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Assessment choice shapes evidence on heat exposure and learning in Brazil

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Assessment choice shapes evidence on heat exposure and learning in Brazil

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Abstract

Across Brazilian states, 2015–2025 mathematics score changes in PISA and SAEB correlated at r = 0.04. We align PISA and SAEB exposure measures for 27 Brazilian states in 2015 and 2025, and examine learning-period heat and thermal-room provision in 15,724 public schools. All five unadjusted state slopes linking hot days to score changes are negative. With macroregion indicators, the PISA mathematics slope remains −4.56 points per ten additional annual hot days (95% CI −9.13 to 0.01), while the SAEB mathematics and Portuguese slopes shrink to −0.53 and −0.86 points. School-level intervals span zero, with 80% detectable contrasts of about 2.35 mathematics points for heat and 0.95 for the resource differential. Educational heat surveillance therefore depends on the assessment and geographic comparison, while evaluating school adaptation requires measuring the thermal conditions students experience.

Introduction

From 2015 to 2025, Ceará's mean ninth-grade mathematics score rose by 27.2 SAEB points, while its mean PISA mathematics score fell by 18.5 points. In Roraima, annual-average days above 35°C increased by 46.0 between the two exposure windows. Its PISA mathematics mean fell by 34.4 points while its SAEB mathematics mean rose by 2.0. The assessments cover different students and present different accounts of how mathematics performance changed across the same places. Education authorities need to know how those accounts bear on where to investigate heat risk and which classroom conditions to measure. Extreme weather can affect instruction, participation and performance through classrooms, households and communities[1,2,3]. The unequal exposure of younger generations to climate extremes adds a distributional dimension to these decisions[4]. Learning measures complement enrolment and attainment by capturing skills acquired during schooling[5].

Climate risk arises through the interaction of hazards, exposure and vulnerability, and adaptation changes one or more of these components[6]. For education, a hot day is a hazard. Its relevance to learning depends on when students encounter it, how long they are exposed and the conditions in which instruction takes place. A count of hot days over several years describes the thermal background of a population of students. Counting during the school year better aligns weather with the period when instruction can occur. Classroom design, operating equipment and attendance determine the exposure actually experienced during that time. This distinction connects a regional indicator of heat risk to school conditions that can be changed. The assessment, exposure window and geographic comparison each define the learning relationship that an education system can observe. Aligning the exposure across assessments lets us examine how much of the regional pattern is shared and how it changes when comparisons are made within the same macroregion.

The temperature and learning literature illustrates why the timing of exposure matters. Evidence from high-stakes tests in the United States and China links temperature on the assessment day to performance[7,8]. Research using repeated assessments and accumulated school-day heat examines the conditions under which skills are acquired[9,10,11]. Evidence from Korea and India extends the analysis of accumulation to different school and household settings[12,13]. Reviews document substantial variation across exposure definitions, ages and outcomes[14,15,16]. Comparing two assessments is more informative when the dates, geography, and heat metric align, so differences between the instruments can be assessed against the same exposure contrast.

Schools can alter the relationship between outdoor heat and the conditions in which children learn. Research on the indoor environment connects classroom temperature to schoolwork and considers thermal conditions alongside ventilation and air quality[17,18,19,20]. A classroom crossover intervention in Costa Rica and evidence on the design of English classrooms illustrate how conditions inside buildings can be measured alongside educational outcomes[21,22]. Evaluations of thermal and air-quality improvements link these conditions to decisions about operating schools[23]. Task characteristics and exposure intensity shape the estimated thermal-performance relationship[24,25]. Indoor observations during a heatwave show how building conditions can separate outdoor weather from experienced heat[26]. Evidence of adverse learning associations under cold conditions in Australia further illustrates the relevance of the local thermal range[27].

This risk framework motivates a directional comparison of school resources. If greater thermal-room provision reduces the heat students experience during instruction, schools with more provision should tend to have a more favourable heat–score slope under the same outdoor exposure. The stock of installed equipment supplies one measurable part of this pathway. The realised protection depends on where students spend their time and how equipment and buildings perform during hot periods. The distinction matters for equitable adaptation. Research documents unequal access to household cooling in Brazil and other emerging economies, substantial global differences in air-conditioning availability and constraints on energy access[28,29,30]. Operating cooling equipment also affects electricity demand[31]. A school resource measure is consequently most informative when interpreted in relation to its use and the conditions it creates. Work on the implementation of climate education in India shows how formal provision can be separated from classroom practice[32]. In a different setting, controlled tests of a household passive cooler illustrate the importance of directly measuring achieved cooling[33].

