

Microplastics alter soil phosphatase activity and phosphorus mobilization: A global meta-analysis integrated with machine learning

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HIGHLIGHTS

- Microplastics increase soil acid phosphatase activity by 9.89% across 171 global studies.
- Alkaline phosphatase shows no significant overall response but strong context dependence.
- Soil pH governs acid phosphatase responses; clay content governs alkaline phosphatase.
- Interpretable machine learning resolves nonlinear dose–response relationships across studies.
- Clay-rich soils are identified as most vulnerable to ALP functional suppression.

ARTICLE INFO

Keywords:

Microplastics
Phosphorus mobilization
Diffuse pollution
Meta-analysis
Machine learning
SHAP analysis
Soil pH
Clay content

ABSTRACT

Agricultural soils are a major reservoir and conduit within the anthropogenic water cycle, receiving microplastics (MPs) through sewage-sludge/biosolid land application, reclaimed-water irrigation, plastic-mulch degradation and atmospheric deposition, and exporting dissolved nutrients to surface and ground waters via runoff and leaching. Phosphatase enzymes govern organic-phosphorus mineralization and therefore the size of the dissolved phosphorus (P) pool that drives aquatic eutrophication, yet how MPs alter soil acid (ACP) and alkaline (ALP) phosphatase activity, and which conditions create the greatest soil-to-water transfer risk, remains unresolved. We synthesized 171 global studies (866 ACP and 688 ALP observations) in a meta-analysis integrated with an interpretable machine-learning ensemble that stacked XGBoost, LightGBM and Random Forest, with SHAP and accumulated local effects (ALE) interpretation. MPs significantly increased ACP activity by 9.89%, whereas the overall ALP effect was non-significant (+1.40%) but strongly context-dependent, ranging from significant stimulation (e.g., biodegradable MPs: +15.15%; aged MPs: +25.60%) to significant decrease under certain conditions (e.g., with nitrogen addition: −9.45%). Soil pH was the dominant control on ACP responses (mean |SHAP| = 0.088) and clay content on ALP responses (0.062), each ranking first across all five best-performing XGBoost configurations, indicating divergent driver hierarchies for the two enzymes. In the machine-learning analysis, ALP suppression was concentrated in clay-rich soils, whereas low-clay soils showed neutral-to-positive responses. By identifying where MP contamination most strongly perturbs phosphatase-mediated P mobilization, our findings connect a terrestrial contaminant to diffuse nutrient pollution of receiving waters and provide a transferable framework for contaminant–water-quality synthesis.

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<https://doi.org/10.1016/j.watres.2026.126840>

Received 15 June 2026; Received in revised form 10 August 2026; Accepted 31 August 2026

Available online 31 August 2026

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1. Introduction

Agricultural soils are an integral compartment of the anthropogenic water cycle. They receive anthropogenic particulate contaminants, including microplastics (MPs), through sewage-sludge and biosolid land application, irrigation with reclaimed or untreated wastewater, the degradation of plastic mulch films, and atmospheric deposition originating from urban and industrial areas (Rillig et al., 2024, 2019). Because wastewater treatment concentrates MPs into sludge that is subsequently applied to farmland, the land application of biosolids constitutes a direct hydrological link between urban water systems and agricultural soils (de Souza Machado et al., 2018a). Once in the soil, these contaminants do not remain static: soils act as both a sink and a secondary source, exporting particulate and dissolved constituents to surface and ground waters via surface runoff, erosion, preferential flow, and leaching. Soil is therefore not the terminus of MPs pollution but an upstream node governing the quality of receiving waters (de Souza Machado et al., 2018a; Horton et al., 2017). Among the soil processes most relevant to downstream water quality is the mineralization of organic phosphorus, catalyzed primarily by acid (ACP) and alkaline (ALP) phosphatase enzymes. Although both enzyme classes catalyze organic-P hydrolysis, they differ fundamentally in origin and environmental sensitivity: ACP is produced by both plant roots and soil microorganisms, whereas ALP is almost exclusively a bacterial and fungal extracellular enzyme whose functional persistence in soil depends on adsorption to mineral surfaces, particularly clay particles (Allison, 2006; Burns, 1982; Nannipieri et al., 2012). This biochemical asymmetry suggests that MPs may alter ACP and ALP activities through different edaphic pathways, motivating systematic comparison of their divergent responses. These enzymes regulate the conversion of organic P into bioavailable orthophosphate and thus control the size of the dissolved phosphorus (P) pool that can be mobilized to streams, lakes, and aquifers, where P is a principal driver of eutrophication and one of the most urgent water-quality challenges facing human societies (Cordell and White, 2014; Wang et al., 2024a, 2024b). Diffuse, non-point-source nutrient loading from agricultural land is now the dominant control on the trophic status of many freshwater bodies, with agriculture contributing the majority of anthropogenic P inputs to surface waters. Any contaminant capable of systematically altering phosphatase activity could therefore shift the diffuse-P export potential of soils and, by extension, aquatic eutrophication risk, yet the direction, magnitude, and context-dependence of MP effects on soil phosphatases have not been quantitatively synthesized at the global scale (Wang et al., 2024a, 2024b). Resolving these effects, and identifying the soil conditions under which they are strongest, is a prerequisite for assessing how a pervasive anthropogenic contaminant may influence phosphorus mobilization in soil–water continuum.

Microplastics can influence the activities of soil phosphatases by integrated physical, chemical, and biological pathways. Physically, MPs alter soil structure, porosity, water-holding capacity (WHC), and aggregate stability, thereby affecting microbial habitats and rates of substrate diffusion (de Souza Machado et al., 2018b; Wang et al., 2025). Chemically, MPs adsorb phosphate ions and enzymes on their surfaces, limiting substrate accessibility (Dong et al., 2022). Importantly, MPs affect soil pH depending on the polymer: conventional polymers (e.g. polyethylene (PE) and polypropylene (PP)) generally increase soil pH by altering aeration, whereas biodegradable polymers (e.g. polylactic acid (PLA)) decrease pH by the release of organic acid during degradation (Boots et al., 2019). Biologically, MPs determine the compositions and functions of microbial communities, creating distinct ‘plastisphere’ biofilm communities on their surfaces enriched in taxa associated with nutrient cycling (Amaral-Zettler et al., 2020; Zettler et al., 2013). The effect of MPs on phosphatase activity thus depends on the interplay among these pathways, which in turn varies with soil type, MP characteristics, and experimental conditions, a complexity that conventional analytical approaches have difficulty resolving.

