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Introduction

The accelerating climate crisis poses a significant threat to the development of young children across the globe. Climate change is considered one of the main challenges of the new ecology of early childhood, a unique set of circumstances currently shaping young children's ecosystems in unprecedented ways, creating new challenges for both children and the adults who support them (Fisher & Lombardi, 2025). The concerns around climate change as an adversity in human development derive from its potential to affect and disrupt many layers of an individual’s ecological system simultaneously, leading to compounded consequences to children and families (Bronfenbrenner, 2005; Cuartas et al., 2024; Fisher & Lombardi, 2025).

Young children are especially vulnerable to the effects of the climate crisis due to accentuated neural and biological plasticity, exposing the developing brain and other biological systems to physical and psychosocial risks (Black et al., 2017; Cuartas et al., 2024; Rees, 2021; UNICEF, 2022). Recent scholarship has highlighted the particular importance of the so-called ‘next 1000 days’, a critical yet understudied developmental phase. The ‘next 1000 days’ refers to a second phase in early childhood (i.e., roughly ages 2-5 of a child’s life, following the ‘first 1000 days’ of a child’s life, which encompasses the pre-natal period through a child’s second birthday; Black et al., 2017; Fox et al., 2010) that offers a window of opportunity to promote nurturing and caring environments, establish healthy behaviours, and build on early gains to facilitate resilience in ecological systems and support trajectories of healthy development (Draper et al., 2024).

During this period, exposure to extreme weather events may be particularly harmful, as it can disrupt access to early learning environments, increase caregiver stress, compromise nutrition and health services, and heighten the risk of exposure to violence or neglect, factors known to adversely affect brain development and emotional regulation during this sensitive developmental window (Cuartas et al., 2024). Additionally, this is a pivotal window for investment and intervention, and documenting pathways of vulnerability and resilience is key for governments and agencies to successfully direct resources to support children’s development during this period and beyond (Aguayo & Britto, 2024; Nores et al., 2024).

As we elaborate below, extreme precipitation is a type of climate change-induced hazard that may pose particularly serious risks to young children and their families, due to its potential to affect both proximal and distal ecological systems, including biological health and social and caregiving systems (Aguilar & Vicarelli, 2022; Thapa et al., 2025). Given the importance of this developmental period and the urgent need to understand how extreme weather events in general, and extreme rainfall in particular, affect child development, we leverage openly available weather data matched to a high-quality population-based developmental index in South Africa to examine how exposure to extreme precipitation during early learning experiences affects developmental outcomes at age 4.

To assess differential vulnerability, we integrate different measures of access to services and resources, situated at different loci of a child's bioecological system, to examine its potential role as a moderator of the effect of extreme rainfall. By focusing on this critical developmental window and emphasizing structural conditions that shape resilience, our study addresses a key gap in the literature linking climate variability to early childhood development and offers new evidence to inform targeted interventions.

Extreme weather events

The increasing frequency of extreme weather events is a key mechanism through which climate change poses risks to child development. An extreme weather event is a time and place in which weather or climate conditions - such as temperature, precipitation, drought, or flooding - exceed a threshold value near the upper or lower ends of the range of historical measurements (Herring, 2020). Over the past 15 years, research has demonstrated that global warming has made many extreme events more likely, more intense, longer-lasting, or larger in scale than they would have been without it (Herring, 2020).

Exposure to such events at high frequency has drastic implications for children's physical, cognitive, and emotional development. At the physical level, higher rates of vector-borne diseases and water contamination, as well as diminished access to safe housing and nutrition disrupt developmental trajectories in harmful ways, especially in the early years (e.g., Helldén et al., 2021; Walker et al., 2011). Extreme weather events also affect families, communities, and societies by, for example, disrupting social networks of economic activities, separating and relocating families and communities, and impeding educational experiences (Cuartas et al., 2024). These disruptions have the potential to impair early learning and prevent young children from reaching their developmental potential in cognitive and socioemotional skills. In 2024, at least 242 million students from pre-primary to upper secondary education across the globe have experienced extreme weather-related disruptions in their learning experiences (UNICEF, 2025). Importantly, such risks are not distributed equally across countries. 74 percent of the 242 million affected students are in low- and lower-middle-income countries, with heatwaves, floods, and tropical cyclones being the leading causes of disruptions (UNICEF, 2025). In the continent of Africa, for example, climate change-related disasters have put 20 million children at risk of dropping out of school, in addition to the 107 million children who already do not have access to school-based learning (UNICEF, 2025).

Extreme rainfall

Extreme rainfall is a type of extreme weather events that can affect children and families in particularly harmful ways. Globally, up to 1.81 billion people face significant flood risks because of extreme precipitation, making floods the most common type of natural disaster, particularly in low- and middle-income countries (Rentschler et al., 2022). Recent research from NASA indicates that the proportion of people worldwide living in flood-prone areas has risen by up to 24% since 2000 - an increase 10 times greater than expected - driven largely by intensified rainfall, rising sea levels, and more intense hurricanes (Tellman et al., 2021). Climate change has significantly altered the precipitation patterns in many regions of the world, turning previously flood-safe areas into flood-prone areas (Goswami et al., 2006; Guhathakurta et al., 2011; Hashim & Hashim, 2016). Extreme precipitation affects many facets of the lives of families and young children (ARNEC, 2024). It increases water contamination and the risk for waterborne disease, negatively impacting health outcomes for children and families and increasing overall mortality (Chhetri et al., 2019; Dimitrova & Bora, 2020; Mallett & Etzel, 2018, 2018; Taylor et al., 2011; Wang et al., 2022).

Extreme rainfall can also damage crops, affecting household incomes and often leading to higher food prices, which in turn impacts household food security and children's nutritional intake (Mai & Hibiki, 2023; Nguyen & Le, 2025; Vu, 2023). Societal and community implications of flooding and extreme rainfall are also far-reaching. Flooding has been shown, for example, to exacerbate the risk of political conflict, especially in politically unstable regions (Ghimire & Ferreira, 2016; Lee et al., 2017). The chaos during and after extreme rainfall events and floods also heightens the risk of child abuse, exploitation, and trafficking, as displacement and overcrowded shelters expose children to unsafe environments (ARNEC, 2024).