Brazil offers a setting in which to connect regional surveillance with school-level evidence. The country spans large climatic differences and has national and international measures of learning. Work on public-school dropout associates accumulated school-year heat with disengagement, while a study of ENEM reports a negligible relationship between test-day weather and examination performance[34,35]. A recent correspondence has also identified heatwaves as a concern for educational inequality in Brazil[36]. The next question is how the relationship with learning appears across assessments when they use the same exposure comparison, and how much variation in heat sensitivity can be distinguished across schools with different resources.

We compare the Programme for International Student Assessment (PISA) and Brazil's Basic Education Assessment System (SAEB) in 2015 and 2025, assigning the same annual-average hot-day exposure change to each of the 27 states in both assessments. We compare the state-level relationships before and after accounting for macroregion means and examine their precision under alternative assumptions about geographic dependence. We then link a separate panel of public schools in 2019 and 2023 to nominal learning-period heat and their baseline thermal-room provision. These designs address two decisions that education systems face as heat risks change. The state comparison shows how regional learning evidence depends on the assessment and geographic comparison. The school comparison estimates how much the local heat–score relationship varies with reported provision.

Results

State mathematics changes differ across assessments

The common-period analysis covers all 26 Brazilian states and the Federal District. The PISA samples comprise 23,141 students in 841 schools in 2015 and 30,140 students in 1,053 schools in 2025. From the downloaded SAEB historical school workbook, 29,620 schools have valid mathematics and Portuguese scores in 2015 and 33,454 in 2025. The main SAEB comparison retains 24,344 schools with both subjects available in both years and consistent state membership, yielding 48,688 school-year records. Supplementary Table 1 gives state-level coverage in each cycle.

Both assessments use the identical state-level change in the annual mean number of days above 35°C over the three complete calendar years preceding each assessment. Exposure changes differ substantially across states

(Fig. 1). A separate school panel links 15,724 public schools in 4,175 municipalities to assessment-year nominal learning-period heat in 2019 and 2023. Baseline thermal-room provision is uneven: 69.3% of these schools report no thermally controlled classrooms and 14.4% report full provision. Mean learning-period exposure rises from 12.03 to 14.29 hot days (Supplementary Fig. 1a,b).

Across the 27 states, the two mathematics changes correlate weakly (Pearson r = 0.042). The equal-state mean change is −6.44 PISA points and +6.54 SAEB points.

All five slopes are negative before geographic adjustment

PISA and SAEB show the same direction of association under the common exposure definition (Fig. 2, Table 1 and Supplementary Fig. 2). In PISA, ten additional annual hot days are associated with −4.87 (95% CI −8.34 to −1.41) mathematics points, −5.75 (95% CI −9.59 to −1.90) reading points and −5.21 (95% CI −9.65 to −0.77) science points under independent-state HC3 inference with plausible-value pooling. In the paired-school SAEB analysis, the corresponding slopes are −2.25 (95% CI −3.78 to −0.72) mathematics points and −2.46 (95% CI −3.89 to −1.03) Portuguese points. These coefficients describe differences in score change across states. A negative slope can also indicate smaller gains in a state with increasing heat. The unadjusted PISA mathematics slope is −0.049 units of the original 100-point PISA mathematics reference standard deviation per ten additional annual hot days[37].

The strength of the interval evidence varies with the dependence model. With five-macroregion CR2 inference, the PISA mathematics interval is −29.29 to 19.55 points, and the paired-school SAEB mathematics interval is −6.40 to 1.90 points. The SAEB Portuguese slope retains a negative interval, −3.62 to −1.30 points. Using all available schools in the historical workbook produces negative SAEB point estimates in both subjects: −2.82 for mathematics and −3.06 for Portuguese. Complete state-model outputs are reported in Supplementary Tables 2, 4 and 5.

Macroregion adjustment attenuates the SAEB slopes

The slopes respond differently to macroregion adjustment (Table 1). The PISA mathematics slope moves from −4.87 to −4.56 points per ten additional annual hot days (95% CI −9.13 to 0.01, P = 0.05025). The corresponding reading and science slopes are −4.86 and −4.12 points. The paired-school SAEB slopes move from −2.25 to −0.53 for mathematics (95% CI −3.30 to 2.25, P = 0.69577) and from −2.46 to −0.86 for Portuguese (95% CI −3.28 to 1.55, P = 0.46589). The mathematics slope shrinks in magnitude by 6% in PISA and 76% in SAEB. These percentages describe attenuation within each assessment's native scale. Table 1 gives marginal intervals for each outcome.

