communications earth & environment

A Nature Portfolio journal

Article

Article in Press

https://doi.org/10.1038/s43247-026-04061-2

Clean-air regulation reduces childhood wasting and overweight in China

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Whether large-scale air-quality policies improve child nutrition remains uncertain. Here we show that China's Air Pollution Prevention and Control Action Plan reduces wasting and overweight among children under five. We use annual data from 2759 counties between 2005 and 2017 and a matched difference-in-differences design to evaluate the policy as a natural experiment. The policy is associated with a 0.760% reduction in wasting and a 3.950% reduction in overweight relative to control areas. Reductions in fine particulate matter explain an estimated 57.7% and 68.9% of these respective effects. The benefits are generally larger in northern regions, resource-based cities, and counties with greater initial pollution or stronger regulation. The policy also generates at least US $120.87 million in direct health-care savings across pilot areas. These findings provide population-level evidence that clean-air regulation improves early-childhood nutrition and suggest that coordinating air-quality management with child-health policy can deliver substantial health and economic benefits in highly polluted settings.

Childhood wasting and overweight now coexist at alarming levels in many low- and middle-income countries (LMICs), constituting a growing double burden of malnutrition (DBM). In 2022, an estimated 45 million children under five were affected by wasting and 37 million by overweight, with most wasting and nearly half of overweight concentrated in Africa and Asia[1]. These conditions elevate mortality risk[2] and predisposes to lifelong non-communicable diseases[3,4], underscoring the need for strategies that curb wasting without fueling overweight.

The drivers of DBM span dietary, socioeconomic, and environmental factors, yet evidence remains scant on interventions that can shift wasting and overweight in opposite directions[5–7]. Emerging studies implicate ambient air pollution as a shared, upstream risk factor (for details, see Appendix S1), potentially aggravating wasting via respiratory, cardiovascular, and infectious disease pathways while promoting overweight through oxidative stress and inflammation[8–11]. Beyond these biological pathways, changes in air quality may also shape nutrition-relevant behaviors and access, including time outdoors, care-seeking, and access to healthier food environments[12–14]. However, rigorous evaluations testing whether air-quality interventions improve child nutrition outcomes are rare, especially in resource-constrained settings where the DBM is most acute.

China combines some of the world's highest ambient pollution levels with subnational clustering of childhood DBM. Using a pragmatic definition (>5% prevalence of both wasting and overweight within the same year at the subnational level), such clusters were already evident in parts of central-western and southwestern China in 2005 (Fig. S3). As China tightens air-quality standards, these highly burdened areas warrant rigorous evaluation of policy impact on child nutrition.

Landmark air-quality regulations—from the 1970 US Clean Air Act Amendments to Germany's Low Emission Zones and the 2008 Beijing Olympics controls—have demonstrably improved child health by cutting particulate exposures[5,13,15,16]. Yet these policy episodes were concentrated in high-income settings or brief windows, limiting generalizability to LMICs.

Launched in 2013, the Air Pollution Prevention and Control Action Plan (APPCAP)—the "2013 Ten Measures"—was China's most ambitious clean-air effort to date, backed by ~US$ 270 billion investment[17–19] and nationwide mandates to cut $PM_{2.5}$ levels (See detailed policies in Appendix Sections S2–S3). By 2017, $PM_{2.5}$-attributable deaths had declined by 64,000 nationally and by 47,240 in the 74 key cities, averting an estimated 710,020 life-years[17,19]. Despite documented mortality and morbidity benefits, no study has rigorously assessed APPCAP's impact on childhood wasting and overweight. APPCAP's large and uneven reductions in $PM_{2.5}$ create a policy-induced natural experiment for estimating impacts on child nutrition, and $PM_{2.5}$ is a suitable primary pollutant given its central role in the policy, established health burden and plausible links to child growth and nutrition.

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We assembled annual county-level panel data for 2759 counties (2005–2017) and used a Gobillon–Magnac (GM) matched difference-in-differences (DID) design to estimate APPCAP's causal impact on childhood wasting and overweight. Propensity-score matching on pre-intervention covariates and outcome trends strengthened identification, and we examined mediation by $PM_{2.5}$ before translating these health gains into direct healthcare cost savings to inform policy. We hypothesized that APPCAP would lower both outcomes—predominantly via $PM_{2.5}$ reductions[20]—with larger benefits in more polluted and strictly regulated regions.

Results

Divergences in childhood wasting and overweight in pilot versus non-pilot areas

We mapped prefectural APPCAP pilot designations to constituent counties and recorded the implementation year for each county. APPCAP exposure was coded as a binary indicator $APPCAP_{it}$ equal to 1 for county-year (it) at or after implementation and 0 otherwise. Under APPCAP, 47 prefecture-level cities[20] in the Beijing–Tianjin–Hebei, Yangtze River Delta, and Pearl River Delta regions were designated as pilots (Table S2), with all other cities serving as comparators. Between 2013 and 2017, pilot counties experienced larger declines in $PM_{2.5}$ concentrations and in the prevalence of childhood wasting and overweight than non-pilot counties (Fig. 1). In pilots, wasting fell sharply in the first post-implementation year and then partially rebounded over the next two years. These descriptive contrasts motivate our quasi-experimental analysis, in which rigorously matched treatment and control counties are used to identify APPCAP's causal effects on wasting and overweight. Descriptive statistics for key variables are provided in Table S1.

Effects of APPCAP on childhood wasting and overweight

Table 1 presents estimates from the conventional DID and GM hybrid models. Both approaches detect statistically significant declines in childhood wasting and overweight after APPCAP implementation, with the GM hybrid yielding lower mean-squared error (MSE), consistent with better control of post-intervention, time-varying unobserved differences across counties. In our preferred GM hybrid specification, APPCAP implementation is associated with a 0.760% ($P < 0.001$) reduction in wasting (95% CI 0.417–1.094) and a 3.950% ($P < 0.001$) reduction in overweight (2.543–5.348) relative to control counties. These effects indicate that stringent air-quality regulations can meaningfully reduce the double burden of malnutrition in early childhood.