Further, extreme precipitation can severely impair responsive caregiving and learning. Flood-related disruptions in educational experiences are estimated to have affected around 8 million students in Southern and Eastern Africa in 2024 alone (UNICEF, 2025). Floods can damage education infrastructure and induce prolonged closures of schools and childcare centres, leading to potential deficits in cognitive development (Venegas Marin et al., 2024; Mai & Hibiki, 2023; Nguyen & Le, 2025; Vu, 2023). The hardships associated with extreme precipitation and floods can also decrease caregivers' ability to provide responsive care to young children, for example through heightened distress from coping with extreme weather (Hrabok et al., 2020) and increased long-term risk for mental health complications in parents (Mallett & Etzel, 2018; Saenz, 2025).

Recent events in South Africa

Recent major floods and extreme rainfall events in South Africa have led to significant humanitarian and infrastructural crises. In the regions of KwaZulu-Natal and Free State, for example, a series of floods in April 2022 resulted in over 400 deaths and widespread displacement, and more recent extreme rainfall in January 2024 affected an additional 6,400 people, with dozens of fatalities, and widespread crop losses and displacement. In June of the same year, more record-level precipitation caused by a tropical storm resulted in the destruction of over 7000 houses and dozens of fatalities, totalling over USD $68.6 million in damages (Engel, 2024). In the Eastern Cape, another large flood in October 2024 displaced over 3,000 people, with more than 10 fatalities and severe infrastructure damage. These events highlight the recurring and escalating nature of flood disasters in the region.

In South Africa, the consequences of extreme rainfall may be compounded by persistent structural inequalities. The country remains one of the most unequal societies in the world (Francis & Webster, 2019), with profound inequalities persisting between geographical areas, largely inherited from apartheid-era segregation policies, and manifesting in access to resources and opportunities, directly affecting early childhood development (Ashley-Cooper et al., 2019). From a bioecological systems perspective, these inequalities manifest at different levels of a child's ecological system (Bronfenbrenner, 2005; Fisher & Lombardi, 2025). At a more distal level (i.e., exo- and macro-systems), families in historically under-resourced areas may carry disproportionate risk of detrimental impacts of extreme rainfall due to inadequate drainage and sewer systems (Pandey et al., 2022; Sutherland et al., 2015), diminished access to health care services (Stuckler et al., 2011), and slow recovery efforts from government agencies (Van Niekerk et al., 2018). At a more proximate level (i.e., microsystems and proximal processes), families may be subjected to more vulnerable housing infrastructure (Ngcamu, 2022; Pandey et al., 2022), higher levels of caregiver stress and maladaptive parenting practices (Cuartas et al., 2025) and more disruptions to education and formal schooling (Venegas Marin et al., 2024).

Consequently, floods not only cause immediate destruction but also reinforce long-standing socioeconomic and racial-ethnic disparities, limiting recovery opportunities for the most vulnerable populations. This dynamic reflects a core concern in the climate justice literature: that climate-related hazards tend to exacerbate pre-existing structural inequalities, disproportionately affecting those with the least capacity to prepare for or recover from such shocks (Cuartas et al., 2024, 2025; Deivanayagam et al., 2023).

Current study

Research on how extreme precipitation and floods affect human development is vast. To date, many studies have looked at how floods affect family income and economic opportunities (e.g., Baez et al., 2017; Bangalore et al., 2019; Boansi et al., 2021), child health (e.g., Helldén et al., 2021; Mallett & Etzel, 2018; Thai & Falaris, 2014), and cognitive and educational outcomes later in life (Aguilar & Vicarelli, 2022; Dasgupta & Karandikar, 2021; Huang & Dong, 2025; M. T. Nguyen & Le, 2025; Nübler et al., 2021; Pazos et al., 2024; Thai & Falaris, 2014; Zimmermann, 2020). However, a paucity of studies remains about how exposure to extreme rainfall relates to cognitive and emotional development specifically during formal early learning experiences (Draper et al., 2024; Nores et al., 2024).

As such, the present study leverages recent exogenous variation in rainfall in South Africa to answer the following overarching research question: How does exposure to extreme rainfall affect cognitive and emotional development of young children? Specifically, we investigate two research questions:

1) Does exposure to extreme rainfall events during early learning affect cognitive, socioemotional, and learning outcomes of young children at age 4?
2) Does access to resources and services moderate the hypothesized effect?

For the first research question, we hypothesize that children in early learning programmes (ELPs) exposed to more extreme rainfall events will display greater challenges on developmental assessments (H1). Regarding the second research question, we hypothesize that the impact of extreme rainfall events will be moderated by access to services and resources (H2). Specifically, we expect children whose families and communities are under-served and under-resourced to experience more severe developmental impacts than their more advantaged peers. We chose to examine moderators at different structural levels (i.e., family, ELP, and municipality; see Methods section below) to probe for the role of context at different levels of a child’s bioecological system (Bronfenbrenner, 2005; Fisher & Lombardi, 2025).

Methods

This study is conducted in partnership with DataDrive2030, a South African non-profit whose mission is to leverage the power of data tools to inform and amplify policy impact. In partnership with the South African Department of Education, DataDrive2030 has created Thrive by Five Index, a national early childhood development index that measures the developmental progress of 4-year-old children before they enter school. DataDrive2030 uses a stratified, multistage sampling strategy across regions, districts, and early learning centres to collect nationally representative data on children between 4 and 5 years old. In the 2024 wave, 5001 children enrolled in 1388 ELPs have completed assessments (for more details on sampling, see Giese et al., 2025; Pettersson Gelander et al., 2025).