Macroregion indicators account for 53.6% of the state variation in heat change. The North, Northeast and Centre-West contribute 43.7%, 38.4% and 17.6% of the within-region sum of squares, respectively. Within-region standard deviations are 15.0, 12.1 and 13.4 annual hot days in those regions and 2.1 and 0.6 days in the South and Southeast (Supplementary Table 10). In the five leave-one-region-out comparisons, PISA mathematics slopes range from −5.63 to −3.84 points. The intervals are widest after omitting the North or Northeast (Supplementary Table 9). The magnitude and precision therefore reflect the regional distribution of exposure variation.

Table 1 Associations of annual hot-day changes with state assessment scores

Assessment and outcome	Unadjusted estimate (95% CI)	P	Macroregion-adjusted estimate (95% CI)	P
PISA Mathematics	−4.87 (−8.34, −1.41)	0.00800	−4.56 (−9.13, 0.01)	0.05025
PISA Reading	−5.75 (−9.59, −1.90)	0.00522	−4.86 (−9.57, −0.15)	0.04384
PISA Science	−5.21 (−9.65, −0.77)	0.02354	−4.12 (−9.81, 1.56)	0.14578
SAEB Mathematics	−2.25 (−3.78, −0.72)	0.00572	−0.53 (−3.30, 2.25)	0.69577
SAEB Portuguese	−2.46 (−3.89, −1.03)	0.00157	−0.86 (−3.28, 1.55)	0.46589

Units are assessment points per ten additional annual hot days. Each model gives equal weight to 27 states. Both specifications use HC3 variance, with ten plausible values pooled for each PISA domain. Intervals are marginal and P values are two-sided. Supplementary Table 9 reports standard errors, degrees of freedom and region-omission checks.

School-level heat associations have wide intervals

The 2019–2023 school panel evaluates a more local and recent exposure contrast. School fixed effects and state-by-cycle effects compare score changes within schools while accounting for common state-level changes. Per ten additional nominal learning-period hot days, the mathematics association is 0.47 (95% CI −1.20 to 2.15) points and the Portuguese association is 0.73 (95% CI −0.24 to 1.71) points (Fig. 3). Both intervals span zero. At the fitted standard errors and degrees of freedom, an absolute slope of 2.35 mathematics points or 1.37 Portuguese points per ten nominal hot days corresponds to 80% detection probability (Supplementary Table 6).

The primary comparison uses 2019 and 2023 because the nominal 2021 school calendar is a weaker proxy for classroom time during pandemic disruption[38]. The planned three-cycle sensitivity includes 15,209 schools and gives a Portuguese estimate of 0.71 (95% CI 0.05 to 1.38, P = 0.03683). It estimates a contrast over a different set of cycles and schools. Additional checks vary the July exclusion, term-start definition and temperature threshold (Supplementary Fig. 3 and Supplementary Table 3). The earlier three-year background model uses an annual-average dose and appears separately in Supplementary Table 3.

Thermal-room provision and differences in heat slopes

The resource comparison uses municipality-by-cycle effects to assess differences among schools exposed to the same municipal weather. A 50-percentage-point higher baseline thermal-room share corresponds to a mathematics heat-slope differential of 0.13 (95% CI −0.56 to 0.82) points per ten hot days and a Portuguese differential of 0.40 (95% CI −0.38 to 1.18) points (Fig. 3). Both intervals span slope differences in either direction. At the fitted precision, 80% detection corresponds to a slope difference of 0.95 mathematics points or 1.08 Portuguese points per ten nominal hot days for the 50-percentage-point provision contrast (Supplementary Table 6). Smaller slope differences are less readily distinguished at this precision.

Geographic information is concentrated despite the large number of schools. Residualized heat information is equivalent in concentration to 14.0 equally informative states in the overall design and 7.8 in the resource design (Supplementary Table 8). The corresponding Satterthwaite degrees of freedom are 12.98 and 6.83. Thus, the precision of the resource contrast is governed by the distribution of identifying variation across places as well as the number of observed schools. The estimates from omitting each state are shown in Supplementary Fig. 4 and Supplementary Table 7.

Discussion

The evidence for an educational heat association depends on the assessment and on the geographic comparison. Aligning the dates and heat measure reveals a negative slope across all five state-level outcomes. With macroregion indicators, the PISA slopes change less in magnitude than the SAEB slopes. The school panel estimates a separate relationship over the learning period. Its intervals span zero for both the heat and thermal-resource comparisons.