The GM hybrid analysis retained 704 counties for wasting estimates, covering 30.87% (430.63 million) of China's 2017 population (1.395 billion), and 704 counties for overweight estimates, representing 30.32% (422.95 million). Although matching necessarily omits some counties to construct credible "shadow" controls, the retained sample remains broadly national in scope. To test generalizability, we applied normalized inverse-probability-of-treatment weighting (IPW), which reweights the full untreated cohort to the covariate distribution of the matched sample[21,22]. IPW estimates (Table 1, Columns 3 and 6) closely track the GM hybrid results, supporting external validity.

The DID identification relies on parallel pre-intervention trends[7]. Figure 2 shows closely aligned pre-APPCAP trajectories for both outcomes; a joint test of all pre-intervention leads does not reject parallel trends ($p > 0.1$; for technical details, see Appendix S7). Following implementation, wasting and overweight declined sharply and remain lower over time, consistent with sustained policy effects.

Additional robustness checks (for details, see Appendix S8; Fig. 3) support a causal interpretation: First, placebo tests using the GM hybrid find no spurious effects. Second, tighter matching (caliper reduced from 0.20 to 0.05 on the logit-transformed propensity score) improves balance and yields estimates consistent with the main results[23]. Third, alternative estimators, such as interactive fixed effects (IFE) models that allow for time-varying unobservables, produce similar results[24]. Fourth, Results are unchanged when excluding overlapping policies and when restricting to alternative post-policy windows. Across specifications and checks (Fig. 3), APPCAP is robustly associated with lower childhood wasting and overweight, reinforcing the conclusion that clean-air regulation can safeguard early-life human capital.

To address potential limitations of the LBD estimates, such as spatial smoothing and policy spillovers, we implemented four robustness checks. First, to limit contamination from treated neighbors (Table S3), we dropped

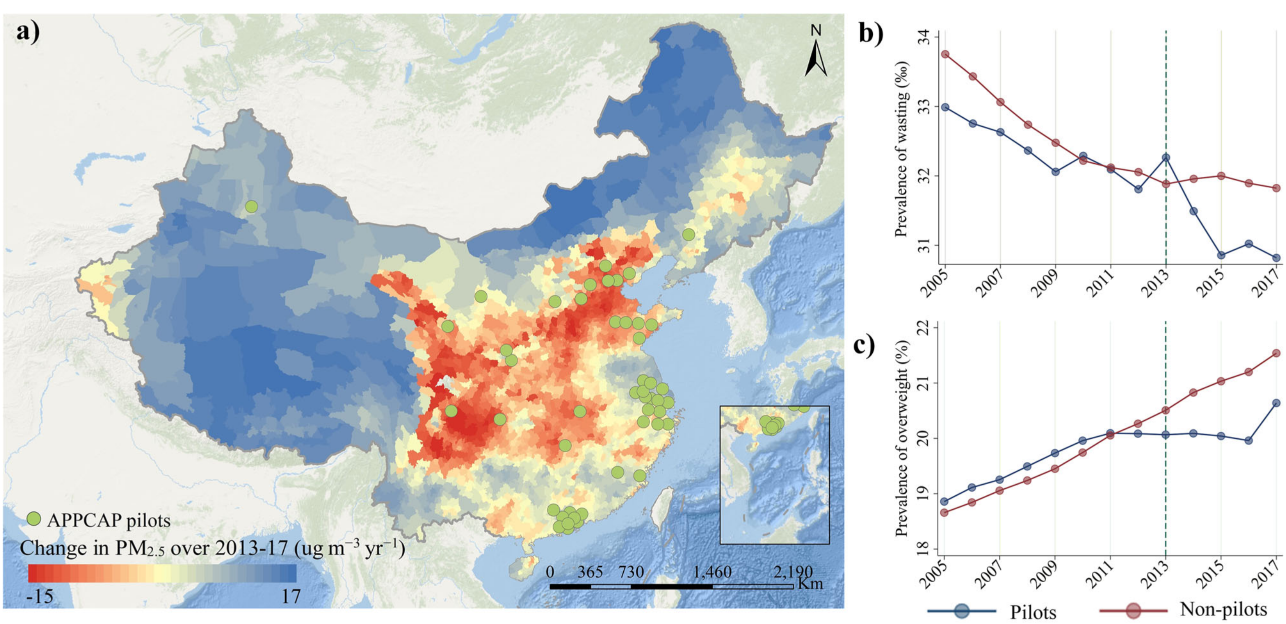

Fig. 1 | Trends in $PM_{2.5}$ and childhood wasting and overweight in APPCAP pilot and non-pilot areas, 2013–2017. **a** maps county-level annual changes in $PM_{2.5}$ (μg/m³ per year) from 2013 to 2017, with APPCAP pilot cities marked. **b**, **c** plot population-weighted prevalence of wasting and overweight for pilot (treatment) and non-pilot (control) counties, computed as estimated cases divided by the under-5 population. Case counts derive from 5 × 5-km² prevalence surfaces; denominators from 100 m WorldPop population estimates. Base map source: Standard Map Service System of the Ministry of Natural Resources of China, approval number GS(2023)2767. Administrative boundaries were not modified.

Table 1 | Impacts of APPCAP on childhood wasting and overweight

	Ln(Wasting)			Ln(Overweight)		
	(1) Conventional DID	(2) GM hybrid	(3) Normalized IPW	(4) Conventional DID	(5) GM hybrid	(6) Normalized IPW
APPCAP	−0.0058***(0.0013)	−0.0076***(0.0017)	−0.0083***(0.0017)	−0.0323***(0.0056)	−0.0395***(0.0071)	−0.0410***(0.0075)
Control	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
MSE	0.0007	0.0005	0.0005	0.0065	0.0046	0.0043
R-squared	0.979	0.976	0.976	0.874	0.916	0.925
Counties	2759	704	827	2759	704	827
Observations	35,867	9152	10,751	35,867	9152	10,751

The GM-hybrid matching stage trims the sample from 2,759 to 704 counties, a deliberate restriction that sacrifices breadth for comparability, thereby strengthening the validity of the parallel trends assumption. Standard errors clustered by county are reported in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. p values are based on two-sided tests using county-clustered standard errors. No adjustment was made for multiple comparisons.

counties within 25–50 km of policy boundaries[25]; the estimated APPCAP effects remained negative and statistically significant. Second, we added, in turn, a neighbor-treatment indicator and an upwind-weighted exposure variable to capture spillovers[26]; the spillover-related coefficients were small and statistically insignificant, while the APPCAP estimates remained robust (Table S4). Third, we recomputed standard errors (SEs) using Conley (spatial HAC) adjustments with a 100-km cutoff[27]. Fourth, we applied wild-cluster bootstraps with prefecture-level clustering to accommodate spatially correlated shocks[28]. Across all specifications, the estimated effect of APPCAP on childhood outcomes remained negative and statistically significant (Fig. 3), reinforcing the validity of our baseline results.

