 km resolution. The index has been developed by the *Center for Effective Global Action (CEGA)* in collaboration with *Meta's Data for Good*. Based on Machine Learning modeling, the index merges information from various sources including satellite imaging, mobile phone networks, and topographic maps, as well as social media data in the form of aggregated and anonymized connectivity information from Facebook.

C Robustness Checks and Sensitivity Analyses

This section performs a battery of robustness checks and sensitivity analyses related to all parts of the study.

C.1 Technical Checks

First, we vary the model class used for measuring the effect of temperature on exam results. The main specification relies on logistic regression models that distinguishes between the categories 'pass' and 'fail', as well as 'pass with distinction' and 'fail' or 'missing the distinction,' respectively. We re-estimate the same models, but rely on ordinary least squares (i.e., a linear regression model) as estimation technique. Models (1) and (9) in Table 6 report again statistically strongly significant negative effects of elevated temperatures on passing and passing with distinction.

C.2 Measuring Temperature and Thermal Comfort

Further, we test for the sensitivity of results of how we measure the key variable of interest: temperature and, more broadly speaking, thermal comfort.

One caveat of our analysis is that all temperature measures are sourced from a reanalysis dataset (i.e., ERA5-Land). Hence, we perform a robustness check using observational temperature data measured by traditional weather stations. We rely on the maximum daily temperature gridded data reported by the India Meteorological Department (IMD).[17] The data is interpolated from around 180 stations across the country (Srivastava et al., 2009). The primary drawback is that IMD rasters have a resolution of 1°× 1°, which is 100 times lower than the 0.1°× 0.1° resolution of ERA5-Land data. Like in our main approach, we compute the average maximum temperature during schools days, excluding all days in April and May, Saturdays, Sundays and all state-specific and federal public holidays. Models (2) and (11) report the results. The effect of temperature on both the probability of passing and passing with distinction is negative and for distinctions also strongly significant. The log ratios are -0.257 for passing (not precisely estimated) and -0.776 for passing with distinction. A 1°C increase in temperature is predicted

[17] `https://www.imdpune.gov.in`, accessed January 2025.

to decrease the odds of passing by 23% (compared to 47% in the baseline model), and the odds of getting a distinction by 54% (compared to 67% in the baseline model).

Further, our main models include temperature as a continuous variable. Hence, we allow here for a more flexible functional form by including temperature as a sequence of temperature brackets. Models (3) and (12) include brackets of days with a maximum temperature within intervals of span 5°C. Model (3) reveals that adverse effects on the probability of passing the exam are driven by the highest observed temperatures, while lower temperatures are associated with increased pass rates and distinctions. The strongest effect in magnitude is associated with temperatures above 40°C. The odds of passing the exam decreases, for any additional day in a higher bracket, as shown by Figure 4 (Panels c and d).

Additionally, Figure 4 also reports the results from regressing the binary outcomes on the number of school days within a given heat index interval (Panels a and b). We use four intervals that correspond to the U.S. National Weather Service classification of the level of risk associated with heat indices:

- Below 27°C (80°F): low risk.
- 27°C - 32°C (80°F - 90°F): "Caution: fatigue possible with prolonged exposure and/or physical activity."
- 32°C - 41°C (90°F - 105°F): "Extreme Caution: sunstroke, muscle cramps, and/or heat exhaustion possible with prolonged exposure and/or physical activity."
- 41°C - 54°C (105°F - 129°F): "Danger: sunstroke, muscle cramps, and/or heat exhaustion likely. Heatstroke possible with prolonged exposure and/or physical activity."[18]

Again, the adverse effects are driven by hot, humid days, with the strongest marginal effect identified for schooldays with temperatures above 41°C. More days with cool temperatures are associated with a positive effect on passing and passing with distinction. These results are similar to Seppanen et al. (2006) finding a positive effect of *indoor* temperature on various mental activities in an office setting up until 22°C and decreasing performance for higher temperatures.

Table 6 also reports the results for two alternative measures of thermal comfort: wet bulb temperature (Models (4) and (13)) and the heat index (Models (5) and (14)). As detailed in subsubsection 2.3.3, these are often used as metrics for 'actual temperature', as they consider the combined effect of air temperature and air moisture. Thus, we exclude humidity as a separate main effect. For both measures, the effect is similar, in magnitude and sign, to the effect of temperature alone, as expected.