The assessments represent different populations and measurement systems. PISA samples 15-year-olds in public and private schools. The paired-school SAEB series follows published ninth-grade means for the same public schools. The weak correlation in mathematics changes and opposite mean trajectories qualify the agreement in the unadjusted slopes. Both assessments share the same geographic gradient in heat, and state differences in enrolment, education and recovery can enter their score changes differently. The within-macroregion PISA estimates remain negative in all three domains, consistent in direction with earlier international heat and learning evidence[11]. The mathematics and science intervals include zero. The mathematics interval widens most when the North or Northeast is omitted. The attenuation of the two SAEB slopes identifies the importance of the between-region comparison for those outcomes. These differences motivate evaluating whether each assessment captures the population and learning outcome relevant to the adaptation decision.

The different time windows connect the study to two mechanisms of interest in climate adaptation. A three-year annual mean can describe the background heat conditions across several years of skill acquisition and school operation. The cumulative learning-period measure instead aligns heat with a defined period before an assessment. It supports a comparison of changes within schools while accounting for common state or municipal changes. Research distinguishes short-run weather responses from longer-run adjustments involving behaviour and institutions[9,39,40]. The Brazilian ENEM and dropout studies likewise concern different parts of an educational trajectory[34,35]. In our data, the regional and school contrasts also differ in population and adjustment. Reading each coefficient at its own scale preserves the distinction between the evidence needed for monitoring across places and the evidence needed for evaluating a school response.

Thermal-room share locates the adaptation comparison at the point of provision. Schools with the same municipal weather can differ in the number of temperature-controlled classrooms, but the provision-to-exposure pathway depends on which rooms are occupied, when equipment runs and the thermal conditions that result. This helps explain why the recorded share is a valuable starting variable and why a school investment evaluation should measure conditions along the pathway. Classroom interventions and indoor temperature studies give examples of measuring realised exposure alongside performance[21,26]. Linking those measures to the School Census would allow authorities to distinguish equipment coverage, operational availability and achieved classroom temperatures. Attendance and timetable records would then indicate how much of the improved environment reaches students during instruction.

The distribution of provision also matters for targeting. The school panel includes substantial shares at both no provision and full provision, with a wide range between them. A fixed 50-percentage-point contrast is a useful way to express the fitted slope difference across that range. The action it represents depends on each school's starting point and the reliability of operation. Where classrooms lack equipment, design measures such as shade and ventilation can be assessed alongside installation. Where equipment is already recorded, maintenance and actual use are distinct decisions. Studies of cooling access, affordability and electricity demand reinforce the need to examine operating conditions when planning adaptation[28,29,30,31]. These decisions benefit from information on classroom comfort and instruction in addition to the equipment count.

The information available for a resource comparison is distributed unevenly across Brazil. The municipality-by-cycle model identifies the resource contrast from schools that share municipal weather but differ in recorded provision. A state contributes more when it contains more variation in this comparison after adjustment. This is why a panel with thousands of schools can provide more limited precision for a resource gradient than its row count suggests. Clustered inference treats the geography of variation as part of the estimation problem[41,42,43]. The information shares in Supplementary Table 8 and state-omission estimates in Supplementary Fig. 4 show which places sustain the comparison. For a future evaluation, coverage across municipalities with contrasting provision and exposure histories would broaden the set of school conditions represented in the evidence.

The school results describe changes across cohorts during the recovery from pandemic disruption. Brazilian evidence documents learning losses during remote secondary education, and studies across other systems document unequal learning deficits[38,44,45]. Changes in attendance, instruction and recovery can alter how a nominal calendar represents time spent learning at school. The school panel represents the linked cohort with

score coverage in 2019, 2021 and 2023, and its primary heat comparison uses the two endpoint cycles. During 2021, variation in remote and in-person provision can change what a nominal hot day represents. The three-cycle estimate therefore addresses a broader period and a slightly different cohort, both relevant when interpreting its more positive Portuguese association. Interpreting the estimates at the level of the published school means and state aggregates respects the populations represented by each source[46,47].

Education authorities can use these results to plan adaptation in stages. Regional heat indicators and aligned assessments can be used to identify places for closer investigation. The next step is to connect campus locations, classroom conditions, attendance and equipment operation during hot periods. Monitoring those variables before and after a rollout would place the timing and use of investments alongside the outcomes they are meant to change. Staggered upgrades, with credible comparison schools and repeated measurements, could then estimate how much a specific change in classroom conditions alters learning under heat. For Brazil, the immediate implication is to use each assessment in relation to its population, check the geographic source of the heat gradient and link adaptation evaluations to the conditions students experience in their classrooms.