Several meta-analyses have attempted to synthesize the effects of MPs on the activities of soil enzymes (Lan et al., 2025; Li et al., 2025; Liu et al., 2023; Zhou et al., 2024). Liu et al. (2023) found a significant 8.3% increase in ACP activity following exposure to MPs, with effects varying by polymer type and soil pH. Zhou et al. (2024) conducted a meta-analysis of the effects of MPs on P cycling and found that the responses of ACP and ALP were generally not significant but that biodegradable MPs had stronger negative effects on available P than did conventional MPs. These syntheses provided valuable insights through subgroup analysis and meta-regression, yet these approaches are inherently limited in their ability to simultaneously control for multiple continuous predictors or to detect nonlinear relationships, which provides a legitimate rationale for complementing them with machine learning methods. These syntheses established the first-order effects of MPs on soil enzyme activity and identified soil pH, polymer type, and exposure duration as important modulators.

Machine-learning (ML) methods offer a different analytical framework for addressing these limitations. Gradient-boosted decision-tree algorithms such as XGBoost (Chen and Guestrin, 2016) and LightGBM (Ke et al., 2017) natively identify nonlinear relationships, handle high-dimensional collinear predictor spaces, and model complex multiple interactions without a priori specification. SHapley Additive exPlanations (SHAP) (Lundberg and Lee, 2017) connect cooperative game theory to ML model interpretation, decomposing each prediction into feature-level contributions with guaranteed theoretical properties. Subgroup analysis and meta-regression, however, evaluate moderators either one at a time or under an assumption of linearity; they cannot simultaneously control for multiple continuous covariates, nor detect threshold or saturating responses. Because MP effects on phosphatases are plausibly governed by several interacting continuous edaphic variables, we complement, rather than replace, these approaches with an interpretable machine learning framework capable of resolving nonlinearity and high-order interaction while holding all covariates jointly.

We present a meta-analysis integrated with ML that synthesized 171 global studies (866 ACP observations and 688 ALP observations) to evaluate the influences of MPs on the activities of soil phosphatases. Specifically, we aimed to address two questions: (1) What were the dominant environmental and experimental factors driving heterogeneity in the responses of ACP and ALP to MPs exposure, and did these two classes of enzymes share common drivers? (2) Were the dose-response relationships or ecological thresholds for the effects of key drivers (e.g. soil pH, clay content, exposure duration, MPs concentration) on phosphatase activity nonlinear? We hypothesized that ACP and ALP would respond to different environmental controls under MP exposure due to their divergent pH optima, biological origins, and mechanisms of mineral interactions. We therefore distinguish two roles of soil pH that have often been conflated. Initial soil pH acts as a background condition: it determines the catalytic optimum of each phosphatase class, governs enzyme sorption to mineral surfaces, and structures the microbial community that produces them. Separately, MPs can perturb pH directly, with conventional polymers generally raising and biodegradable polymers generally lowering soil pH through the release of degradation intermediates. Our machine learning framework uses initial pH as a predictor and therefore addresses the first role: it asks in which soils phosphatase activity is most responsive to microplastic exposure, not whether microplastics act by shifting pH.

2. Materials and methods

2.1. Data collection

To ensure the comprehensive retrieval of evidence, we conducted a systematic literature search across the Web of Science (<http://www.webofknowledge.com>), the China National Knowledge Infrastructure (<https://www.cnki.net>), and Google Scholar (<http://scholar.google>).

com), with publications collected to 12 December 2025. The search aimed to identify all available studies examining the effects of MPs on the activities of ACP and ALP in soil. The search query combined three conceptual blocks using Boolean operators: pollutant terms (microplastic, nanoplastic, and plastic microparticles), target-enzyme terms (acid phosphatase, ACP, alkaline phosphatase, and ALP), and the matrix term (soil).

A systematic procedure for screening and extracting data was applied to select eligible publications. The inclusion criteria were: (1) reporting of ACP and/or ALP activity in soil; (2) a comparative experimental design containing at least one control group and one microplastic-treatment group, with each treatment independently compared to the control; (3) the most comprehensive publication was retained when duplicate data sets were identified; (4) a minimum of three experimental replicates with reported sample sizes; (5) data presented as means $\pm$ standard deviations (SDs) or in convertible metrics (e.g. standard errors, SEs). All stages of this systematic review, including the identification and screening of the literature, assessment of eligibility, and compilation of the final data set, followed the framework of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (Fig. S1). Using this process, 171 global studies qualified for inclusion, yielding 866 observations for ACP (from 94 studies), and 688 observations for ALP (from 88 studies; Fig. S2).

2.2. Data compilation and stratification

The compiled data set from the 171 global studies encompassed two categories of variables: response variables and moderator variables. The response variables consisted of the activities of ACP and ALP. The moderator variables spanned experimental conditions, soil properties, and microplastic characteristics. Experimental conditions included the presence of toxic substances, plant involvement, nitrogen fertilization, exposure temperature, and exposure duration. Soil properties comprised WHC, clay content, initial soil pH (iSpH), initial concentration of soil organic matter (iSOM), initial concentration of soil total phosphorus (iSTP), and initial concentration of soil available phosphorus (iSAP). MPs characteristics included polymer composition (PC: polyamide (PA), poly(butylene adipate-co-terephthalate) (PBAT), polyethylene (PE), polyethylene terephthalate (PET), polylactic acid (PLA), polypropylene (PP), polystyrene (PS), and polyvinyl chloride (PVC)), MP type (virgin vs aged), MP degradability, MPs size, and MP concentration. For each observation, means, SDs, and sample sizes (n) were extracted directly from the texts or tables or were digitized from figures using WebPlotDigitizer (v4.7, <https://automeris.io/WebPlotDigitizer/>). When SEs were reported, they were converted to SDs using the formula $SD = SE \times \sqrt{n}$.