Models (6) and (15) use again our main temperature and humidity variables, but also add their interaction to see whether this naive combination of measures points in the same direction. We

[18] See the Heat Index Chart of the U.S. National Weather Service: `https://www.weather.gov/ffc/hichart`, last accessed in June 2024. Heat indices above 54°C (130°F) are classified as "Extreme Danger", but such values are not observed in our sample.

use the “double-demeaned” within estimator for the interaction (Giesselmann and Schmidt-Catran, 2022). For both outcomes, the estimated coefficient is not significant.

Models (7) and (16) assess the impact of cooling during night: *Diurnal temperature range (DTR)* measures the difference in air temperature between the maximum and minimum near-surface air temperature within 24 hours. We hypothesize that high temperatures are particularly harmful if there is a minimal cooling effect over night, i.e., if DTR is small. This is not confirmed as the effect is statistically insignificant for passing and negative and significant for passing with distinction.

To shed more light on the driving forces of this effect, models (8) and (17) make use of the concept of tropical nights, i.e., days with the minimum temperature remaining above 20°C. On such days, high minimum temperatures prevent the body to cool-off during the night. Exposure to heat during the night has been shown to have negative health and daytime activities. Furthermore, insomnia imposed by heat has been shown to have particularly negative effects if paired with high humidity (Okamoto-Mizuno and Mizuno, 2012). Results clearly show that more tropical nights are associated with a decreased likelihood of passing as well as fewer distinctions.

Finally, we rely on the concept of *heat waves*: Inspired by the definition of the World Health Organization (WHO) (`https://www.who.int/india/heat-waves`), we count the number of days in a school year that fulfill the criteria of a heatwave. These are: the temperature is greater or equal to 30°C and deviates form the historical (1990-2010) mean maximum temperature for that calender day by at least 4.5°C, or the overall daily maximum temperature measured exceeds 45°C. Furthermore, days are only counted if (at least) two days in a row meet these criteria. Models (9) and (18) report results: As expected, the estimated effect associated with the number of heat wave days is negatively related with both, the likelihood to pass and pass with distinction. However, the effect is not statistically significant.

Table 6: Robustness Checks – Cumulative Effects.

	Pass									Pass with Distinction								
	(1) *OLS*	(2) *Logit*	(3) *Logit*	(4) *Logit*	(5) *Logit*	(6) *Logit*	(7) *Logit*	(8) *Logit*	(9) *Logit*	(10) *OLS*	(11) *Logit*	(12) *Logit*	(13) *Logit*	(14) *Logit*	(15) *Logit*	(16) *Logit*	(17) *Logit*	(18) *Logit*
Temperature	-0.036***					-0.680***	-0.942			-0.180****					-1.077****	-0.382		
	(0.014)					(0.243)	(0.900)			(0.026)					(0.138)	(0.259)		
IMD Temperature		-0.257									-0.776****							
		(0.187)									(0.126)							
Days below 10°C			0.121***									0.056****						
			(0.046)									(0.013)						
Days 10-15°C			0.082*									0.063****						
			(0.046)									(0.012)						
Days 15-20°C			-0.018									-0.003						
			(0.011)									(0.004)						
Days 25-30°C			-0.019**									-0.002						
			(0.008)									(0.004)						
Days 30-35°C			-0.026***									-0.014***						
			(0.010)									(0.005)						
Days 35-40°C			-0.027**									-0.010						
			(0.013)									(0.007)						
Days above 40°C			-0.052**									-0.022						
			(0.021)									(0.014)						
Wet Bulb Temperature				-0.503**									-0.454****					
				(0.210)									(0.123)					
Heat Index					-0.229*									-0.338****				
					(0.137)									(0.070)				
Temperature*Humidity						-0.075*									0.029			
						(0.045)									(0.019)			
Temperature*Avg. Diurnal Temp. Range							0.032									-0.079***		
							(0.094)									(0.028)		
Tropical Nights								-0.009***									-0.011****	
								(0.003)									(0.002)	
Heat Wave Days									-0.014*									-0.005
									(0.008)									(0.004)
Humidity	Y	Y	Y	N	N	Y	Y	Y	Y	Y	Y	Y	N	N	Y	Y	Y	Y
Wind	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Precipitation	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Air pollution	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
School FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
School year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,602,831	2,600,164	2,602,815	2,602,815	2,574,706	2,602,815	2,602,815	2,602,815	2,602,815	18,606,927	18,589,270	18,606,807	18,606,807	18,396,780	18,606,807	18,606,807	18,606,807	18,606,807
Adjusted R^2 / Pseudo R^2	0.27	0.303	0.304	0.303	0.304	0.304	0.304	0.304	0.303	0.22	0.181	0.183	0.181	0.181	0.182	0.182	0.181	0.180
BIC	279,195	1,277,616	1,277,413	1,278,182	1,264,126	1,277,742	1,278,046	1,277,959	1,278,391	21,277,414	20,439,682	20,442,135	20,483,546	20,230,065	20,445,419	20,444,452	20,469,235	20,490,727