Mediation effects

The mediation analysis (Fig. S8) attributes 0.436 percentage points of the decline in childhood wasting (95% CI 0.163–0.726), or 57.7% of the APPCAP-attributable effect, to APPCAP-induced declines in $PM_{2.5}$. For overweight, the indirect effect is 2.719 percentage point (1.915–3.486), accounting for 68.9% of the APPCAP-attributable effect. These shares indicate that improvements in ambient $PM_{2.5}$ are a major pathway by which APPCAP reduces DBM, but they do not explain all observed declines during 2013–2017; secular changes and policies unrelated to APPCAP are absorbed by year fixed effects and are not attributed here. Results were similar when $PM_{2.5}$ exposure was alternatively constructed as a county-year mean weighted by the under-five population using WorldPop estimates (Tables S8–S9), indicating that the mediation findings are not sensitive to the exposure aggregation rule. The remaining portion of APPCAP's effect likely reflects non-$PM_{2.5}$ channels (e.g., fuel switching, industrial restructuring, income/food-environment shifts) and statistical uncertainty. County-level exposure-response patterns are consistent with earlier cohort studies[17] linking lower particulate pollution to improved child growth outcomes. Taken together, these results suggest that clean-air policy can contribute meaningfully, though not exclusively, to DBM reduction, while broader nutrition and social policies remain essential[29]. Cross-sectoral design features of APPCAP (emissions targets and coordination) may inform LMICs strategies addressing the double burden of malnutrition.

Heterogeneity of the APPCAP effects

We estimated stratum-specific APPCAP-attributable effects within pre-specified clusters: sex, socioeconomic conditions (income and education), region, industrial structure, baseline pollution, and regulatory intensity—to describe variation in policy's impact (Fig. 4 and Table S11). Unless otherwise noted, p values are unadjusted for multiple comparisons; false-discovery–rate–adjusted results are provided in the Tables S10–S11.

By sex, APPCAP reduced wasting to a similar degree in girls and boys: 0.521% (95% CI 0.206–0.837) and 0.572% (0.250–0.894), respectively (between stratum $p = 0.394$). In contrast, the reduction in overweight was smaller for girls than for boys: 1.595% (0.316–2.874) versus 2.335% (1.002–3.668; $p = 0.045$). These sex differences warrant prospective, mechanism-focused studies that directly measure resources, diet, and gender norms to test—rather than infer—the drivers of divergence[30].

Socioeconomic conditions also shaped the magnitude of policy benefits. Using pre-policy county-level per-capita GDP to proxy local economic status, we found larger APPCAP-attributable reductions in higher-income counties. For wasting, the estimated reduction was 1.168% (0.625–1.711) in higher-income counties versus 0.688% (0.158–1.218) in lower-income counties ($p < 0.001$). For overweight, the corresponding estimates were 4.533% (2.649–6.418) and 3.006% (1.222–4.790; $p < 0.001$). These gradients are consistent with the possibility that socioeconomic resources condition the translation of air-quality improvements into child-health gains, underscoring the need for complementary health, nutrition, and social policies in lower-income areas[12,31].

A similar socioeconomic pattern emerged for female educational attainment. Using pre-policy county-level female educational attainment as a proxy for maternal human capital, APPCAP-attributable reductions were larger in counties with higher female education[32,33]. For wasting, the estimated reduction was 1.123% (0.658–1.588) in higher-education counties, compared with 0.435% (−0.081 to 0.951) in lower-education counties ($p < 0.001$). For overweight, declines were 6.270% (4.404–8.136) and 3.299% (1.508–5.090; $p < 0.001$). These education-related gradients suggest that maternal education may amplify the nutritional co-benefits of clean-air regulation by strengthening caregivers' child-feeding, care-seeking, and health-protection capacities.

Geographically, effects were larger in northern than southern counties, consistent with greater pollution related to winter heating in the north[34]. For wasting, the APPCAP-attributable reductions were 0.947% (0.358–1.537) in the north versus 0.445% (0.144 to 0.745) in the south ($p = 0.022$). For overweight, the corresponding estimates were 2.977% (0.951–5.003) and 1.663% (0.065–3.261; $p = 0.028$). These patterns accord with higher baseline exposures and the composition of sources in northern regions.

Industrial structure also marked clear differences. In resource-based cities (RECs), wasting declined by 1.803% (1.227–2.378) compared with 0.447% (0.031–0.863) in non-RECs ($p = 0.000$). For overweight, declines were 6.405% (3.891–8.920) in RECs and 3.255% (1.355–5.156) in Non-RECs ($p < 0.001$). Larger policy benefits in RECs are consistent with stricter source controls implemented from higher baseline emissions and industrial intensity[35].

Strata defined by baseline ambient pollution showed gradients that align with exposure–response expectations[35]. In high-pollution counties, wasting fell by 1.161% (0.738–1.584) compared with 0.638% (0.129–1.147) in low-pollution counties ($p = 0.018$). For overweight, the corresponding