We classified all moderator variables into discrete subgroups for systematic comparison to determine how the effects of MPs on the activities of soil phosphatases varied across ecological and experimental factors. These classification criteria (Table 1) were established based on ecologically meaningful thresholds derived from previous studies (Li et al., 2025; Liu et al., 2025; Sun et al., 2024; Xiang et al., 2025, 2024). These categorical classifications were applied to the conventional meta-analytic subgroup comparisons. For the ML analyses (Section 2.3.2), continuous variables were preserved in their original format to maximize information retention and enable the detection of nonlinear dose-response relationships.

2.3. Data analysis

2.3.1. Meta-analysis

The natural log of the response ratio (lnRR) was used as the metric of effect size to quantify the impact of exposure to MPs on the activities of soil phosphatases. LnRR was calculated as the logarithm of the ratio of the means between the treatment and control groups (Eq. (1)) (Hedges et al., 1999):

Table 1

Categorization of environmental variables and attributes of microplastics included in the meta-analysis. Abbreviations for 1) polymer composition: PA, polyamide; PBAT, poly(butylene adipate-co-terephthalate); PE, polyethylene; PET, polyethylene terephthalate; PLA, polylactic acid; PP, polypropylene; PS, polystyrene; PVC, polyvinyl chloride. 2) MP degradability: Bio., biodegradable MPs; Con., conventional MPs.

Category	Environmental variable	Abbreviation	Subgroups
Experimental condition	Toxic substances	TS	Yes, No
	Plant involvement	Plant	Absent, Present
	Nitrogen addition	NYN	Yes, No
	Exposure temperature (°C)	ET	<25, 25–27, >27
	Exposure duration (days)	ED	<30, 30–90, >90
Soil property	Water-holding capacity (%)	WHC	<55, 55–65, >65
	Soil clay content (%)	SCC	<20, 20–32, >32
	Initial soil pH	iSpH	<6.5, 6.5–7.5, >7.5
	Initial concentration of soil organic matter (g kg ⁻¹)	iSOM	<10, 10–30, >30
	Initial concentration of soil total phosphorus (g kg ⁻¹)	iSTP	<0.3, 0.3–0.9, >0.9
	Initial concentration of soil available phosphorus (mg kg ⁻¹)	iSAP	<10, 10–20, >20
	Polymer composition ¹	PC	PA, PBAT, PE, PET, PLA, PP, PS, PVC
Microplastic attribute	MP type	MPT	Virgin, Aged
	MP degradability ²)	MPD	Bio., Con.
	MPs size (µm)	MPS	<50, 50–150, >150
	MP concentration (g kg ⁻¹)	MPC	<5, 5–10, >10

$$\ln RR = \ln(\bar{X}_t / \bar{X}_c) = \ln(\bar{X}_t) - \ln(\bar{X}_c) \quad (1)$$

where $\bar{X}_t$ and $\bar{X}_c$ represent the mean responses of the treatment (with MPs) and control (without MPs) groups, from which the response ratio was derived.

Multiple effect sizes often originate from shared control groups within the same study, so we constructed a variance-covariance matrix to account for the resulting statistical non-independence (Supporting Information) (Knapp and van der Heijden, 2018). The matrix was computed using a modified version of the covariance.commonControl() function in the “metagear” package (Viechtbauer, 2010).

A multivariate random-effects meta-analytic model was fitted to account for heterogeneity both within and between studies. The overall effect of exposure to MPs was considered significant if its 95% confidence interval (CI) excluded zero but was otherwise considered not significant. For intuitive presentation, the weighted lnRR (lnRR₊) and its 95% CI were transformed into percent change using the equation: Effect size (%) = [exp(lnRR₊) – 1] × 100. Heterogeneity between studies was quantified using the I^2 statistic and Cochran’s Q-test. Subgroup analyses were performed to identify moderating factors, with heterogeneity between subgroups evaluated using the Q_M statistic (between-group heterogeneity).

We conducted a comprehensive suite of sensitivity analyses and publication-bias diagnostics to ensure the robustness of the meta-analytic findings. The influence of individual effect sizes on the overall estimate was evaluated using a leave-one-out approach. Publication bias was assessed using Egger’s regression test and the trim-and-fill procedure (Figs. S3, S4). These diagnostics should be interpreted with caution in the present context. Their statistical properties are best characterised under low to moderate heterogeneity; where I^2 approaches 99%, funnel-plot asymmetry may reflect genuine effect modification by study-level moderators rather than selective

publication, Egger's test shows inflated Type I error, and trim-and-fill can impute non-existent studies and over-adjust the pooled estimate (Sterne et al., 2011). We therefore present these analyses as exploratory, and we do not interpret the absence of detected asymmetry as positive evidence that publication bias is absent.

2.3.2. Machine-learning analysis

We identified the key factors driving the heterogeneity of the effects of MPs on the activities of soil phosphatases by applying three ML algorithms: eXtreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016), Light Gradient-Boosting Machine (LightGBM) (Ke et al., 2017), and random forest (RF) (Breiman, 2001). These algorithms were selected for their demonstrated capacity to identify nonlinear relationships, model high-order interactions among predictors, and ability to use collinear feature spaces, properties that address the principal limitations of traditional meta-regression (Senior et al., 2016). The predictor set comprised 17 moderator variables spanning experimental conditions (experimental setting, soil source, co-exposure to toxic substances, plant involvement, nitrogen addition, exposure temperature, and exposure duration), soil properties (WHC, clay content, initial soil pH, initial SOM, initial SAP), and MP characteristics (polymer composition, degradability, type, size, and concentration (Table 1). Experimental setting and soil source were used only in the machine-learning models and were not analyzed as subgroup strata; they are therefore not listed in Table 1. Initial STP was retained in the subgroup analyses (Fig. 4i, j) but excluded from the ML predictor set owing to sparse reporting. Separate models were trained for ACP ($n = 866$) and ALP ($n = 688$).