Note: Cluster-robust standard errors are reported in parentheses. Statistical significance is coded following the standard notation: *p<0.1; **p<0.05; ***p<0.01; ****p<0.001

C.3 Altering the Way we Measure Forrest Cover Loss

We assess measurement choices related to forest cover loss. Table 7 reports the results of using the same empirical approach of section 4, but measuring tree cover density within a larger radius, i.e., 0.5 and 1 km, respectively. The results are consistent, showing that the loss of forest cover in the proximity of schools has a negative effect on the probability of passing (with distinction). As expected and in-line with the notion that only forest cover in the immediate proximity is relevant, the magnitude and significance of the average marginal effect of one additional hectare of forest (reported in square brackets) decays with distance. This is particularly true when modeling distinctions.

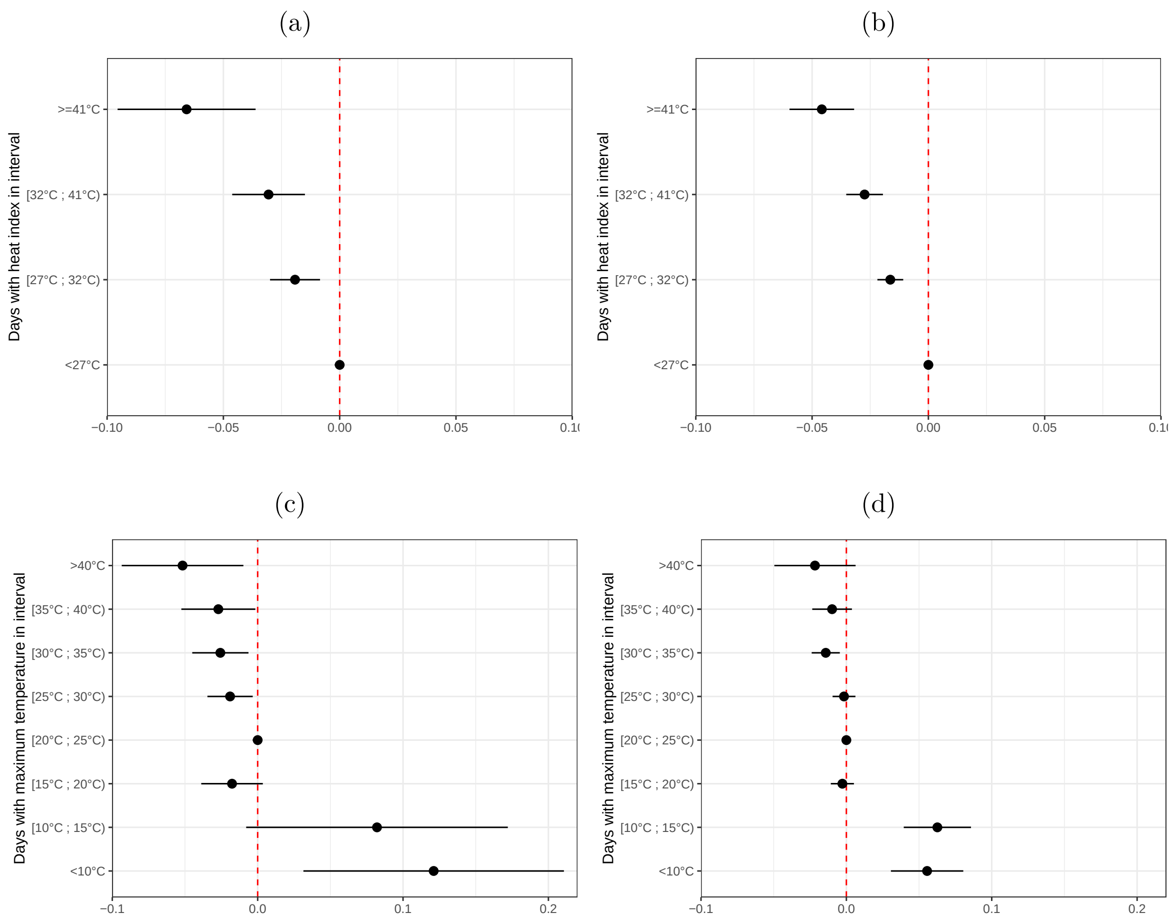
Table 7: Tree Cover Effect, 0.5km and 1km radius.