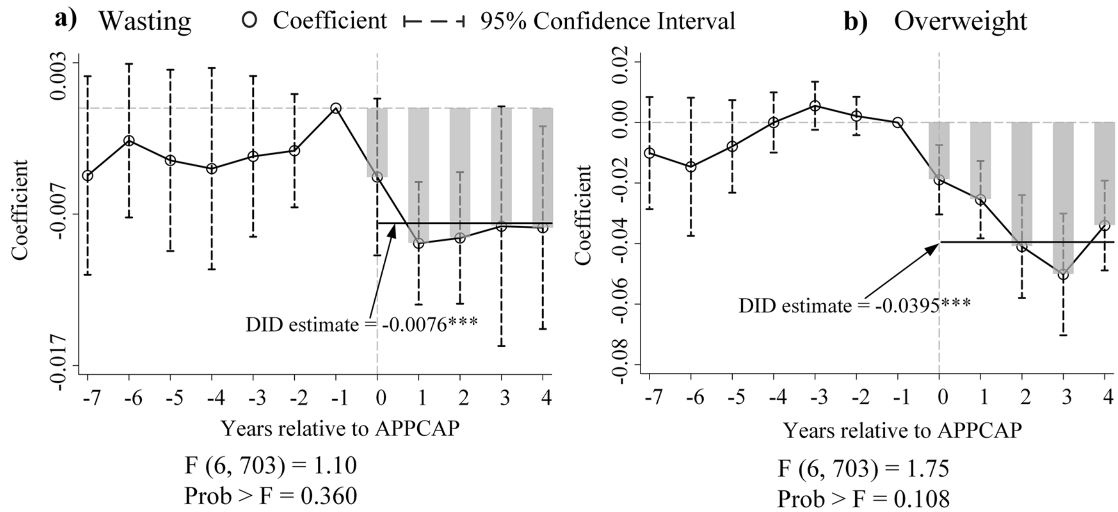

Fig. 2 | Parallel trends assumption test results. **a**, **b** present the parallel trends assumption test results for childhood wasting and overweight, respectively. The pre-implementation year is omitted as the reference period to enable identification of the time-varying effects of APPCAP on childhood wasting and overweight. Points represent event-time coefficient estimates, and error bars indicate 95% confidence intervals. For both panels (**a**, childhood wasting; **b**, overweight), the analysis includes 704 counties and 9152 county-year observations; *n* denotes county-year observations.

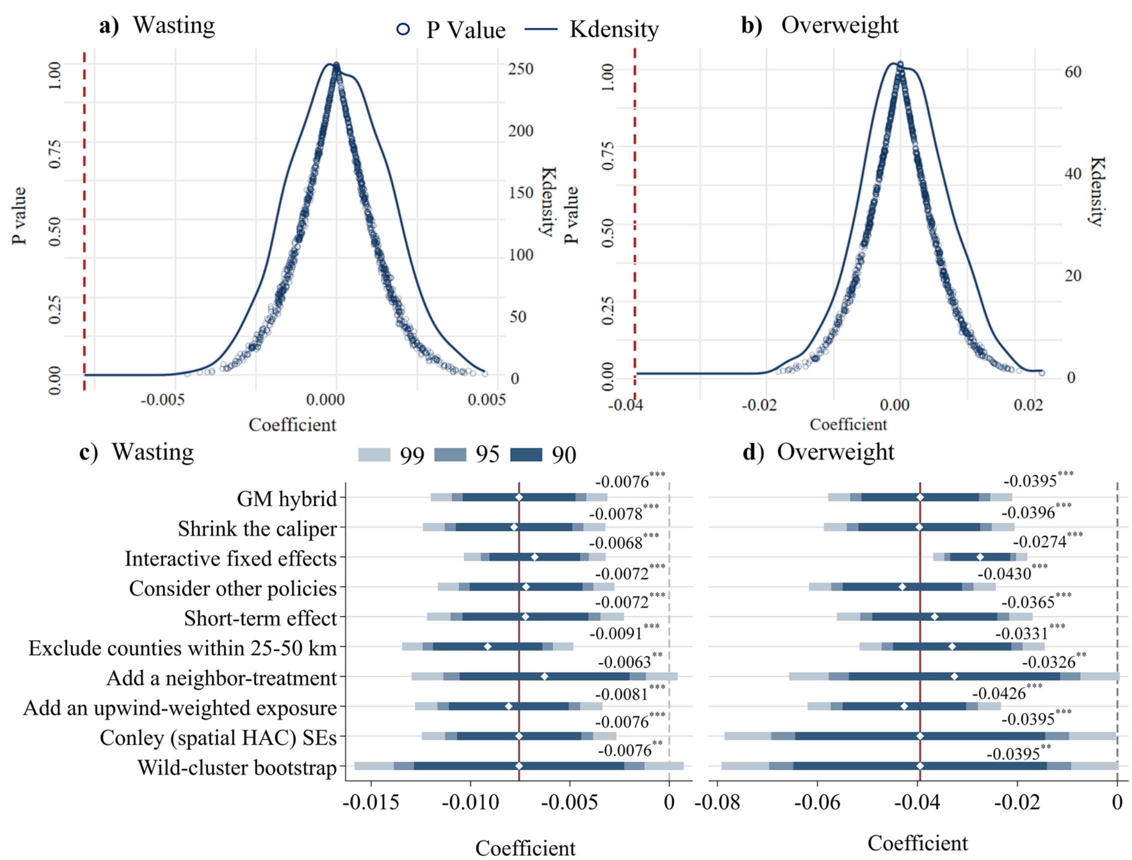

Fig. 3 | Robustness of APPCAP's impact on child wasting and overweight. **a**, **b** present the placebo-test results; **c**, **d** present additional robustness checks. Detailed estimates of the robustness checks are provided in Tables S3–S5 and Fig. S7.

estimates were 5.137% (3.275–6.998) and 2.796% (0.570–5.021; $p = 0.004$). These results suggest that APPCAP's nutritional co-benefits are greater where ambient $PM_{2.5}$ burdens are higher.

Finally, variation by regulatory intensity indicates that stronger enforcement is associated with larger policy gains. By constructing an environmental-goal index from municipal work reports (2011–2015) and splitting counties at the median (Table S9), we found that wasting declined by 0.890% (0.372–1.407) in high-intensity counties versus 0.485% (0.007–0.964) in low-intensity counties ($p = 0.048$). Overweight declined by 4.643% (2.458–6.828) and 2.511% (0.491–4.531) in the high- and low-intensity groups, respectively, with between stratum $p = 0.004$.