Methods

Assessments and study populations

We used the public PISA 2015 and 2025 student files[48,49], retaining Brazil and the public state geography that can be linked consistently across the two cycles. The analysis covers 27 state-level units. Ten plausible values were used for each of mathematics, reading and science, with a common valid denominator across the 30 plausible-value fields. State estimates use final student weights. Plausible-value and secondary-analysis procedures follow the measurement principles described for large-scale assessments[47,50,51]. The source samples include both public and private school students within the PISA target population.

For SAEB, we extracted published ninth-grade mathematics and Portuguese means from the school-level historical workbook distributed with the 2025 IDEB results[52]. These fields report subject proficiency. The IDEB composite separately combines achievement and progression. School identifiers link records across years. The common-period main sample requires valid values in both subjects in 2015 and 2025 and the same state in both years. Schools are weighted equally within a state. The publication-coverage sensitivity uses every school with both subjects available in each year of the downloaded workbook. Coverage counts refer to the workbook's historical roster.

The school-level panel starts from the previously linked 2019, 2021 and 2023 public-school score cohort. School Census characteristics and calendars[53] and the required socioeconomic and weather information define the linked sample. The current-year main analysis retains schools with eligible calendars and complete fixed exposure windows in 2019 and 2023, producing 15,724 schools, 4,175 municipalities and 31,448 records. Removing 2021 from the primary fit retains the original three-cycle score-availability selection. The school means represent successive student cohorts.

Heat exposure at state and municipal scales

The state comparison uses the OECD regional extreme-temperature series, version 2.0, measure HD_PW_EXP and threshold H_35[54]. We calculate the population-weighted mean annual number of hot days over 2012–2014 for the 2015 assessment and 2022–2024 for the 2025 assessment. The OECD series is based on ERA5 reanalysis[55]. Exactly the same state exposures are assigned to PISA and SAEB. The regression dose is the change in this annual mean divided by ten. This dose captures observed change in the three-year annual average.

For the school panel, we use daily maximum temperature from BR-DWGD version 3.2.4 and the retrieved 2001–2025 Tmax member, whose actual time coordinates were checked[56,57]. Daily indicators above 35°C are area-weighted across each municipality. The reference term start is the municipal median among active public lower-secondary schools with valid reported calendars. At least 80% of the reference schools must meet the calendar rule. The window ends on 20 October, before the earliest nationally documented SAEB start in the

included cycles. The main approximation excludes weekends, national holidays and all of July and requires at least 100 candidate weekdays. Individual school calendars must also be eligible. The resulting variable is a cumulative nominal learning-period exposure, with area weighting allowing fractional hot-day totals.

School thermal resources and covariates

The baseline resource is the 2019 proportion of classrooms reported as thermally controlled. The source definition includes air conditioning, heating and other temperature-control equipment. We preserve that definition throughout the analysis. The recorded share measures equipment coverage at baseline. Other baseline variables are socioeconomic status, rural location, administrative network and log lower-secondary enrolment. Baseline socioeconomic status comes from INEP's 2019 school-level INSE workbook. We match the school code and require agreement on the municipality code.

Common-period state models

For each assessment a and domain d, we estimate a separate state-level first-difference model:

$$\Delta Y(s,a,d) = \alpha(a,d) + \beta(a,d) \times \Delta H(s)/10 + \varepsilon(s,a,d).$$

All 27 states receive equal regression weight. For SAEB, ΔY is the change in the equal-school state mean. For PISA, the model is fitted separately to each plausible value and coefficients are pooled. We report HC3 covariance with finite-sample t inference for the independent-state model. For $m = 10$ plausible values, W is the mean within-value regression variance, B is the sample variance of the slope estimates, and $T = W + (1 + 1/m)B$ is the total variance. We use the Barnard–Rubin small-sample t approximation[58]. With $\lambda = (1 + 1/m)B/T$, $\nu_{old} = (m - 1)/\lambda^2$ and $\nu_{obs} = \nu_{com}(\nu_{com} + 1)(1 - \lambda)/(\nu_{com} + 3)$, the pooled degrees of freedom are $(1/\nu_{old} + 1/\nu_{obs})^{-1}$. For HC3 models, ν_{com} is the number of states minus the number of fitted coefficients. Table 1 reports the unadjusted and macroregion-indicator specifications using the same HC3 variance procedure. Five-macroregion CR2 covariance with Satterthwaite inference for the unadjusted slopes is a separate dependence sensitivity[43]. For the five-cluster PISA CR2 sensitivity, the minimum per-value Satterthwaite degrees of freedom supplies ν_{com} for approximate pooling.