	Pass				Pass with Distinction			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature	-0.607**	-0.607**	-0.619***	-0.618***	-1.103****	-1.105****	-1.102****	-1.105****
	(0.239)	(0.239)	(0.239)	(0.240)	(0.143)	(0.143)	(0.143)	(0.143)
	[-0.0047]	[-0.0047]	[-0.0048]	[-0.0048]	[-0.1686]	[-0.1689]	[-0.1685]	[-0.1690]
Forest (0.50 km)	0.324*	0.323*			0.092**	0.077*		
	(0.171)	(0.185)			(0.044)	(0.047)		
	[0.0025]	[0.0025]			[0.0141]	[0.0118]		
Temperature*Forest (0.50 km)		0.008				0.597***		
		(0.670)				(0.195)		
		[0.0001]				[0.0913]		
Forest (1.00 km)			0.072	0.071			0.031**	0.030**
			(0.066)	(0.062)			(0.014)	(0.013)
			[0.0006]	[0.0005]			[0.0048]	[0.0045]
Temperature*Forest (1.00 km)				0.006				0.235****
				(0.239)				(0.052)
				[0.0001]				[0.0359]
Humidity/Wind/Precipitation	Y	Y	Y	Y	Y	Y	Y	Y
Air pollution	Y	Y	Y	Y	Y	Y	Y	Y
School FE	Y	Y	Y	Y	Y	Y	Y	Y
School year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,602,815	2,602,815	2,602,815	2,602,815	18,606,807	18,606,807	18,606,807	18,606,807
BIC	1,277,820	1,277,835	1,277,924	1,277,939	20,446,392	20,446,034	20,446,277	20,445,477
Adj. Pseudo R^2	0.304	0.304	0.304	0.304	0.182	0.182	0.182	0.182

Note: Average partial effects are reported in square brackets. Cluster-robust standard errors are reported in round bracket. Statistical significance is coded following the standard notation: *p<0.1; **p<0.05; ***p<0.01; ****p<0.001

D Additional Figures and Tables

Figure 4: Effect of an additional day in each heat index and temperature bin – Cumulative Effects.



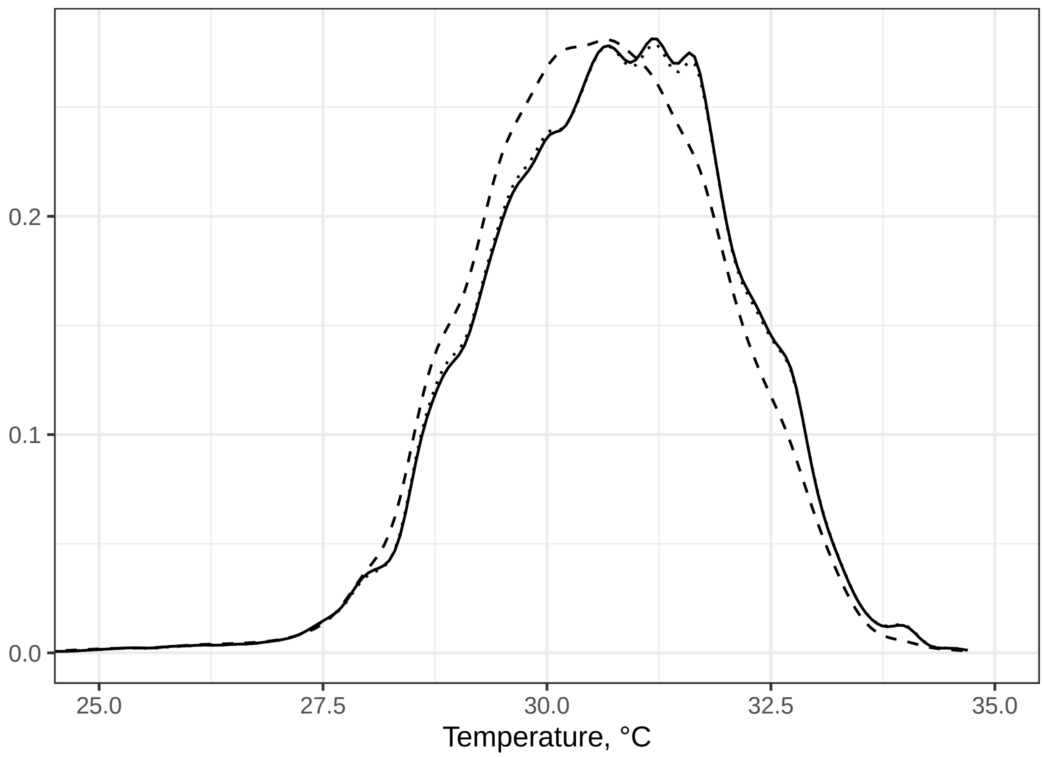
Notes: The figure shows the estimated effect of an additional school day in each heat index bracket (a,b) or a given temperature bin (c,d) on the probability of passing the exam (a,c), and on the probability of passing with distinction (b,d).