Data preprocessing followed a recipe-based workflow fitted independently within each cross-validation fold using only the training data, so that no information from held-out studies influenced imputation, level collapsing or variable selection. Missing values were imputed by bagged regression trees (25 trees) using all remaining predictors as donors (Stekhoven and Bühlmann, 2011); categorical levels representing <3% of training observations were collapsed into an "Other" category; predictors were one-hot encoded with no reference level omitted, so that each retained level receives its own SHAP attribution. The full preprocessing sequence is given in Supplementary text, S1.7.

Hyperparameters for XGBoost and LightGBM were optimized using Bayesian optimization (40 iterations following 15 initial configurations) (Snoek et al., 2012). Tuned parameters included the number of trees (200–2000), tree depth (3–10), learning rate (0.01–0.32 on a log10 scale), mtry, minimum node size (5–30), and loss reduction (XGBoost only; 10^{-5} to 1). RF was tuned over a 30-point random grid for mtry and minimum node size (trees fixed at 1000). Full hyperparameter ranges are provided in Table S1. Model training used a grouped k-fold cross-validation strategy designed to prevent data leakage arising from non-independent effect sizes within the same experiment. All model performance statistics were estimated by grouped cross-validation in which folds were defined at the level of the study group rather than the individual observation. Groups were defined solely by design and site descriptors that do not vary with treatment within an experiment (experimental setting, initial soil pH, initial SOM, clay content, water-holding capacity, and exposure temperature); treatment factors, polymer composition, MP type, dose and exposure duration, were deliberately excluded from the grouping key, because including them subdivides a single experiment across folds and permits within-experiment information to leak between training and validation sets (Nakagawa et al., 2023). This yielded 122 groups for ACP and 96 for ALP. Ten outer folds were used for both enzymes. Because the stacking ensemble contains a meta-learner that is itself fitted to out-of-sample predictions, ensemble performance was estimated by nested cross-validation: within each outer fold, hyperparameter selection, base-learner fitting and meta-learner blending were repeated using only the training studies (five inner grouped folds), and predictions were generated for the withheld studies.

The three models were integrated using a stacking ensemble

framework (Breiman, 1996; Wolpert, 1992). The five best hyperparameter configurations (ranked by inner-fold RMSE) for each algorithm were retained as candidate members, a number chosen to balance diversity in the ensemble against the risk of including degenerate configurations that produce near-constant predictions. These candidates were combined using a penalized linear meta-learner (Least Absolute Shrinkage and Selection Operator (LASSO) regression with non-negative constraints), which assigns optimized blending weights that leverage the complementary strengths of each algorithm while penalizing redundant contributions. The stacking procedure was implemented using the "stacks" package (Couch and Kuhn, 2022).

2.4. Model interpretation and statistical analyses

Model interpretability was evaluated using two approaches: SHAP analysis and plots of accumulated local effects (ALE). SHAP values were calculated for the best-performing XGBoost configuration using the TreeSHAP algorithm (Lundberg et al., 2020). ALE plots (Apley and Zhu, 2020) were constructed for the six numeric features per enzyme, selected from among the highest-ranked predictors by mean |SHAP| subject to the availability of a continuous ALE grid across the observed range, to characterize continuous, model-agnostic feature effects; the ALE curve for MP concentration is shown in Fig. S6.

All ML analyses were performed in R v4.3.3 using the "tidymodels" ecosystem (Kuhn and Silge, 2022), with "xgboost" (Chen et al., 2015) and "bonsai" (Couch and Kuhn, 2023) for LightGBM, and "ranger" (Wright and Ziegler, 2017) for RF. SHAP values were calculated using "shapviz" (Mayer, 2023), and the ALE plots were constructed using "iml" (Molnar and Schratz, 2020). Visualizations were produced using "ggplot2" (Wickham, 2016) and "patchwork" (Pedersen, 2024).

3. Results

3.1. General response of the activities of soil phosphatases to MP exposure

The meta-analysis identified divergent overall effects of MP exposure on ACP and ALP activities (Fig. 1a, b). Exposure to MPs significantly increased ACP activity by 9.89%, with 63.05% of individual observations indicating positive effects. In contrast, the overall effect on ALP activity was not statistically significant (1.40%), although 51.45% of observations indicated a positive directional response.

The frequency distributions of lnRR values for both ACP and ALP were well described by Gaussian fits (Fig. 1c, d; $R^2 = 0.98$ and 0.99 , respectively), indicating approximately symmetric effect-size distributions. Substantial between-study heterogeneity was detected for both enzymes, with I^2 values of 99.41% and 99.18% for ACP and ALP, respectively (both $p < 0.001$). These exceptionally high I^2 values indicate that the global mean effect sizes should be interpreted with caution, as they subsume substantial context-dependent variation. This heterogeneity highlights the necessity of the subsequent ML approach to disentangle the sources of variation across studies.

3.2. Effect of MPs on the activities of soil phosphatases under experimental conditions

Experimental conditions differentially affected MP-induced changes in ACP and ALP activities (Fig. 2). Co-exposure to toxic substances amplified the increase in ACP activity to 18.56%, almost four-fold greater than under non-toxic conditions (4.45%, $p < 0.05$), but did not significantly differentiate ALP responses. Plant presence was associated with a significant increase in ACP activity (8.76%), although the between-subgroup contrast was not significant for either enzyme. Nitrogen addition was the strongest experimental moderator for ALP ($p < 0.01$), reversing the MP effect from enhancement (5.63% without nitrogen) to significant inhibition (−9.45% with nitrogen), whereas ACP subgroups did not differ significantly. Temperature did not significantly