Operationalization

Precipitation data

Rainfall data was obtained from Climate Hazards InfraRed Precipitation with Stations (CHIRPS; Funk et al., 2015) version 3.0. CHIRPS is a high-resolution (~0.05°) quasi global (50°S–50°N) precipitation dataset, combining infrared (IR) satellite Cold Cloud Duration data with extensive ground station measurements, spanning from 1981 to near present. Historical daily precipitation statistics were computed using CHIRPS data for each ELP location in our sample, spanning the years 1981–2010. ELP location was chosen as the unit for extreme rainfall impact as (1) our research questions underscore the importance of early learning experiences (Draper et al., 2024) and (2) no information on family household location is available. For each calendar day and ELP location, we calculated 99 precipitation percentiles. These robust statistics are well-suited to highly skewed distributions such as rainfall (Wilks, 1990).

Subsequently, we extracted daily precipitation data for each ELP location during the 18 months preceding each child's assessment date. This time window was selected because, first, it corresponds to a key window of early learning when South African children are expected to be enrolled in ELPs and engaging in curriculum-based learning ECE (3-5 years; Department of Basic Education, 2015), as our sample mean age is 4.5 years. Additionally, this time window allows us to be conservative regarding our confidence that extreme weather events at the ELP location were in fact experienced by the child and their family, as roughly 60% of caregivers interviewed stated their child was already enrolled in their local ELP at 18 months prior to assessment (although we restrict the sample for moderation analysis, see Moderators subsection).

Extreme rainfall exposure was measured as the number of days in those 18 months with precipitation exceeding the historical 99th percentile for the corresponding calendar day and occurring within the local rainy season, in accordance with extreme rainfall research defining exposure variables in terms of frequency of experiencing events above a certain threshold (Zhang et al., 2011). A 99th percentile threshold was chosen as recommended by South African hydrology research (Vermeulen et al., 2024). For detailed information of how rainy season was defined according to an ELP's location, as well as what 99 percentiles look like across provinces, please refer to Appendix 1.

Child outcomes

Child cognitive and socioemotional outcomes are measured with the Early Learning Outcome Measure (ELOM) tool as well as an adult-report socioemotional functioning scale (SEF; for a full description and technical report on the measurement tool, see Giese et al., 2025, Pettersson Gelander et al., 2025). For this study, we include the following ELOM domains: emergent numeracy and mathematics (ENM), emergent literacy and language (ELL), and cognitive and executive functioning (CEF). Children's social and emotional functioning was assessed using standardized items on self-care, peer interactions, and emotional regulation. Social functioning included measures of independence, cooperation, and conflict resolution, rated on a four-point scale (e.g., "Does the child cooperate with peers without prompting?"; 1 = None of the time to 4 = All of the time). Emotional functioning captured adaptability, confidence, and self-initiation, rated on a three-point scale (e.g., "Does the child adjust well to changes in routine?"; 0 = No to 2 = Often). These four domains (SEF, CEF, ELL, and ENM) were chosen as they map into the main areas of interest of the study: socioemotional functioning, cognition and executive functioning, and early learning (in particular, numeracy and literacy). Motor coordination subscales were not included as they are not relevant to the constructs under investigation in this study.

Moderators

We operationalized access to services and resources at three different levels: family, ELP, and municipality. To derive a composite indicator of family SES, we constructed an index combining information on material assets, caregiver education, employment, and internet access. This variable represents a child's level of access to services and resources at its most proximal ecosystem: the family household (Bronfenbrenner, 2005). Binary indicators were created for ownership of key household items: vacuum cleaner, washing machine, computer, and car, as well as for caregiver education (at least secondary education), current employment, and internet access. Each variable was coded as 1 if present and 0 otherwise. Because all indicators were dichotomous, we estimated a tetrachoric correlation matrix to capture the underlying associations among them.

A principal component analysis (PCA) was then performed on this matrix, and the first unrotated component was extracted to represent the latent SES dimension. Factor scores from this component were computed using the Thurstone method and standardized to form the continuous SES index used in subsequent analyses.

The second moderation analysis utilizes ELP monthly fees as a centre-level indicator of access to services and resources, a further key micro-system harbouring proximal processes and driving early learning (Bronfenbrenner, 2005). This variable was constructed according to Pettersson Gelander et al. (2025, Annex 2), which integrates principal-reported fees and primary caregiver-reported payments using predefined rules. In this process, the principal's report is used by default unless contradictory evidence exists, with caregiver reports informing the value only when principal data are missing, zero, or substantially discrepant (i.e., differences exceeding R50 or 25%).

At the municipal level, access to services and resources was operationalized with the South African Multiple Deprivation Index (SAIMD; Gasior et al., 2024). This indicator represents exo- and macrosystem characteristics of children's bioecological systems, as it reflects the broader structural and institutional conditions that shape the quality and stability of children's immediate settings but lie beyond their direct, everyday experience. SAIMD aggregates municipality-level information on employment deprivation (i.e., exclusion from the world of work, formal and informal), education deprivation (i.e., lack of secondary education or higher), material deprivation (i.e., lack of specific necessary household goods) and living environment deprivation (i.e., lack of service delivery and adequate housing), combining indicators into a composite measure of multiple deprivation. The most recent version of SAIMD was developed with South African Census data from 2022.

Analysis and specification

Analysis was conducted in R (R Core Team, 2021) with mixed-effects models, and framed within a model comparison paradigm.

Hypothesis 1
For each dependent variable (ENM, ELL, CEF, SEF), a baseline model was generated with covariates and moderators as predictors. Exposure models were generated to test Hypothesis 1, where exogenous variation in exposure to extreme rainfall was added under the assumption that anomalous extreme precipitation events are as-good-as-randomly assigned over time and space. Models were compared with covariates-only specifications via likelihood ratio tests.