Table 8: Heterogeneity Analysis: Rural-Urban and Relative Wealth Index.

	Pass			Pass with Distinction		
	(1)	(2)	(3)	(4)	(5)	(6)
Temperature	-0.449*	-0.764***	-0.790****	-1.103****	-1.143****	-1.130****
	(0.270)	(0.236)	(0.235)	(0.138)	(0.154)	(0.154)
Temperature*Rural (*Ref.:* Urban)	-0.327**			-0.003		
	(0.159)			(0.039)		
Temperature*RWI		0.396**	0.592**		0.071	-0.003
		(0.167)	(0.236)		(0.054)	(0.058)
Temperature*Rural*RWI			-0.561*			0.201***
			(0.303)			(0.064)
Humidity/Wind/Precipitation/Air Pollution	Y	Y	Y	Y	Y	Y
School FE	Y	Y	Y	Y	Y	Y
School year FE	Y	Y	Y	Y	Y	Y
Observations	2,602,815	2,558,890	2,558,890	18,606,807	18,305,378	18,305,378
BIC	1,277,629	1,256,512	1,256,244	20,446,582	20,106,062	20,105,152
Adj. Pseudo R^2	0.304	0.305	0.305	0.182	0.182	0.182

Notes: The table reports heterogeneous resuls of the cumulative heat exposure. RWI denotes the relative wealth index. Cluster-robust standard errors are reported in round bracket. Statistical significance is coded following the standard notation: *p<0.1; **p<0.05; ***p<0.01; ****p<0.001

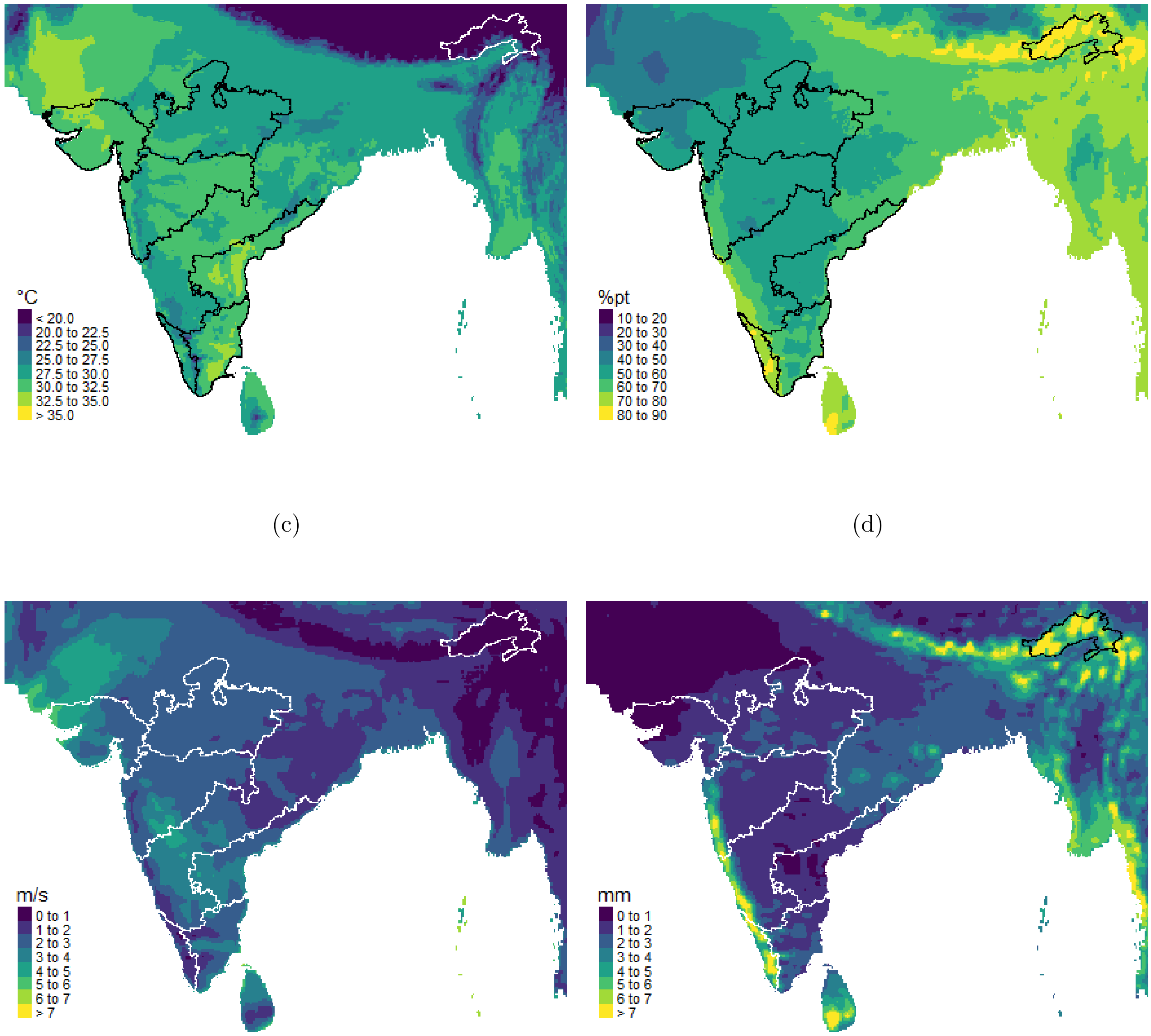
Figure 5: Distribution of Observed Cumulative Temperature, °C.