PISA final and 80 replicate weights were also used in the existing state-aggregation and sampling-variance diagnostics. The latter preserve replicate covariance across states within a cycle. We report these sampling diagnostics separately from the aggregate-regression HC3 and CR2 intervals. The displayed PISA intervals therefore follow the stated aggregate-regression variance model. PISA and SAEB slopes are reported in their respective score units. The PISA mathematics rescaling divides by 100 points, the original reference standard deviation for the OECD mathematics scale[37]. This fixed reference differs from the observed dispersion of Brazilian state mean changes.

Within-macroregion state models

We add four indicators for Brazil's five macroregions to the state model:

$$\Delta Y(s,a,d) = \alpha(a,d) + \Sigma_r \gamma(r,a,d)\, I(s \text{ belongs to } r) + \beta(a,d) \times \Delta H(s)/10 + \varepsilon(s,a,d).$$

The common slope is estimated from variation around macroregion means in the 27 states. HC3 covariance and the same plausible-value pooling apply as in the unadjusted analysis. Complete-data residual degrees of freedom are 21 with macroregion indicators and 25 without them. We rerun all five adjusted models after omitting each macroregion in turn. We describe exposure support using the standard deviation in annual hot days and the share of the within-region exposure sum of squares. The South and Southeast have limited within-region exposure variation, so we report pooled slopes and omission checks. Pearson correlation and equal-state means describe the two mathematics change series, with PISA plausible values averaged within each state for these descriptions.

School-level overall and resource models

Let Y(i,t) be a published school subject mean, H(m,t) the municipal nominal learning-period exposure divided by ten, and R(i) the baseline thermal-room share. The overall design includes school fixed effects, state-by-cycle effects, H(m,t), candidate-day duration, and heat interactions with centered baseline thermal-room share, socioeconomic status and rural status. Baseline thermal resources, socioeconomic status, rural status, administrative network and log enrolment are also interacted with cycle. Centering makes the reported heat coefficient the model slope at the sample means of the interacted baseline variables.

The resource design replaces state-by-cycle with municipality-by-cycle effects. Municipal heat and candidate-day duration main effects are absorbed. The heat-by-resource coefficient describes how the heat–score slope differs with baseline provision among schools in the same municipality. We multiply it by 0.5 to report a 50-percentage-point resource contrast. Schools receive equal weight. Standard errors use CR2 covariance clustered by 27 states and Satterthwaite degrees of freedom. The four main school contrasts are accompanied by Holm-adjusted p values in the full tables. Plotted intervals are marginal 95% intervals.

Fixed sensitivity analyses retain July, fix term starts to their 2019 reference, lower the threshold to 30°C, add 2021, and use the prior three-year annual-average exposure. The last changes the exposure dose and is reported separately in the supplementary table. Five-macroregion intervals are also retained for the four main school contrasts. Interval estimates describe the range of heat–score differences compatible with the fitted comparisons. Equivalence testing requires a substantively chosen margin[59].

Information concentration and analytical sequence

We residualize the focal design column against the remaining columns, sum its squared residuals within state, and divide by the total to obtain state information shares. The reciprocal sum of squared shares describes concentration in units of equally informative states. We calculate the inferential degrees of freedom separately using the Satterthwaite procedure.

The common-period assessment comparison followed the earlier state and school analyses. The PISA macroregion specification was already part of the Brazil model set. The paired SAEB macroregion analysis and the full set of region-omission checks were added in the manuscript revision after inspecting the unadjusted comparisons. The dated records preserve that sequence and the complete estimates.

Statistics and reproducibility

We report marginal 95% confidence intervals and exact two-sided t-test P values for zero slopes, using $\alpha = 0.05$. Inference for state models uses HC3 to account for unequal residual variance and leverage with 27 observations. The separate CR2 analyses account for residual dependence within macroregions or, for school-level models, within states. Satterthwaite degrees of freedom accompany CR2 estimates. The four primary school contrasts also have Holm-adjusted P values. The state analyses use 27 states and the paired SAEB aggregation uses 24,344 schools and 48,688 school-year records. The primary school analyses use 15,724 schools and 31,448 school-year records. Model-specific counts, degrees of freedom, and exact P values are given in Supplementary Tables 2–5 and 9. The correlation, exposure variation and school state-omission point estimates are descriptive diagnostics.