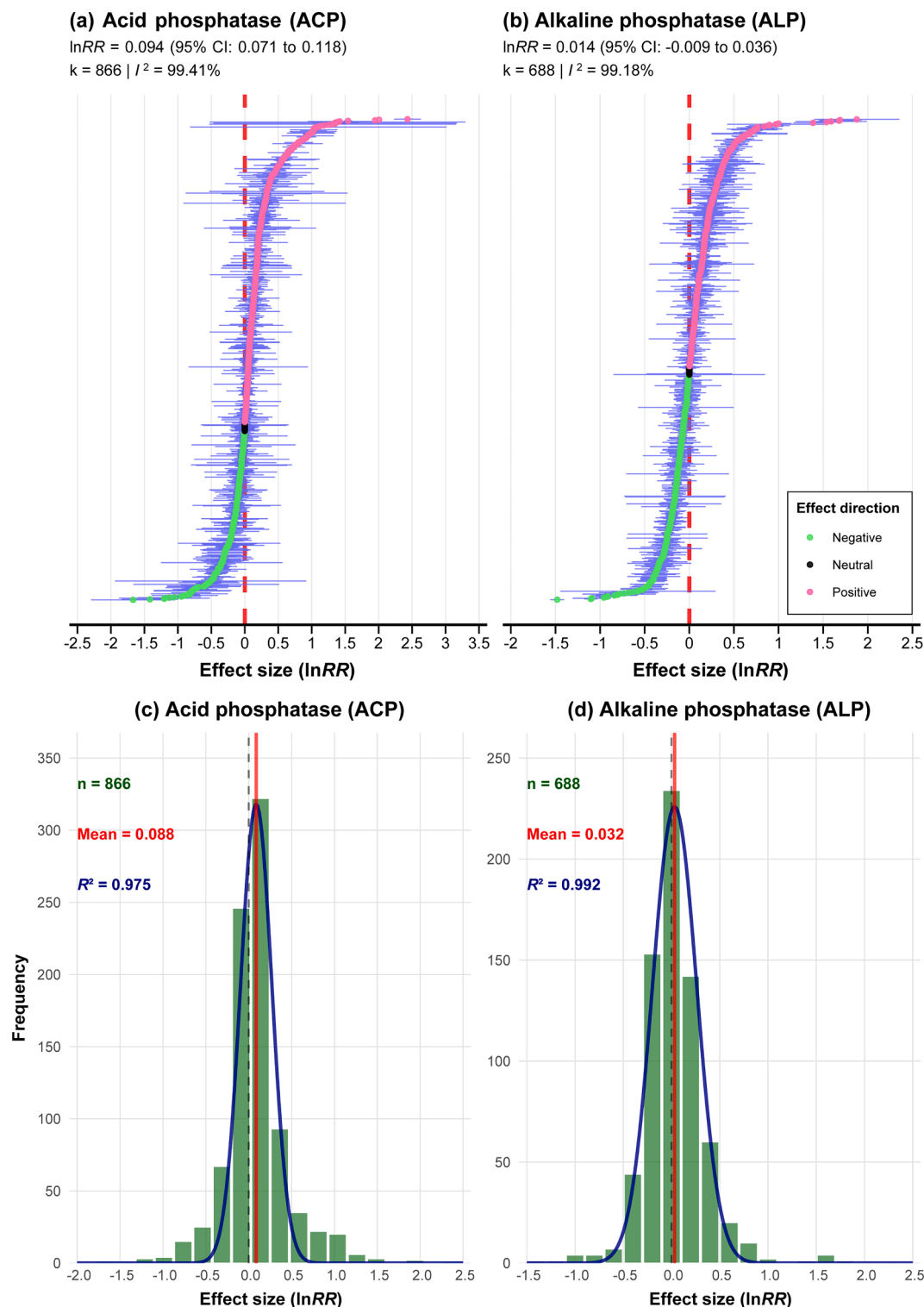


Fig. 1. Overall effects of microplastics on the activities of soil phosphatases. Forest plots of individual effect sizes (log response ratio, $\ln RR$) for (a) acid phosphatase (ACP, $k = 866$) and (b) alkaline phosphatase (ALP, $k = 688$). Each point represents an individual effect size from a primary study. The vertical red dashed lines ($\ln RR = 0$) indicate no effect. Points are colored by the direction of the effect: pink, green, and black for positive, negative, and neutral effects, respectively. The overall weighted mean effect sizes and 95% confidence intervals are reported above each panel. Frequency distributions of individual effect sizes for (c) ACP and (d) ALP, fitted with Gaussian models (blue curves). The red dashed vertical lines indicate the overall mean $\ln RR$ s. Sample sizes (n), mean $\ln RR$ s, and R^2 values for the Gaussian fits are displayed in each panel.

differentiate subgroups for either enzyme. Exposure duration significantly affected ACP ($p < 0.01$), with peak stimulation between 30 and 90 days (9.59%); ALP subgroups did not differ significantly, though activity increased during this interval (6.08%).

3.3. MP characteristics as mediators of the activities of soil phosphatases

MP characteristics significantly affected phosphatase activities, with distinct response patterns for ACP and ALP (Fig. 3). Polymer