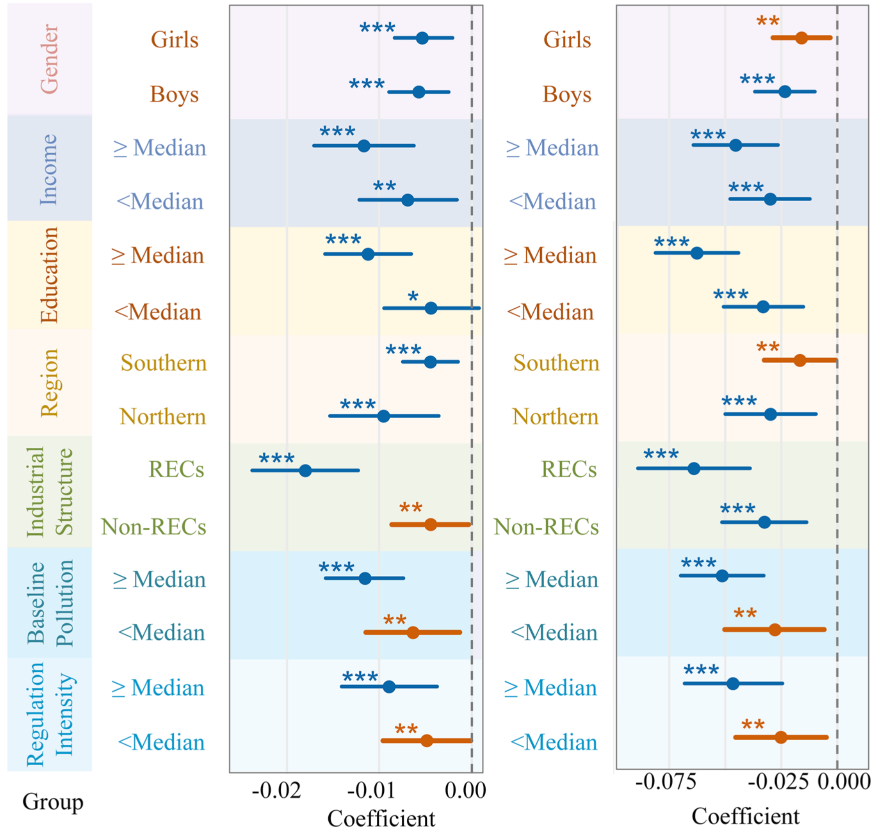

Fig. 4 | Heterogeneous impacts of APPCAP on childhood wasting and overweight. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Between-stratum p values are based on two-sided tests of equality between subgroup estimates. Unless otherwise stated, p values are unadjusted for multiple comparisons. Points represent stratum-specific APPCAP-attributable coefficient estimates, and error bars indicate 95% confidence intervals. Detailed estimates of the heterogeneous impacts of APPCAP on childhood wasting and overweight are provided in Supplementary Information Tables S12 and S13.

Taken together, these stratified results show that the APPCAP-attributable effect varies meaningfully across sex, socioeconomic conditions, geography, industrial context, baseline exposure, and enforcement intensity. Given multiple comparisons, emphasis should rest on effect sizes, confidence intervals, and consistency with prior knowledge rather than on any single p value. The patterns can inform where complementary clean-air and nutrition actions may yield the largest marginal benefits.

Estimated economic benefits

We estimated APPCAP's health-economic impact by translating cases averted into direct health-care savings. Between 2013 and 2017, implementation averted 10938 cases of childhood wasting (95% CI 5995–15737) and 675,578 cases of overweight (441,152–915,285). In the most polluted Beijing–Tianjin–Hebei (BTH) region, cities such as Beijing, Baoding, and Tianjin each avoided an estimated 20000–40000 cases, whereas lower-pollution cities (e.g., Sanming, Zhuhai) saw modest declines (Fig. 5). Applying published unit costs of US$118 per wasted child and US$176.9 per overweight child[36–38], these reductions yielded at least US$120.87 million (77.69–163.77) in avoided healthcare spending across pilot cities. Savings were largest in northern and central-western pollution hotspots (Fig. 5), consistent with greater nutritional co-benefits where $PM_{2.5}$ exposures are higher. For context, the State Council's 21 June 2022 Report on Child Health Promotion documented US$676.6 million invested in nutrition programs for children in poverty-stricken areas (2012–2021); APPCAP-related savings correspond to 17.86% (11.48–24.20) of that investment.

Early-life malnutrition carries substantial lifetime consequences. The double burden—wasting and overweight—is linked to elevated mortality for wasting and heightened risks of early-onset obesity and non-communicable diseases for overweight[39]. These conditions generate direct medical costs and indirect losses[40,41] (productivity, household income, and life-years). In particular, childhood overweight imposes indirect costs that can exceed medical spending; without intervention, overweight youth in China face an estimated lifetime economic loss of US $276 300 per person[19,41].

Aggregating long-run impacts, APPCAP generated at least US$186.77 billion in economic benefits over 2013–2017 (95% CI 120.23–252.89), implying a benefit–cost ratio of 0.69 (0.45–0.94) against the plan's ~US$270 billion investment. We do not report a lifetime cost estimate for wasting because of acute variability and limited robust long-term data. Importantly, these figures are conservative lower bounds: They focus on nutritional outcomes and exclude benefits from reduced child mortality, enhanced mental health and cognition, caregiver time savings, and broader environmental and productivity gains. As such, the true social return to clean-air regulation is likely higher.

Discussion

This national quasi-experimental study finds that implementation of China's Air Pollution Prevention and Control Action Plan (APPCAP) was associated with measurable reductions in the prevalence of childhood wasting and overweight. In our preferred Gobillon-Magnac hybrid specification, wasting fell by 0.760% (95% CI 0.417–1.094) and overweight by 3.950% (2.543–5.348) relative to control counties, with sustained post-implementation declines in event-time analyses (Fig. 2 and Table 1). Mediation results indicate that APPCAP-induced reductions in ambient $PM_{2.5}$ account for 57.7% of the APPCAP-attributable decline in wasting and 68.9% of that in overweight (Fig. S8). Translating cases averted into direct medical costs, we estimate US$120.87 million (77.69–163.77) in health-care savings across pilot areas (Fig. 5), with larger gains in high-exposure settings. Stratified estimates further show that APPCAP's effects varied across population and contextual characteristics: reductions were larger in northern regions, resource-based cities, counties with higher baseline pollution and stronger regulatory intensity, and socioeconomically advantaged counties, as indicated by higher pre-policy per-capita GDP and female educational attainment; overweight reductions were smaller in girls than in boys, whereas wasting effects were comparable by sex (Fig. 4).