We use a two-sided noncentral-t approximation to calculate the absolute effect size associated with 80% detection probability at $\alpha = 0.05$, holding the fitted model standard error and degrees of freedom fixed (Supplementary Table 6). This calculation describes precision for hypothetical effect magnitudes.

Secondary data and computational assistance

The study used publicly released, de-identified PISA student records and published SAEB school-level results, alongside public school and weather data. The secondary analysis involved no primary data collection,

contact with participants or access to identifiable student records. Ethics approval was not required for this secondary analysis.

Data Availability

PISA public-use files are available through the OECD[48,49]. Published school outcomes, School Census files and their documentation are available through INEP[52,53]. Regional heat data are available through the OECD extreme-temperature dataflow[54], and BR-DWGD through the provider's public distribution[56,57]. The accompanying Brazil_heat_learning_reproduction.zip archive contains the state and school analysis inputs, derived municipal weather and calendar data, and figure source data. Its README maps the files to their original sources.

Code Availability

The accompanying Brazil_heat_learning_reproduction.zip archive contains the Python and R scripts to build the nominal learning-period windows from daily municipal summaries, fit the school models, recalculate the common-period state HC3 comparisons and redraw the figures. Its README provides the execution order and software requirements.

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Author contributions

W.L. designed the study, compiled and linked the datasets, carried out the statistical analyses and precision calculations, prepared the figures, and wrote the manuscript.

Competing interests

The author declares no competing interests.

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Figure 1 Observed change in hot-day exposure across Brazil

Changes in population-weighted annual-average days with maximum temperature above 35°C between 2012–2014 and 2022–2024, the three complete calendar years preceding the 2015 and 2025 assessments, for all 27 Brazilian states. The colour scale is centred on zero and spans −50 to +50 annual hot days. State outlines use the official IBGE 2022 mesh, simplified for printing and rendered in an Albers equal-area projection; abbreviations follow IBGE.

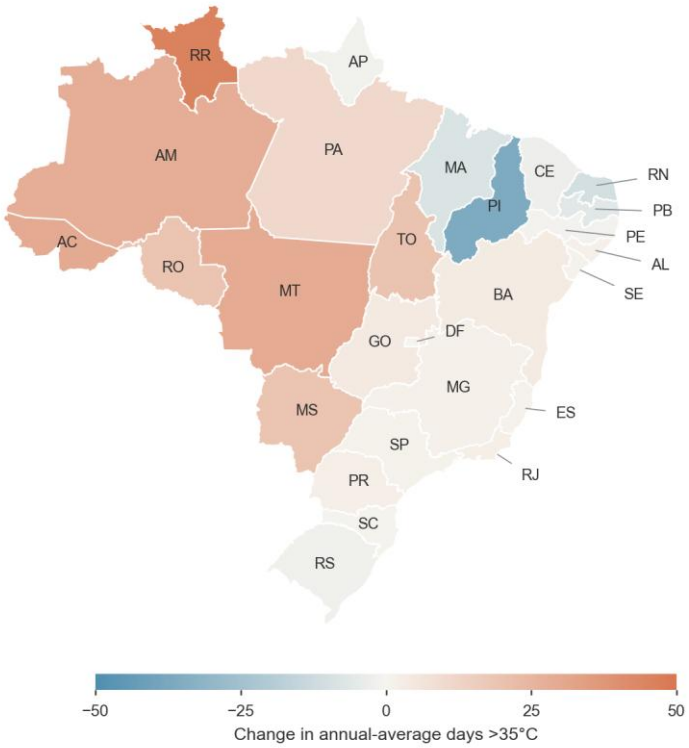


Figure 2 State changes in mathematics and heat exposure in PISA and SAEB

a, PISA mathematics. b, SAEB mathematics. Each panel shows the same 27 Brazilian states and the same change in annual-average days above 35°C between 2015 and 2025. Score changes use the native scale of each assessment. PISA state means use final student weights and average ten plausible values. SAEB state means give equal weight to the 24,344 public schools with both subjects and cycles available and consistent state membership. Solid lines are the unadjusted equal-state regressions. Labels identify states with an absolute exposure change of at least 20 annual hot days. Table 1 compares unadjusted and macroregion-adjusted slopes.