Hypothesis 2

For Hypothesis 2, a restricted dataset was used only with children whose caregivers reported that they were enrolled in the ELP at the time of the beginning of the exposure window (i.e., 18 months prior to assessment). That methodological decision was based on the fact that the moderators were largely not comparable across children who were vs. were not enrolled at 18 months prior to assessment. Children who were not enrolled at 18 months prior to assessment had lower family SES (standardized mean difference (SMD) = 0.2 SDs, $p < .001$), were living in municipalities with higher levels of deprivation (SMD = 0.07 SDs, $p < .01$), and attended ELP with slightly lower, although comparable fees (SMD = .02, ns). These differences indicate that children with fewer resources and less stable access to services are more likely to switch ELPs during the exposure window. Including such cases in moderation analysis would introduce endogenous selection into the treatment variable, generating non-random variation in the moderators and undermining our identification strategy. Results from a moderation analysis with an unrestricted sample can be found in Appendix 3.

We generated an interaction model for every moderator and outcome, with the interaction term between exposure and the moderator added and compared with an exposure-only model with a likelihood-ratio test. All models include person-level (age, gender, primary language) and ELP-level Learning Programme Quality Assessment (LPQA; Biersteker et al., 2025) domain scores as covariates. The LPQA tool consists of 22 items across five domains: (i) Materials and equipment which evaluates available learning materials and their use in the classroom; (ii) planning and assessment which measures the use of the curriculum, programme planning and how children are monitored; (iii) the learning programme which examines the daily schedule and the quality of activities related to literacy, numeracy, group sessions, and free play; (iv) teaching strategies, that evaluates the strategies used by practitioners to support and extend children's learning, and whether practitioners encourage independence; and (v) relationships and interactions, which looks at the interactions between staff and children, and how staff encourage positive peer interactions among children. Each item was rated and coded numerically as 1 (Inadequate), 2 (Basic) and 3 (Good), and the numeric codes for all 22 items were summed and divided by the maximum possible score of 66. The derived percentages were then mapped to the following three categories at both the domain level and total level: (i) inadequate (Less than 60% of the domain total score), (ii) basic (60% - 80% of the domain total), and (iii) good (80% or more of the domain total).

All models include nested random intercepts for ELPs. In models with SAIMD as a moderator, municipality random intercepts are also included. Detailed information on the equations for each model is available in Appendix 2. Descriptives for both the full and restricted sample can be found in Appendix 4.

Results

Hypothesis 1

Results from Hypothesis 1 can be found in Table 1.

Table 1: Regression Results: Extreme Rainfall Exposure and Child Development Outcomes Coefficients from Multilevel Models

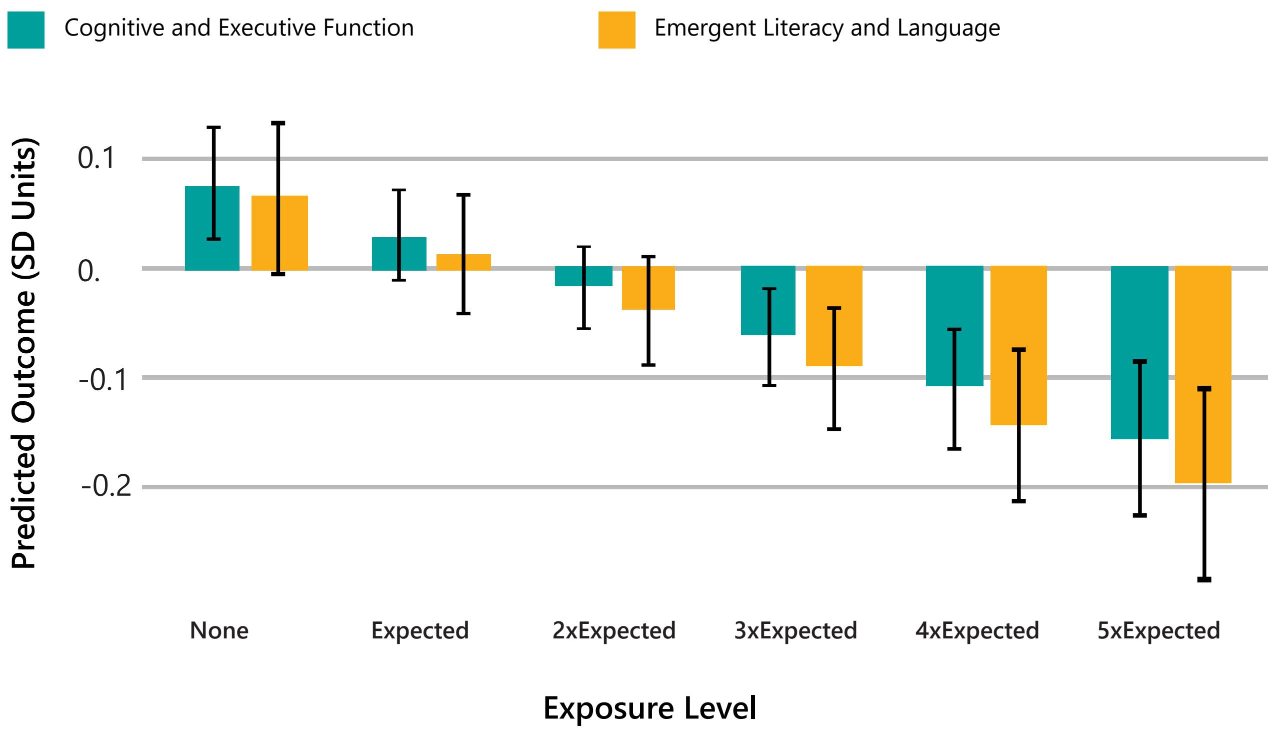
Outcome	Emergent Literacy & Language	Emergent Numeracy & Mathematics	Cognition & Executive Function	Emergent Literacy & Language
Model	Exposure	Exposure	Exposure	Exposure
Extreme Rainfall (std.)	**-0.07***	-0.04	**-0.06***	0.05
Marginal R^2	0.078	0.089	0.132	0.072
ΔR^2	**0.003***	0.003	**0.003***	0.001
p-value	**0.029**	0.189	**0.011**	0.177

Note: ΔR^2 and p-values are given to the comparison to a baseline model without the exposure to extreme rainfall variable

In comparison to the covariate-only model, the exposure model exhibited better model fit for ELL ($\Delta R2 = 0.003$, $p<.05$) and CEF ($\Delta R2 = 0.003$, $p<.05$) with a 1SD increase in rainfall during rainy season (i.e., ~ 4 additional days) significantly associated with approximately .06 and .07 SDs decrease in literacy and cognition and executive functioning, respectively. Models that included the rainfall exposure variable did not fit better for ENM ($\Delta R2 =0.003$, $p = .189$) or SEF ($\Delta R2 = 0$, $p = .177$), with respectively non-significant β coefficients between -.07 and .08.
Figure 1 illustrates the predicted outcome mean for CEF and ELL in accordance with the level of extreme rainfall days experienced during rainy season.