Taken together, these findings support a planetary health interpretation in which environmental regulation contributes to reducing the double

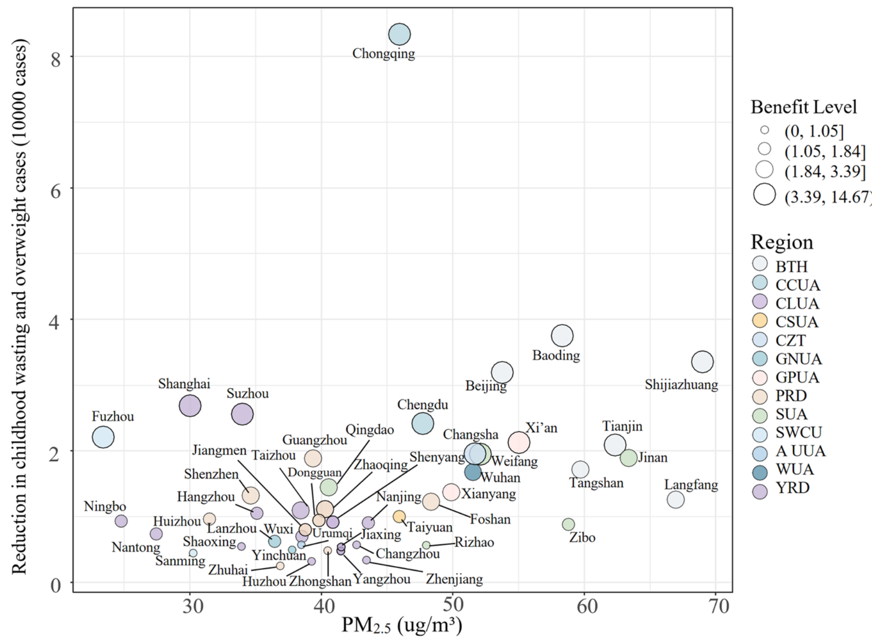

Fig. 5 | Estimated economic benefits of implementing APPCAP. X-axis shows 2012 $PM_{2.5}$ concentrations (μg/m³); Y-axis shows reductions in childhood wasting and overweight cases attributable to APPCAP. Bubble size reflects economic benefits (USD million), color indicates urban agglomeration. Detailed estimates are reported in Supplementary Information Table S14.

burden of malnutrition by alleviating a shared upstream exposure. The sizeable mediated shares through $PM_{2.5}$ are consistent with evidence that particulate pollution can impair child growth through inflammatory, oxidative, respiratory, and infectious pathways. Reductions in these burdens may improve appetite, nutrient absorption, and the allocation of energy toward growth and metabolic regulation, providing a plausible explanation for the exposure–response patterns observed here[8,12,42]. At the same time, cleaner air may also change the environments in which children are fed, cared for, and physically active, including caregiver mobility and care-seeking[13,43,44]. Moreover, our mediation framework answers a specific question: which portion of APPCAP's own effect operates through APPCAP-induced changes in $PM_{2.5}$. It does not attribute all national improvements during 2013–2017 to the policy, and the remaining (direct) component of the APPCAP effect may reflect non-$PM_{2.5}$ channels, such as fuel switching affecting indoor exposures, industrial restructuring with income and food-environment consequences, or concurrent governance changes, as well as statistical uncertainty.

The policy implications are threefold. First, design and enforcement matter: larger APPCAP benefits where exposure and regulatory intensity were greatest suggest that stringent, source-oriented controls and clear accountability can maximize nutritional co-benefits. Second, targeting high-burden places—northern heating zones, resource-based cities, and high-pollution counties—could yield outsized returns, but the socioeconomic gradients suggest that cleaner air may translate into larger child-health gains where local resources and maternal human capital are stronger. Lower-income and lower-education areas may therefore require complementary health, nutrition, caregiver-education, and food-access interventions. Third, clean-air policy is complementary rather than substitutive to nutrition and social programs: aligning air-quality management with child-nutrition strategies could accelerate progress toward population-level targets, while accounting for sex-related and socioeconomic differences in policy responsiveness. Lessons from APPCAP's cross-sector coordination may be transferable to other LMICs pursuing health-centered environmental governance, subject to baseline exposures, social conditions, and institutional capacity.

Our economic estimates underscore potential value while remaining conservative. Using published unit costs for wasting and overweight[36–38], we quantify direct medical savings only; long-run benefits from improved child health and human capital are far larger but less certain, and our aggregate benefits and benefit–cost ratio reflect lower-bound assumptions. Early-life malnutrition imposes substantial lifetime health and economic burdens—including elevated mortality risk among wasted children and higher risks of obesity and non-communicable diseases among those with overweight—amplifying the long-term payoff of prevention[39–41]. Future evaluations should adopt broader societal costing (eg, productivity, caregiver time, cognition) and track cohorts over time to refine returns.

This study has notable strengths: a policy-induced natural experiment at national scale; high-resolution outcome surfaces aggregated to policy-relevant units; and a matched DID estimator that strengthens identification when unobserved differences evolve. We corroborate identification with parallel trends assumption tests[7], alternative DID specifications and interactive fixed-effects models[24], and reweighting to assess external validity[25–28], We also propagate uncertainty from both the effect estimates and the outcome surfaces.

Limitations remain. First, outcome measures are modeled LBD surfaces, not administrative registries; although extensively validated, local error is possible and could attenuate effects. Second, ecological aggregation to the county level precludes individual-level inference and may mask within-county disparities. Third, mediation relies on assumptions about mediator–outcome confounding and exposure-induced pathways; sensitivity analyses mitigate but cannot eliminate these concerns. Fourth, spillovers (e.g., pollution transport or economic reallocation) could bias estimates toward or away from zero; our robustness checks reduce but do not rule out such bias. Finally, while China provides a critical test case, generalizability to other LMICs depends on baseline exposures, sectoral structure, and enforcement capacity.