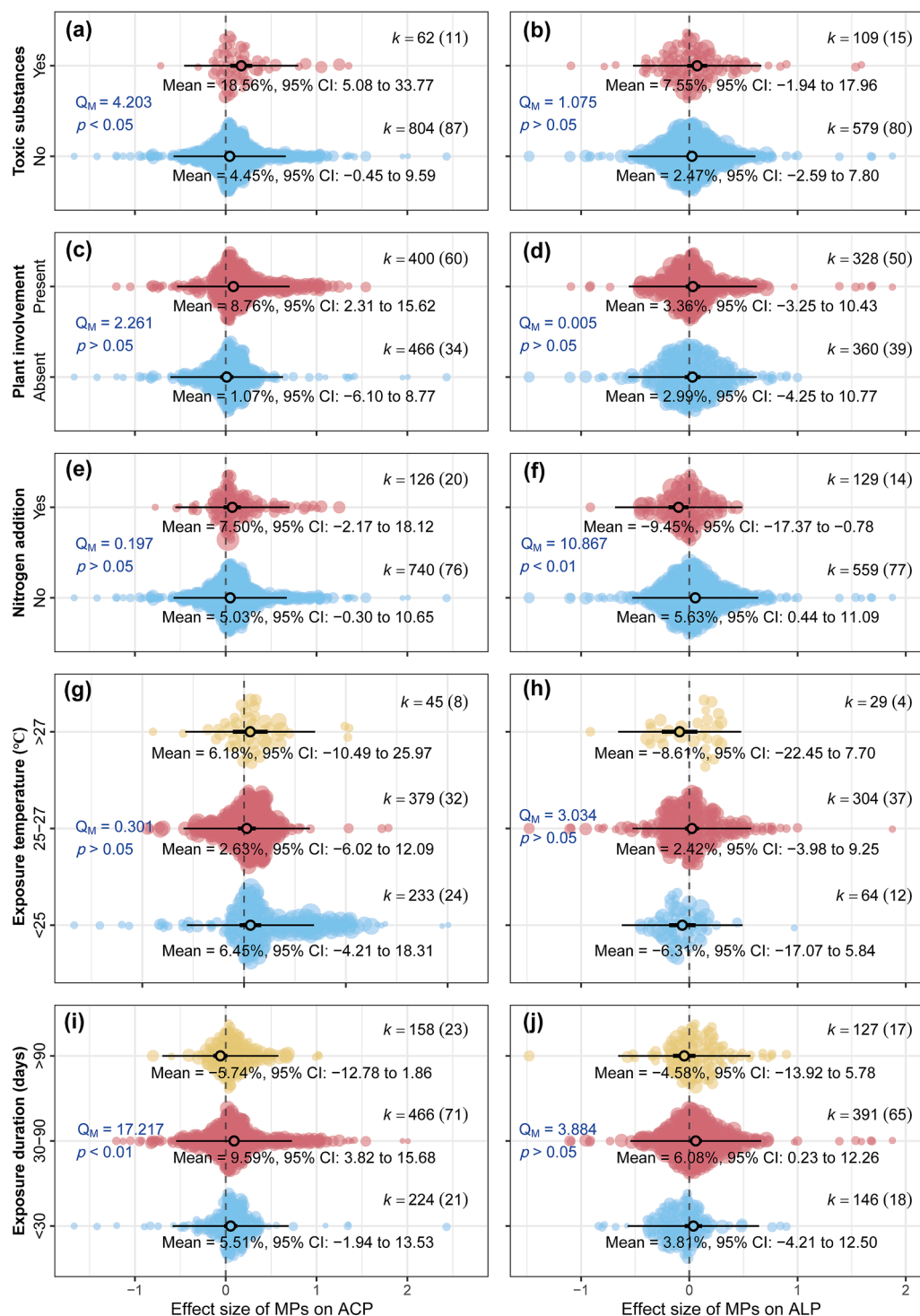


Fig. 2. Subgroup analyses of the effects of microplastics on the activities of soil phosphatases stratified by experimental conditions. Left panels (a, c, e, g, and i) show the effects on acid phosphatase (ACP), and right panels (b, d, f, h, and j) show the effects on alkaline phosphatase (ALP). Moderating factors are: (a, b) co-exposure to toxic substances, (c, d) plant involvement, (e, f) nitrogen addition, (g, h) exposure temperature, and (i, j) exposure duration. Each point represents an individual effect size (percent change relative to control), and the diamonds represent the weighted mean effect size, with the horizontal error bars representing the 95% confidence interval for each subgroup. The number of observations and studies for each subgroup are shown as k = number of observations (studies). The Q_M statistic and associated p value for the tests of heterogeneity between subgroups are displayed in each panel. The vertical dashed lines indicate no effect (no change). Subgroup categories are <25 , $25-27$, and >27 °C for temperature and <30 , $30-90$, and >90 days for exposure duration.

composition differed significantly between subgroups for both enzymes: PP induced the largest ACP increase (22.31%, $p < 0.01$), whereas PLA induced the strongest ALP stimulation (14.39%, $p < 0.05$). Aging status did not significantly affect ACP, but was a significant moderator for ALP ($p < 0.05$), with aged MPs enhancing activity by 25.60% while virgin

MPs had no significant effect. Similarly, degradability did not significantly differentiate ACP subgroups, but was highly significant for ALP ($p < 0.01$): biodegradable MPs increased ALP activity by 15.15%, whereas conventional MPs had no significant effect. MP size significantly influenced both enzymes but with distinct patterns: the smallest