Figure 1

Predicted Outcomes by Exposure to Extreme-Rain Days During Rainy Season



Hypothesis 2

Interaction models with municipality-level SAIMD yielded a significant interaction coefficient for SEF (β = -.09, $\Delta R2$ = 0.005, $p<.05$) and a marginally significant coefficient for literacy (β = -.07, $\Delta R2$ = 0.004, p = .07). ENM and CEF models did not yield significant coefficients. For literacy, exposure to extreme rainfall was not significantly associated with scores at low deprivation (β = 0.004, SE = 0.044, 95% CI [–0.083, 0.090]) and only marginally at average deprivation (β = –0.070, SE = 0.041, 95% CI [–0.150, 0.010]). However, at high levels of deprivation (+1 SD), greater exposure to extreme rainfall was associated with lower literacy performance (β = –0.144, SE = 0.072, 95% CI [–0.285, –0.003]). For social–emotional functioning, simple slopes showed a similar pattern in direction but did not reach statistical significance at any level of deprivation. The effect of extreme rainfall exposure was positive and nonsignificant at low deprivation (β = 0.058, SE = 0.045, 95% CI [–0.030, 0.147]), negative and nonsignificant at average deprivation (β = –0.030, SE = 0.042, 95% CI [–0.112, 0.052]), and negative but nonsignificant at high deprivation (β = –0.118, SE = 0.074, 95% CI [–0.262, 0.026]).

Interaction models with ELP fees yielded a significant interaction coefficient for CEF ($\beta = .04$, $\Delta R2 = 0.002$, $p<.05$) and a marginally significant coefficient for numeracy ($\beta = .03$, $\Delta R2 = 0.001$, $p = .09$). Simple slopes estimated at low (–1 SD), average (0 SD), and high (+1 SD) monthly fees provided further insight into these interactions. For numeracy, exposure to extreme rainfall was marginally negatively associated with performance at low-fee centres ($\beta = -0.03$, SE = 0.033, 95% CI [–0.090, 0.040]), and not associated at average-fee centres ($\beta = 0.005$, SE = 0.024, 95% CI [–0.042, 0.053]), or high-fee centres ($\beta = 0.04$, SE = 0.027, 95% CI [–0.017, 0.089]). For cognitive executive functioning, the pattern was similar: at low-fee centres, higher exposure to extreme rainfall was marginally associated with lower EF scores ($\beta = -0.06$, SE = 0.033, 95% CI [–0.129, 0.00]), whereas associations at average-fee ($\beta = -0.027$, SE = 0.024, 95% CI [–0.074, 0.020]) and high-fee centres ($\beta = 0.010$, SE = 0.027, 95% CI [–0.042, 0.062]) were nonsignificant.

Interaction models with family SES index did not yield significant coefficients for any outcome. Interaction coefficients were small and nonsignificant for numeracy ($\beta = -0.006$, $p = .714$), literacy ($\beta = 0.025$, $p = .121$), cognitive EF ($\beta = 0.014$, $p = .366$), and social–emotional functioning ($\beta = 0.018$, $p = .269$), with all confidence intervals crossing zero.

Discussion

This study leveraged exogenous variation in rainfall to assess the impact of exposure to extreme rainfall during early learning in cognitive, socioemotional, and early learning outcomes across a representative sample of 4-year-olds in South Africa. We found significant main effects of exposure on CEF and ELL, and some evidence that effects differ across levels of access to resources and services. Below, we discuss each of these findings in detail.

Exposure to extreme rainfall impacts on CEF and ELL

In partial accordance with Hypothesis 1, two out of four of our investigated outcomes (CEF and ELL) were significantly affected by exposure to extreme rainfall. This finding complements the literature documenting detrimental effects of extreme rainfall in cognitive and educational outcomes (e.g., Aguilar & Vicarelli, 2022; Nguyen & Le, 2025; Thai & Falaris, 2014), by shedding specific light on its effects during the crucial 'next 1000 days' period.

At the same time, the specificity of our finding is puzzling, with unclear reasons why ENM and SEF are not affected. On the one hand, methodological reasons may be salient. For example, our SEF measure is very “trait-like” and asks about dispositional characteristics of children that may not capture signal from short-term environmental disruptions in comparison other more ‘state-like’ measures. Further, this finding may point to specific instructional dynamics in ELPs, in line with evidence from other DataDrive2030 reports indicating ELP attendance to benefit ELL and CEF more strongly than ENM (Giese et al., 2025).

Although beyond the scope of the present study, there are many possible pathways through which extreme rainfall may have exerted its effect on cognition and EF and literacy, including biological pathways (e.g., higher likelihood of illness and diminished nutrition; Pham & Nguyen, 2025), diminishing opportunities to attend formal education (e.g., through road closures, forced reallocation, and disruption of family routines and livelihood; Venegas Marin et al., 2024) as well as limiting enriching activities inside the home or community setting (Karaba Bäckström et al., 2024; H. T. Nguyen et al., 2021). Future research should investigate each of these mechanisms more closely, with direct implications for efforts to build climate resilience to community and education settings in the face of increasingly common extreme rainfall events.