Several priorities for future work emerge. First, mechanism-focused studies that collect direct measures of household resources, diet, and gender norms are needed to test—rather than infer—the drivers of the sex differences observed for overweight. Second, replication in other settings using quasi-experimental designs and open data/code would clarify where clean-air policies yield the largest nutritional co-benefits and how they can be integrated with targeted nutrition programs. In aggregate, our results indicate that clean-air regulation can meaningfully, though not exclusively, reduce the double burden of malnutrition. Aligning environmental governance with child-health goals offers a pragmatic route to planetary-health gains at population scale. Future work should examine whether these policy benefits extend to adults, for whom air pollution may act mainly through cumulative cardiometabolic and respiratory pathways rather than early-life growth and nutritional trajectories.

Methods

Childhood wasting and overweight data

We focused on children under five because early childhood is a sensitive window of rapid growth and heightened vulnerability to environmental insults[45]. Their shorter exposure histories and limited independent mobility help reduce concerns about selective migration and long-term accumulated exposure[46]. This focus allows us to assess whether clean-air regulation can generate measurable nutritional benefits during a critical stage of human development. At the individual level, DBM is often framed as childhood undernutrition coexisting with adult overweight; at the population level, it is assessed by the prevalence of childhood wasting and overweight. To evaluate policy effects, we used high-resolution geospatial estimates of under-5 wasting and overweight aggregated to policy-relevant administrative units. We selected wasting as the undernutrition comparator for overweight because both use harmonized WHO cut-offs and support construction of bivariate DBM categories[47]. Wasting (weight-for-height z score [WHZ] <–2 standard deviations [SD]) reflects acute energy deficit due to inadequate intake or illness, whereas overweight (WHZ >+2 SD) indicates excess energy intake. National averages can mask large within-country disparities; some districts exhibit severe co-occurrence of wasting and overweight despite moderate national prevalence. We analyzed annual under-5 wasting and overweight for 2759 Chinese counties in 2005–2017.

The Local Burden of Disease (LBD) Double Burden of Malnutrition collaborators produce 5 × 5-km maps of under-5 wasting and overweight across 105 LMICs for 2000–2017 under GATHER reporting standards[48,49]. A Bayesian spatiotemporal mixed-effects framework ensembles predictions from generalized additive models, boosted regression trees, and LASSO, with 1000 posterior draws to characterize uncertainty. Inputs include height, weight, and age for more than three million under-5 children from 420 georeferenced surveys (eg, Demographic and Health Surveys, Multiple Indicator Cluster Surveys, Living Standards Measurement Study rounds, four China-specific studies, and other nationally representative nutrition assessments). When precise cluster coordinates were unavailable, observations were linked to the smallest available administrative unit to minimize spatial misclassification while preserving sample size. LBD grid-level estimates, derived from the best available data sources and methods, are widely used as reference surfaces in population health research[50–52].

Following the LBD framework, we aggregate 5 × 5-km grids to the county level using population weights. For each grid cell, we multiplied prevalence by the under-5 population from WorldPop to obtain expected cases; county-level prevalence equals the sum of expected cases divided by the sum of under-5 population, yielding a population-weighted mean (not a simple spatial average). All rasters were harmonized in projection and resolution; grid cells crossing county boundaries were assigned to the county containing the cell centroid. Cells with missing data or zero population were excluded to avoid denominator bias. Although modeled surfaces carry uncertainty, they provide consistent, high-resolution estimates that reveal subnational disparities obscured in national averages[53].

We combined the county-level child-health outcomes described above with air pollution and covariate data to construct a balanced county-year panel for 2759 Chinese counties from 2005 to 2017. Air pollution exposure was measured using annual ground-level $PM_{2.5}$ estimates from the Washington University Atmospheric Composition Analysis Group GWRPM25 HybridPM25 China product[54–56]. This satellite–model–monitor fusion product combines multi-instrument satellite aerosol optical depth retrievals, GEOS-Chem chemical transport simulations and ground-monitor calibration through geographically weighted regression. Annual gridded PM2.5 surfaces were converted into county-year exposure measures in ArcGIS 10.8 by overlaying the rasters with the 2012 county boundaries and calculating county-level annual means through zonal averaging. In this implementation, grid cells intersecting multiple county polygons were assigned to the county containing the cell centroid. The annual resolution of the $PM_{2.5}$ product is therefore consistent with the county-year structure of the child-health panel.

Control variables were assembled from multiple sources. Night-time lights were obtained from the improved DMSP-OLS-like dataset; educational attainment, exclusive breastfeeding prevalence, moderate anemia prevalence and access to any improved water source were obtained from the Global Health Data Exchange. Meteorological variables were obtained from ERA5 monthly averaged reanalysis data and ERA5-Land hourly data, with the latter used to construct temperature-extreme measures. To maintain a stable spatial unit over time, gridded covariates were processed in ArcGIS 10.8 or Google Earth Engine and aggregated to county-year values using the 2012 county boundaries as a fixed spatial reference. All variables were then harmonized to the county-year level and merged by county identifier and year to form the final analytical panel.

Conventional DID model

We compare how child wasting and overweight changed over time in areas covered by APPCAP versus areas not covered, before and after implementation. This "difference-in-differences" (DID) approach helps separate the policy's effect from background trends[57]. A conventional DID model in the context of this study can be specified as follows:

$$DBM_{it} = \alpha_0 + \alpha_1 APPCAP_{it} + \alpha_2 X_{it} + \gamma_t + \theta_i + \varepsilon_{it} \tag{1}$$

Where DBM_{it} refers to prevalence of childhood wasting (in ‰) or overweight (in %) in county i and year t; $APPCAP_{it}$ is the policy exposure indicator (=1 from the year APPCAP was implemented in that county's prefecture onward, and 0 otherwise); X_{it}comprises socio-economic and environmental covariates (Table S1), measured by stable nighttime light intensity, mean years of education among women 15–49 years, anemia prevalence, exclusive breastfeeding rates in infants under 6 months, access to improved water sources, and climatic factors (Tmax days ≥ 27.5 °C, Tmin days ≤ 2 °C, precipitation, and soil moisture); γ_t and θ_i are the year and county fixed effect, respectively, and ε_{it} is the error term. The coefficient of interest is a_1, which reflects the intention-to-treat of APPCAP on the outcome DBM_{it}.