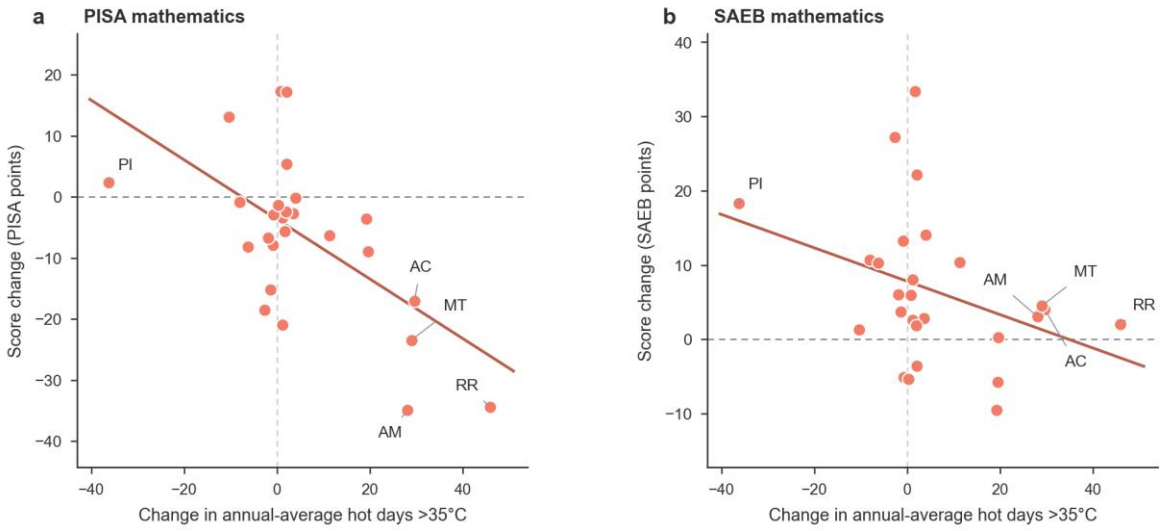
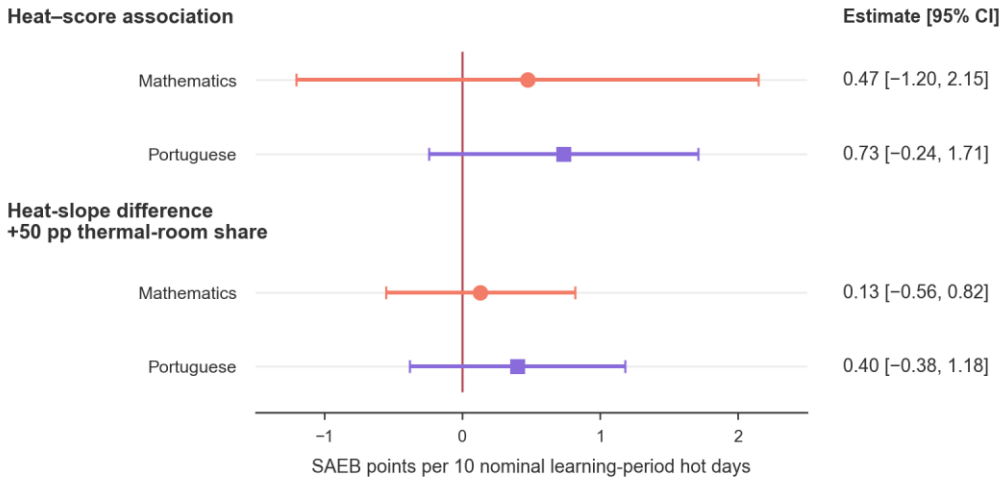


Figure 3 Learning-period heat and school thermal resources

The upper rows show the association of ten additional nominal learning-period hot days with school SAEB mathematics and Portuguese scores. The lower rows show the change in this slope associated with a 50-percentage-point higher 2019 thermal-room share. The overall comparison uses school and state-by-cycle effects. The resource comparison uses school and municipality-by-cycle effects. Points and bars show estimates and marginal 95% state-clustered CR2 confidence intervals. Circles identify mathematics and squares Portuguese. The cohort comprises 15,724 schools, 4,175 municipalities and 31,448 school-year records in 2019 and 2023. Satterthwaite degrees of freedom are 12.98 for the heat association and 6.83 for the resource contrast. Supplementary Fig. 3 shows the fixed sensitivity analyses. Supplementary Fig. 4 shows state-omission estimates.



Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryInformation.pdf