Although small in magnitude, the strength of effects must be considered in the context of the distribution of exposure to extreme rainfall. As depicted in Figure 1, the predicted levels of CEF and ELL for children who were exposed to an expected amount of extreme rainfall days during the rainy seasons of their respective exposure windows (i.e., ~3 days across 18 months) are average. However, for children who had higher levels of exposure, the differences are more concerning. Children who have been exposed to 4x or 5x the expected amount of extreme rainfall days during rainy season (i.e., ~ 12 days, 10% of the sample) are expected to score 0.2 SDs below those who have not been exposed at all. This difference is equivalent to about half of the observed effect from interventions on cognitive outcomes in children, according to a recent meta-analysis (Hart et al., 2024).

Access to services and resources as a moderator

We found weak overall support for Hypothesis 2, with small differential effects appearing at different levels of SAIMD and ELP-fees. Surprisingly, the outcomes for which these interactive effects appeared were precisely non-overlapping at different ecological systems levels: SAIMD appeared as a moderator for SEF and ELL, and ELP-fees appeared as a moderator for CEF and ENM.

A conservative interpretation of this pattern in favour of a null effect is plausible, with small imprecise effects appearing non-systematically across statistical tests. In this case, the effect of extreme rainfall on child outcomes would not depend on local infrastructure, ELP-level factors, or family resources. In other words, access to resources and services at different ecological systems levels would not protect children from the effects of extreme rainfall, where it is present.

According to stories from South African news, even in comparatively well-resourced areas, the intensity of extreme rainfall events at times outstripped local infrastructure and service capacity. During the 2022 KwaZulu-Natal floods, for example, damage extended well beyond informal settlements: middle- and upper-income suburbs in Durban such as Umhlanga and Durban North experienced extensive housing destruction, road washouts, and school closures, and insurance companies reported unprecedented volumes of claims. This case suggest that extreme rainfall can impose pervasive shocks that even wealthier communities are not insulated from.

At the same time, where present, interactive effects follow a clear trend: exposure to extreme rainfall is more negatively associated with child outcomes among more vulnerable populations (i.e., lower family SES, lower ELP-fees, higher multiple deprivation). In our data, this pattern appears clearly in two cases: in municipalities with high (+1SD) levels of multiple deprivation, greater exposure to extreme rainfall was associated with lower literacy performance; and in ELPs with low fees, greater exposure to extreme rainfall was associated with lower cognition and EF. In this context, our data provides additional corroboration to the general understanding that distal and proximal factors from children's ecological systems may increase vulnerability to the negative effects of climate change-related extreme weather events (Cuartas et al., 2024, 2025).

Additionally, we contribute by showing that such vulnerability factors may be nested at both proximal and distant loci of a child's ecological system, underscoring climate change as a pervasive challenge in young children's ecology (Fisher & Lombardi, 2025). Future research may benefit from examining the specific mechanisms (and their location in a child's ecological system) through which environmental disruptions exacerbate existing structural inequalities, for example, by linking extreme weather events to fluctuations in attendance, instructional time, caregiver stress, or learning conditions in ELPs.

Limitations

The current study has several limitations. First, our study is cross-sectional, and so no conclusions can be made about cognitive, socioemotional, or learning trajectories. From our analysis, it is not possible to infer, for example, whether the observed effects are transient (i.e., likely to disappear in the long term), stable (i.e., likely to remain of the same magnitude in the long term) or compounding (i.e., likely to increase in magnitude over the long term). Future longitudinal research will be key to accurately assessing the dynamics of exposure to extreme weather events and development over time, especially as extreme weather events become more frequent and more extreme.

Second, as previously mentioned, we lack data about the daily processes and mechanisms that may underpin the hypothesized effects and thus are limited in our ability to make mechanistic conclusions. We do not have access to longitudinal data that may help with more nuanced moderation analyses, such as family routines, financial hardship, and caregiver stress. In the future, studies should focus on establishing temporal precedence of such mechanisms and investigating their additive and interactive roles in shaping child outcomes.

Third, our analysis relies on quasi-experimental variation in extreme rainfall to draw conclusions, and naturally occurring inequalities to investigate the effects of extreme rainfall on child outcomes. Although it is not possible to experimentally manipulate the weather, future studies may be able to experimentally manipulate mediating mechanisms to draw inferences about the pathways of interest between extreme rainfall and child outcomes. This has important implications for policy, as experimental paradigms that are successful in strengthening resilience pathways (e.g., climate-resilient infrastructure, Koks et al., 2019; economic and psychosocial support during crises, Purgato et al., 2018; Stoeffler & Premand, 2020) may pave the way for large scale investments by governments and international funding agencies. In tandem with the accumulated evidence from this and prior research, the results of future investigations will be key in facilitating the way for the flourishing of children during the 'next 100 days' and beyond.

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Appendix 1. Definition of Rainy Season and Provincial Rainfall Thresholds

To classify rainfall exposure, we defined rainy and dry seasons according to the climatological regime of each province in South Africa. Information was retrieved from the South African Weather Service (**https://www.weathersa.co.za/**).

In the Western Cape, which follows a Mediterranean rainfall pattern, the rainy season was defined as May to October, with November through April considered dry. In the Northern Cape, late summer rains predominate, and the rainy season was defined as January to June. In the Eastern Cape, summer rainfall is concentrated between October and March, while April to September was coded as dry. For all other summer-rainfall provinces (Free State, Gauteng, KwaZulu-Natal, Limpopo, Mpumalanga, and North West), the rainy season was defined as October to March, with April to September considered dry.

For each child, rainfall exposure was measured during the 18 months preceding their assessment date. The assessment date was calculated from the child's date of birth and recorded age in months, and the observation window was defined as the period from 18 months before this date up to the date of assessment. All rainfall observations within this window were assigned a season according to the province-specific rules described above.

Extreme rainfall was operationalized as days exceeding the 99th percentile of rainy-season daily rainfall within each province. Table A1 summarizes the 99th percentile thresholds across provinces. These values capture the typical magnitude of extreme daily rainfall events in each rainfall regime.