Matched DID (Gobillon–Magnac hybrid)

Conventional DID handles unobserved differences that are stable over time; bias can arise if such differences evolve[58]. The Gobillon–Magnac (GM) hybrid strengthens causal identification by (i) creating closely comparable treated and control counties and (ii) absorbing any unobserved factors that emerge only after APPCAP begins. **Step 1: Create comparable groups**. We match each treated county to a similar control county on pre-intervention covariates, outcome levels and trends, and estimated unit effects, using one-to-one nearest-neighbor matching with a 0.2 caliper. Operationally, the matching stage relies exclusively on pre-policy information. We first estimate county-level latent fixed effects from the pre-intervention panel to capture persistent unobserved differences across counties, and calculate pre-treatment outcome means to summarize baseline child-health conditions before APPCAP implementation. Using the 2012 pre-intervention cross-section, treated counties are then matched to control counties with similar observed covariates, pre-treatment outcome means, and estimated county effects. This yields a "shadow" control group whose pre-policy trajectories closely parallel those of treated counties. Balance diagnostics show all standardized mean differences <0.10 (Supplementary Information Fig. S6), and pre-treatment trends are well aligned (Supplementary Information Fig. S4 and S5). **Step 2: DID within the matched sample**. We then re-estimate DID in the matched data and include interactions between estimated county effects and post-policy time dummies to soak up any unobserved factors that emerge only after APPCAP begins (for details, see Appendix S4). The resulting coefficient on treatment is our preferred causal estimate of APPCAP's impact on wasting and overweight. As robustness checks, we report spatially robust inference in the Appendix S8.

Mediation analysis

Our mediation analysis addresses a specific question: through which pathway does APPCAP itself affect child nutrition? Specifically, we quantify the share of APPCAP's effect that operates via APPCAP-induced changes in ambient $PM_{2.5}$. This decomposition does not attempt to explain all nationwide reductions in wasting or overweight during 2013–2017; secular improvements and changes unrelated to APPCAP are absorbed by year fixed effects and are not attributed to the policy[59,60].

We use regression-based mediation to decompose the total policy effect into: (i) an indirect effect operating through $PM_{2.5}$ (APPCAP → lower $PM_{2.5}$ → lower wasting/overweight) and (ii) a direct effect capturing all other APPCAP pathways (eg, fuel switching affecting indoor exposure, industrial restructuring altering incomes/food environments) and statistical noise. Practically, we estimate (a) the effect of APPCAP on $PM_{2.5}$, (b) the association between $PM_{2.5}$ and each outcome (adjusting for APPCAP and covariates), and (c) the total effect of APPCAP on each outcome[61]. The mediated (indirect) effect is the product of (a) and (b); the mediated proportion is the indirect effect divided by the total effect (for technical details, see Appendix S5). We state identification assumptions (no unmeasured mediator–outcome confounding that changes with treatment; no exposure-induced mediator–outcome confounders) and provide sensitivity analyses. Please note that reductions unrelated to APPCAP (eg, broader economic changes, nutrition programs, unrelated clean-energy policies, measurement drift) are not part of the total APPCAP effect and thus not credited to the policy in this decomposition[62,63].

Estimated economic benefits of APPCAP

We estimated the direct healthcare cost savings from APPCAP-attributable reductions in childhood wasting and overweight using a simple cost-of-illness approach anchored to the pre-policy baseline year (2012). For each county, we (i) estimated baseline cases by applying 5 × 5-km prevalence surfaces to WorldPop under-5 population counts; (ii) converted the DID-estimated reduction in prevalence for each outcomes ($\hat{\beta}_{1y}$, where $y \in$ {wasting, overweight}; see Appendix S4 for Notation and equation) into cases averted; and (iii) multiplied by unit healthcare costs[36–38] (Appendix S6). Monetary values are reported in 2012 US$ at PPP and, where relevant, discounted at 3% per year.

Data availability

Data Sources: The childhood wasting and overweight data are available from the Global Health Data Exchange at https://ghdx.healthdata.org/record/ihme-data/lmic-double-burden-of-malnutrition-geospatial-estimates-2000-2017. Population data were obtained from WorldPop (https://hub.worldpop.org/). Annual $PM_{2.5}$ data were obtained from the Washington University Atmospheric Composition Analysis Group GWRPM25 HybridPM25 China product (annual China HybridPM25 NetCDF files; https://sites.wustl.edu/acag/datasets/surface-pm2-5/). The improved DMSP-OLS-like night-time lights data are available from Harvard Dataverse at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GIYGJU. Educational attainment, exclusive breastfeeding prevalence, moderate anemia prevalence data, and access to any improved water source were obtained from the Global Health Data Exchange (https://ghdx.healthdata.org/advanced-search). Weather data were obtained from the ERA5 monthly averaged reanalysis dataset and the ERA5-Land hourly dataset hosted by the Copernicus Climate Data Store (https://cds.climate.copernicus.eu/). The processed county-year panel data is available on Figshare at https://doi.org/10.6084/m9.figshare.33261090.

Code availability

The analytical code used for data processing, econometric estimation, mediation analysis, robustness checks and figure generation is available on Figshare at https://doi.org/10.6084/m9.figshare.33261090.

Received: 3 May 2026; Accepted: 1 September 2026;
Published online: 15 September 2026

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Author contributions

Lili Xu and Laixiang Sun contributed to the study design and conceptualization. Laixiang Sun and Kuishuang Feng contributed to the methodology. Lili Xu and Meiting Fan implemented the data analysis. Lili Xu and Shuai Shao wrote the original draft. Laixiang Sun and Kuishuang Feng revised and edited the draft. Lili Xu, Shuai Shao, and Meiting Fan have directly accessed and verified the underlying data reported in the manuscript. Laixiang Sun, Kuishuang Feng, and Shuai Shao were responsible for the decision to submit the manuscript. All authors discussed the results, commented on the manuscript, and approved the final version.

Funding

We acknowledge the financial support from the National Natural Science Foundation of China (Nos. 72304173, 72243004, 72573116, 72103125 and 72473090) and Shandong Provincial Natural Science Foundation (No. ZR2023QG022).

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s43247-026-04061-2.

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Peer review information *Communications Earth & Environment* thanks Pierre Levasseur and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Primary handling editors: Fobang Liu and Alice Drinkwater. A peer review file is available.

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