Notes: The density plot shows the distribution of the average maximum temperature during school hours over the entire school year among all 20,073,881 schools (solid line); among the 2,556,878 schools with variation in outcome **Pass** (dashed); and among the 18,508,398 schools with variation in outcome **Pass with distinction** (dotted). The distribution is shown as density plots.

Figure 6: Temperature, relative humidity, wind and precipitation - Cumulative.

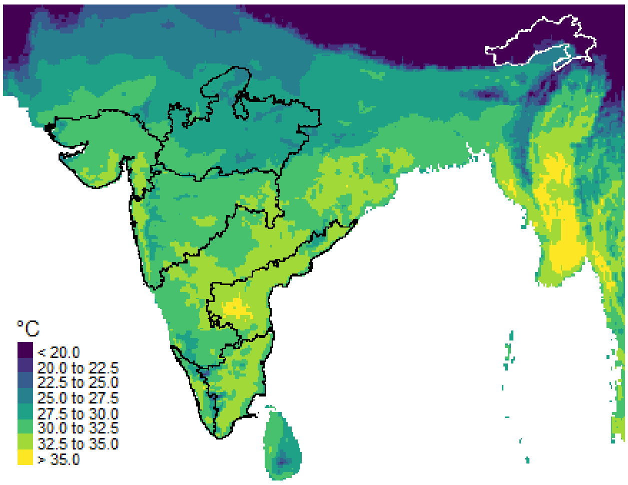
(a) (b)



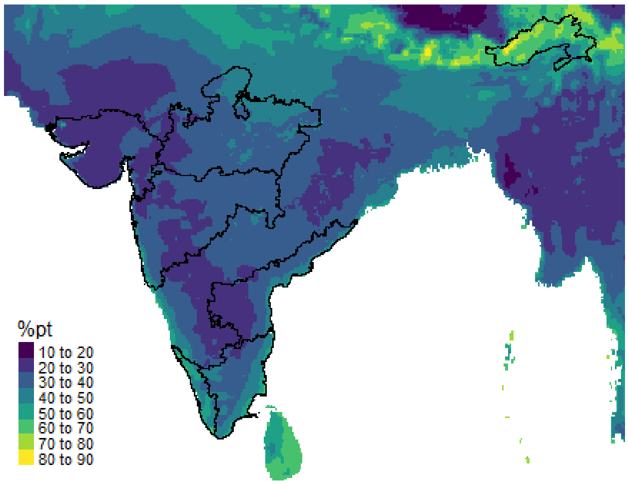
Notes: Panel (a) temperature, Panel (b) relative humidity, Panel (c) wind, Panel (d) precipitation. Aggregated over the school year 2014-15.

Figure 7: Temperature, relative humidity, wind and precipitation - Immediate.