Table A1. Median 99th Percentile of Rainy Season Daily Rainfall (mm) by Province

Province/Region	Median 99th percentile rainfall
Western Cape (WC)	17.25 mm
Northern Cape (NC)	8.85 mm
Eastern Cape (EC)	20.17 mm
KwaZulu-Natal (KZN)	23.23 mm
Gauteng (GT)	19.78 mm
Free State (FS)	18.84 mm
Limpopo (LIM)	18.25 mm
Mpumalanga (MP)	21.42 mm
North West (NW)	17.48 mm

Appendix 2. Model Equations

Baseline Model

Level 1

$$Y_{icm} = \beta_{0cm} + \mathrm{X}'_{\mathrm{cm}}\beta_{C+E} + \epsilon_{icm} \quad \text{where } \epsilon_{icm} \sim N(0, \sigma_\epsilon^2)$$

The Level 1 equation models the outcome variable, denoted by Yicm, for child i nested within center c and municipality m. The term β0cm denotes the expected mean outcome for the average child in center c. This mean is adjusted by the fixed effects, represented by the vector product Xcm'βC+E, where Xcm is the vector of all child- and program-level covariates and βC+E denotes their corresponding vector of fixed slopes. The Level 1 residual term, ϵicm, captures the unique, unexplained variance at the observation level, where ϵicm~N(0,σϵ2).

Level 2

$$\beta_{0cm} = \gamma_{00m} + v_{0cm} \quad \text{where } v_{0cm} \sim N(0, \tau_v^2)$$

The Level 2 equation models the variation in the Level 1 intercept, β0cm. This term is now decomposed into γ00m, which denotes the expected average outcome for municipality m, and v0cm, which denotes the random effect for center c. The term v0cm specifically captures the residual variation between centers within the same municipality, assumed v0cm~N(0,τv2).

Level 3

$$\gamma_{00m} = \delta_{000} + \delta_{SAIMD} \cdot \mathrm{SAIMD}_m + u_{0m} \quad \text{where } u_{0m} \sim N(0, \tau_u^2)$$

The Level 3 equation models the variation in the municipality-level intercept, γ00m. The term δ 000 denotes the overall grand mean. This mean is conditioned by the Level 3 fixed effect, δSAIMD SAIMDm, where δSAIMD denotes the fixed slope for the standardized municipality-level covariate SAIMDm. The Level 3 random residual, u0m, denotes the remaining unexplained variation between municipalities, assumed u0m~N(0,τu2).

Combined Model

$$Y_{icm} = \delta_{000} + \mathrm{X}'_{\mathrm{cm}}\beta_{C+E} + \delta_{SAIMD} \cdot \mathrm{SAIMD}_m + u_{0m} + v_{0cm} + \epsilon_{icm}$$

Exposure Model

Level 1

$$Y_{icm} = \beta_{0cm} + X'_{cm}\beta_{C+E} + \epsilon_{icm}$$

The Level 1 equation remains the same as in the previous model, defining the outcome Yicm as a function of the center-specific mean β0cm and the vector of all child- and program-level covariates Xcm. The term β0cm denotes the expected mean outcome for the average child in center c. This mean is adjusted by the fixed effects, represented by the vector product Xcm′βC+E, where Xcm is the vector of all child- and program-level covariates and βC+E denotes their corresponding vector of fixed slopes. The Level 1 residual term, ϵicm, captures the unique, unexplained variance at the observation level, where ϵicm∼N(0,σϵ2).

Level 2

$$\beta_{0cm} = \gamma_{00m} + \gamma_{rain} \cdot \text{ExtremeRainfall}_c + v_{0cm}$$

The Level 1 intercept β0cm denotes the center's mean outcome. This mean is now decomposed into γ00m, which denotes the average municipality outcome. Crucially, the term γrain ExtremeRainfallc denotes the fixed effect of the center-level exposure, where γrain is the coefficient. The term v0cm denotes the random effect for center c (residual variation between centers within the same municipality), assumed v0cm∼N(0,τv2).

Level 3

$$\gamma_{00m} = \delta_{000} + \delta_{SAIMD} \cdot \text{SAIMD}_m + u_{0m}$$

The term δ000 denotes the overall grand mean. This mean is conditioned by the fixed effect δ SAIMD·SAIMDm, where δSAIMD denotes the fixed slope for the standardized municipality-level covariate SAIMDm. The Level 3 random residual, u0m, denotes the remaining unexplained variation between municipalities, assumed u0m∼N(0,τu2).

Combined Model

$$Y_{icm} = \delta_{000} + X'_{cm}\beta_{C+E} + \gamma_{rain} \cdot \text{ExtremeRainfall}_c + \delta_{SAIMD} \cdot \text{SAIMD\_z}_m + u_{0m} + v_{0cm} + \epsilon_{icm}$$

Interaction Model

Level 1

$$Y_{icm} = \beta_{0cm} + X'_{cm}\beta_{C+E} + \epsilon_{icm}$$

The term β0cm denotes the expected mean outcome for the average child in center c and municipality m. This mean is adjusted by the vector product Xcm'βC+E denoting the fixed effects of the child- and program-level covariates. The Level 1 residual term, ϵicm, captures the unique, unexplained variance at the observation level, assumed ϵicm∼N(0,σϵ2).

Level 2

$$\beta_{0cm} = \gamma_{00m} + \gamma_{10m} \cdot \text{ExtremeRainfall}_c + v_{0cm}$$

The Level 2 equation models the variation in the Level 1 intercept β0cm, which now includes the center-level exposure ExtremeRainfall as a main effect. However, the coefficient for this effect is now allowed to vary across municipalities, as it will be defined by Level 3 terms. The Level 1 intercept β0cm denotes the center's mean outcome. It is decomposed into γ00m, the municipality average outcome when ExtremeRainfall=0. The term γ10m denotes the slope coefficient for the center-level exposure, ExtremeRainfall. Since γ10m has an m subscript, its value is dependent on the municipality. The term v0cm denotes the Level 2 random effect, capturing residual variation between centers within the same municipality, assumed v0cm∼N(0,τv2).