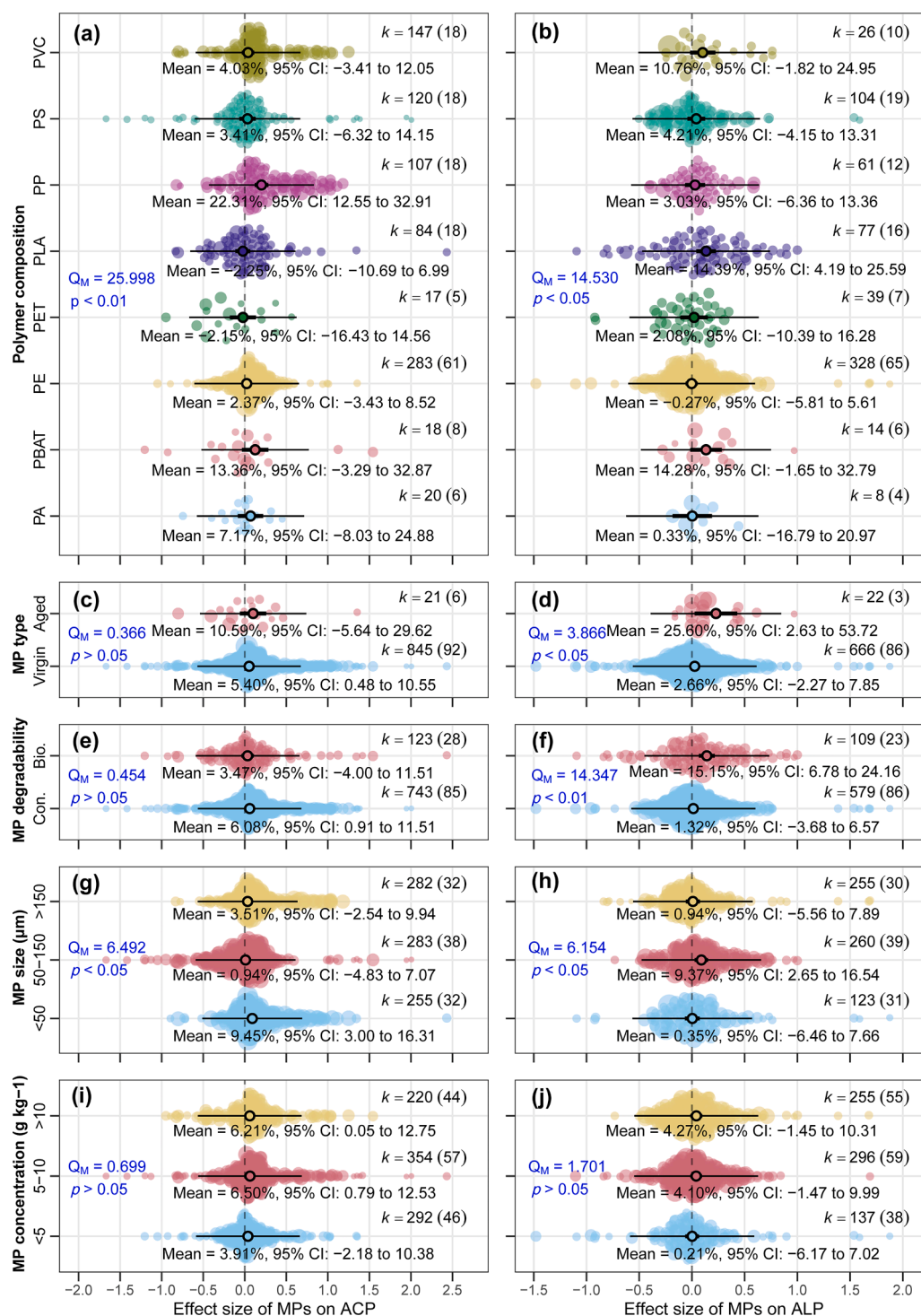


Fig. 3. Subgroup analyses of the effects of microplastics on the activities of soil phosphatases stratified by the characteristics of the microplastics. Left panels (a, c, e, g, and i) show the effects on acid phosphatase (ACP), and right panels (b, d, f, h, and j) show the effects on alkaline phosphatase (ALP). Moderating factors are: (a, b) polymer composition (PA, PBAT, PE, PET, PLA, PP, PS, and PVC), (c, d) MP type (virgin vs aged), (e, f) MP degradability (biodegradable, Bio. vs conventional, Con.), (g, h) MP size (<50, 50–150, and >150 µm), and (i, j) MP concentration (<5, 5–10, and >10 g kg⁻¹). The presentation has the same format as in Fig. 2: each point represents an individual effect size, the diamonds with horizontal error bars represent weighted mean effect sizes and 95% confidence intervals for each subgroup, and k = number of observations (studies). Q_M statistics and p values for the tests of heterogeneity between subgroups are displayed in each panel. The vertical dashed lines indicate no effect. MP, microplastic; PA, polyamide; PBAT, poly(butylene adipate-co-terephthalate); PE, polyethylene; PET, polyethylene terephthalate; PLA, polylactic acid; PP, polypropylene; PS, polystyrene; PVC, polyvinyl chloride.

fraction (<50 µm) increased ACP activity (9.45%, $p < 0.05$), whereas intermediate sizes (50–150 µm) increased ALP activity (9.37%, $p < 0.05$). MP concentration subgroups did not differ significantly for either enzyme.

3.4. Soil modulation of phosphatase activities under MP exposure

Initial soil properties significantly affected the phosphatase activities (Fig. 4). The effect of WHC did not differ significantly between