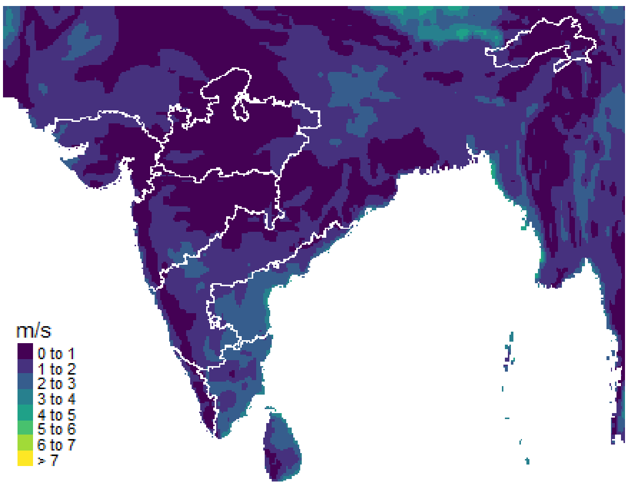
(a)



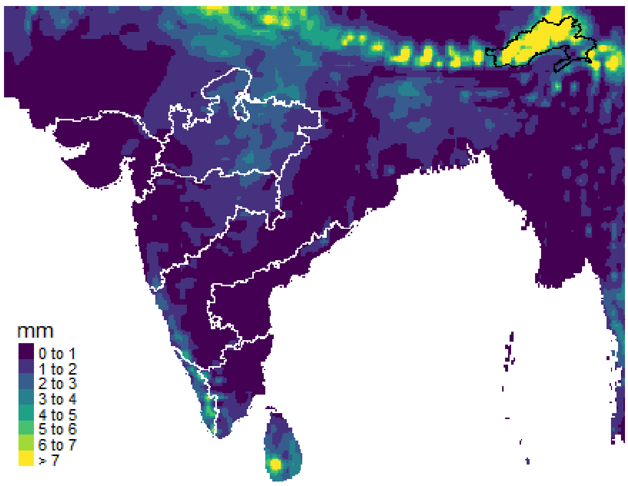
(b)



(c)

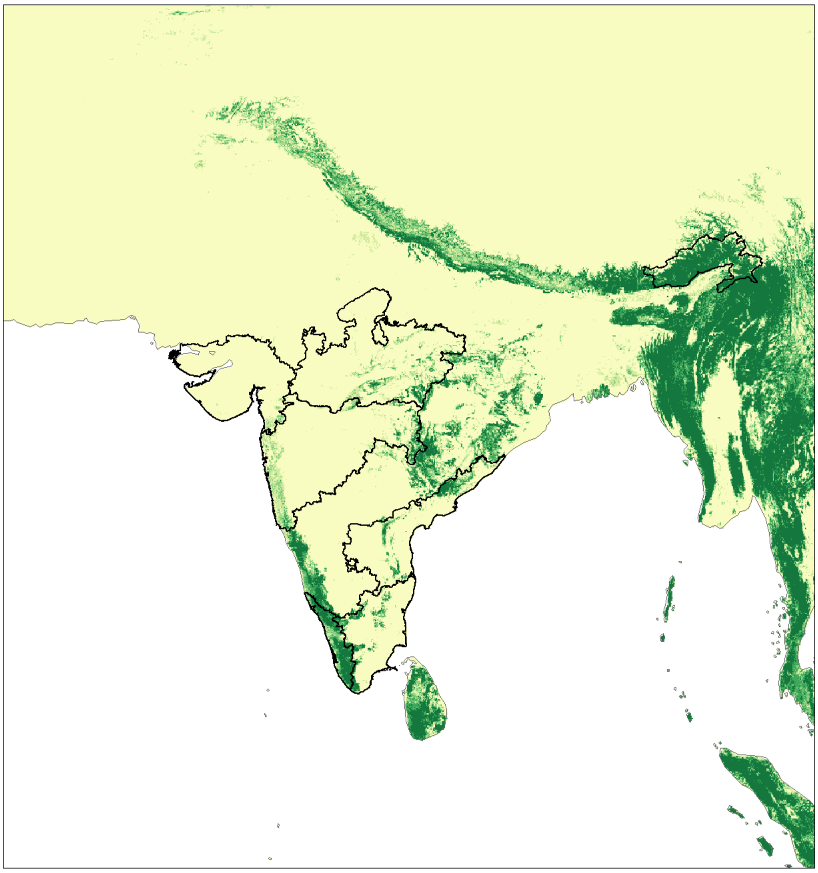


(d)