Level 3

$$\gamma_{00m} = \delta_{000} + \delta_{010} \cdot \text{SAIMD}_m + u_{0m}$$
$$\gamma_{10m} = \delta_{100} + \delta_{110} \cdot \text{SAIMD}_m$$

The Level 3 equation models both the municipality intercept (γ00m) and the slope of the exposure (γ10m) using the Level 3 predictor SAIMD to create the cross-level interaction. The term γ00m denotes the municipality mean outcome when ExtremeRainfall is zero. It is defined by the overall grand mean (δ000) and the main effect of the municipality-level covariate, SAIMD (δ010· SAIMDm). The Level 3 residual u0m denotes the remaining unexplained variation between municipalities, assumed u0m∼N(0,τu2). The term γ10m denotes the slope of ExtremeRainfall in municipality m. It is defined by δ100 (the mean effect across all municipalities) and the cross-level interaction term δ110·SAIMDm. The coefficient δ110 denotes how the effect of ExtremeRainfall changes per unit change in SAIMD.

Combined Model

$$Y_{icm} = \delta_{000} + \delta_{100} \cdot \text{ExtremeRainfall}_c + \delta_{010} \cdot \text{SAIMD}_m + \delta_{110} \cdot \text{ExtremeRainfall}_c \cdot \text{SAIMD}_m + X'_{cm}\beta_{C+E} + u_{0m} + v_{0cm} + \epsilon_{icm}$$

Appendix 3. Moderation analysis with unrestricted sample

Table A3.1 - Regression Results: Extreme Rainfall Exposure and Child Development Outcomes - Coefficients from 3-Level Multilevel Models

Outcome	Emergent Literacy & Language			Emergent Numeracy & Mathematics			Cognition & Executive Function			Social-Emotional Functioning		
Model	Cov-only	Exposure	Interaction	Cov-only	Exposure	Interaction	Cov-only	Exposure	Interaction	Cov-only	Exposure	Interaction
SAIMD (std.)	**-0.10****	**-0.12****	**-0.11****	-0.04	-0.06	-0.05	**-0.11*****	**-0.12*****	-0.13***	-0.01	-0.00	-0.00
Extreme Rainfall (std.)		**-0.07***	-0.06		-0.04	-0.02		**-0.06***	-0.05		0.05	0.04
Extreme Rainfall × SAIMD			0.03			0.05			0.01			-0.01
Marginal R^2	0.074	0.078	0.078	0.087	0.089	0.092	0.136	0.132	0.139	0.066	0.072	0.067
ΔR^2		**0.003***	0.001		0.003	0.003		**0.003***	0		0.001	0
Model Comp p-value		**0.029**	0.45		0.189	0.139		**0.011**	0.564		0.177	0.776

In comparison to exposure models, rainfall X SAIMD interaction models did not fit better for any of the child outcomes (ΔR2s between 0 and .003, βs between -.01 and .02, ps > .139). Our alternative interaction models with ELP fees and family SES index as moderators also did not yield significant results (-.006 < β < .01, ps > .26 for ELP fees; -.004 < β < .01, ps > .31 for family SES). The model with urbanicity as a moderator between exposure to rainfall and child outcomes yielded a significant coefficient (β = .08, SE = .04, p <.05) with a small but significant improvement in model fit (ΔR2 = .002, p < .05) for literacy but not for other outcomes (ΔR2s between 0 and .001, βs between -.04 and .05, ps > .186). Simple slopes analysis indicated exposure slopes for literacy were significantly different in urban vs. rural settings (contrast = 0.08, p < .05) but neither was significantly from zero (β urban = .05, SES = .03, p = .09; βrural = -.03, SE =.02, p = .18).

Appendix 4. Descriptives

Table A4.1. Full Sample Descriptives

	Value
Participants	N = 5001
Female, %	51.0
Age in months, Mean (SD)	54.8 (2.5)
N extreme rainfall days in rainy season, mean (SD)	5.7 (4.1)
CEF, mean (SD)	7.2 (4.2)
ELL, mean (SD)	10.7 (4.4)
ENM, mean (SD)	8.2 (4.0)
SEF, mean (SD)	17.1 (4.3)
Child Primary Language	
Afrikaans	6.0
English	19.5
isiNdebele	0.6
isiXhosa	14.4
isiZulu	21.1
Sesotho	7.8
Sesotho se Leboa (Sepedi)	9.1
Setswana	14.3
siSwati	3.0
Tshivenda	1.8
Xitsonga	2.3
ELPs	**N = 1388**
LPQA: Inadequate, %	26.9
LPQA: Basic, %	41.9
LPQA: Good, %	31.2
SAIMD, Mean (SD)*	106.7 (85.1)
Weather-related closure 2024, %	4.7

*SAIMD naturally ranges from 377.4 for the most deprived municipality and 10.2 for the least deprived municipality in South Africa

Table A4.2. Restricted Sample Descriptives

	Value
Participants	N = 2292
Female, %	51.2
Age in months, Mean (SD)	54.9 (2.5)
N extreme rainfall days in rainy season, mean (SD)	5.6 (4.2)
CEF, mean (SD)	7.3 (4.2)
ELL, mean (SD)	11.0 (4.4)
ENM, mean (SD)	8.4 (4.1)
SEF, mean (SD)	17.5 (4.1)
Child Primary Language	
Afrikaans	5.6
English	18.4
isiNdebele	0.5
isiXhosa	14.5
isiZulu	19.7
Sesotho	11.0
Sesotho se Leboa (Sepedi)	10.0
Setswana	14.0
siSwati	2.0
Tshivenda	2.0
Xitsonga	2.2
ELPs	**N = 1128**
LPQA: Inadequate, %	26.9
LPQA: Basic, %	41.2
LPQA: Good, %	31.2
SAIMD, Mean (SD)*	106.7 (85.1)
Weather-related closure 2024, %	4.7

*SAIMD naturally ranges from 377.4 for the most deprived municipality and 10.2 for the least deprived municipality in South Africa

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