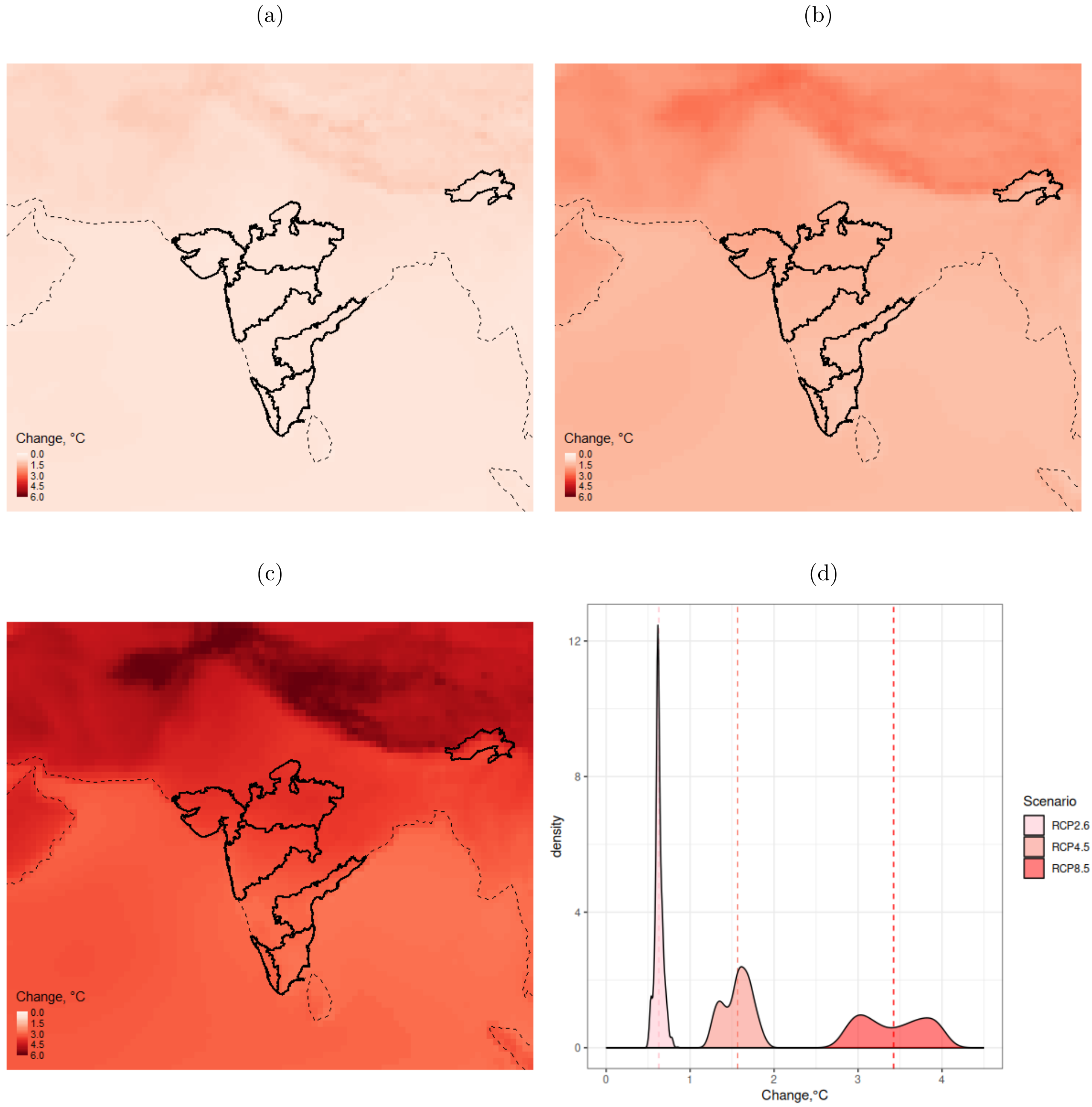
Notes: Panel (a) temperature, Panel (b) relative humidity, Panel (c) wind, Panel (d) precipitation. Aggregated over March 2015.

Figure 8: Forest Extent.



Notes: The figure depicts the geographical distribution of forests in 2014 across India.
Source: GFC

Figure 9: CORDEX South Asia - Mean maximum temperature change - Long Term (2081-2100), relative to 1995-2014 - June to March.



Notes: Panel (a) RCP2.6; Panel (b) RCP4.5; Panel (c) RCP8.5; Panel (d) density and average of temperature change by school (entire sample), by climate change scenario.