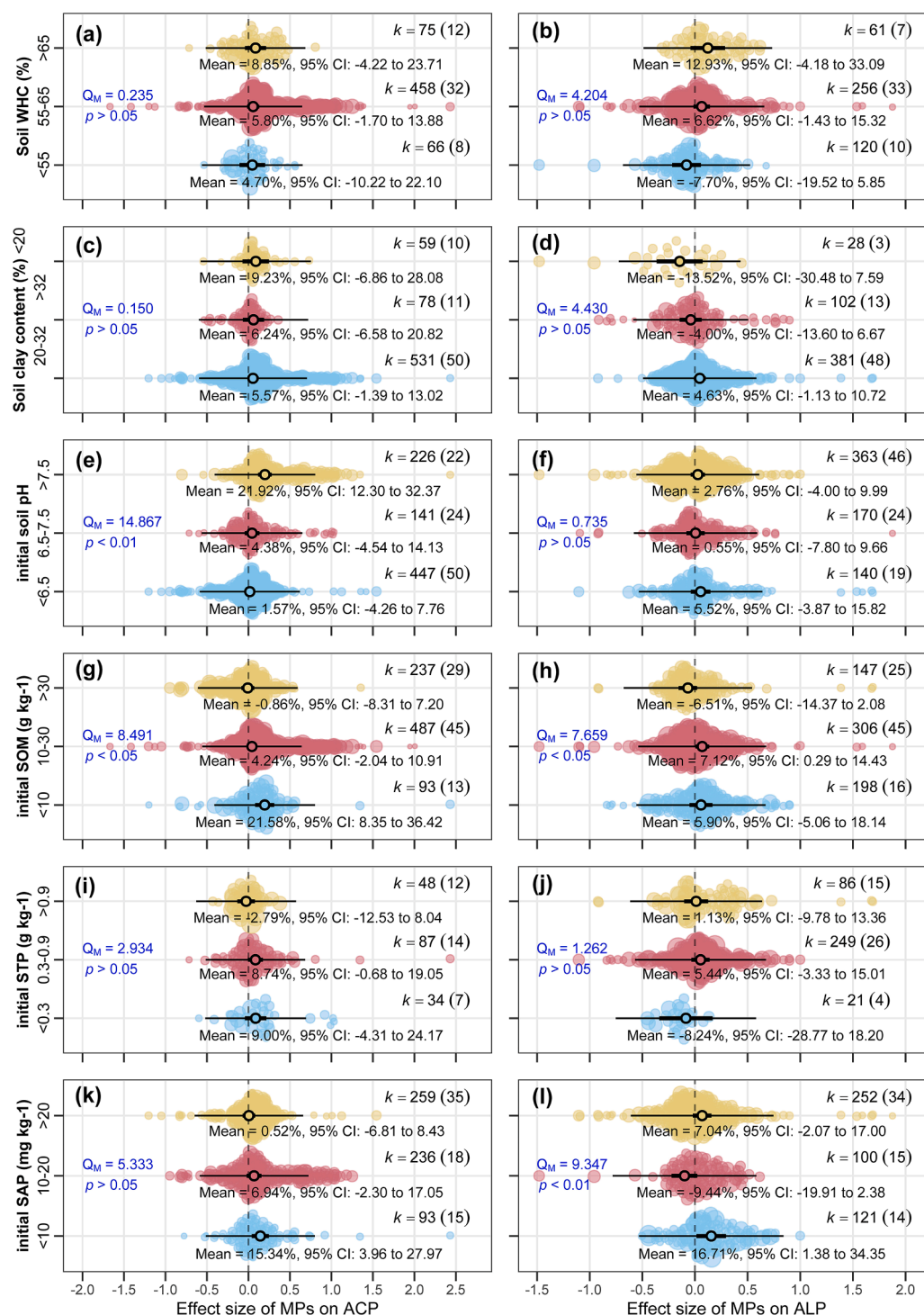


Fig. 4. Subgroup analyses of the effects of microplastics on the activities of soil phosphatases stratified by initial soil properties. Left panels (a, c, e, g, i, and k) show the effects on acid phosphatase (ACP), and right panels (b, d, f, h, j, and l) show the effects on alkaline phosphatase (ALP). Moderating factors are: (a, b) soil water-holding capacity (WHC; <55, 55–65, and >65%), (c, d) soil clay content (<20, 20–32, and >32%), (e, f) initial soil pH (<6.5, 6.5–7.5, and >7.5), (g, h) initial concentration of soil organic matter (SOM; <10, 10–30, and >30 g kg⁻¹), (i, j) initial concentration of soil total phosphorus (STP; <0.3, 0.3–0.9, and >0.9 g kg⁻¹), and (k, l) initial concentration of soil available phosphorus (SAP; <10, 10–20, and >20 mg kg⁻¹). The presentation has the same format as in Figs. 2 and 3: each point represents an individual effect size, diamonds with horizontal error bars represent weighted mean effect sizes and 95% confidence intervals for each subgroup, and k = number of observations (studies). Q_M statistics and p values for the tests of heterogeneity between subgroups are displayed in each panel. The vertical dashed lines indicate no effect.

subgroups for ACP (Fig. 4a) and ALP (Fig. 4b). Effect sizes were nonsignificant across all WHC categories for both enzymes. Soil clay content did not significantly affect ACP (Fig. 4c) or ALP (Fig. 4d) activities.

Initial soil pH was a highly significant moderator of ACP activities (Fig. 4e). Under alkaline conditions (pH >7.5), exposure to MPs significantly increased ACP activities (21.92%), whereas effects in acidic (pH <6.5) and neutral soils (pH 6.5–7.5) were not significant. Differences

between subgroups were not significant for ALP (Fig. 4f).

Initial SOM concentration significantly affected ACP (Fig. 4g) and ALP (Fig. 4h) activities, but with contrasting patterns. ACP had a negative gradient: stimulation was strong in soils with low SOM ($<10 \text{ g kg}^{-1}$; 21.58%), declining to a non-significant +4.24% at intermediate SOM ($10\text{--}30 \text{ g kg}^{-1}$) and -0.86% at high SOM ($>30 \text{ g kg}^{-1}$). ALP activity was significantly higher in soils with intermediate SOM (7.12%), with non-significant effects in both low- and high-SOM categories.

Initial STP did not significantly affect ACP (Fig. 4i) or ALP (Fig. 4j) activities. Initial SAP significantly affected ALP activities (Fig. 4l). The effect of MPs significantly increased ALP activities in phosphorus-depleted soils (SAP $<10 \text{ mg kg}^{-1}$; 16.71%).

3.5. Key factors influencing the activities of soil phosphatases under MP exposure: machine-learning insights

3.5.1. Model performance and the interpretive status of the models

Model performance was assessed under study-level grouped cross-validation, in which entire study groups were withheld. Under this protocol none of the algorithms achieved positive out-of-sample R^2 , and no model outperformed a naive mean-prediction baseline in any of the ten folds for either enzyme (mean RMSE 0.370 vs. 0.365 for ACP; 0.316 vs. 0.301 for ALP; Fig. 5). Squared Pearson correlations between predicted and observed effect sizes were positive but small (0.04–0.11). Apparent (in-sample) fit was substantially higher (XGBoost $R^2 = 0.52$ for ACP and 0.89 for ALP), and the gap between apparent and cross-validated performance quantifies the degree of study-level clustering

in the corpus.

This result is consistent with the extreme between-study heterogeneity of the dataset ($I^2 = 99.41\%$ and 99.18%) and has a clear interpretive consequence: effect sizes in this literature are not predictable from reported moderators across studies. We therefore do not present the models as predictive tools. They are used as multivariate variance-attribution devices: given the compiled data, they quantify which moderators account for variation in effect size while holding all other covariates jointly, which is not obtainable from one-at-a-time subgroup contrasts. The stability of the resulting driver hierarchy, soil pH ranked first for ACP and clay content first for ALP in all five best hyperparameter configurations, indicates that this attribution is a property of the data rather than of any single fitted model. XGBoost was carried forward for SHAP and ALE interpretation because exact TreeSHAP main-effect and pairwise-interaction decomposition is available for it, not because it was the best-performing learner.

3.5.2. SHAP-based feature importance identifies divergent drivers for ACP and ALP

The SHAP analysis of the XGBoost models suggested different hierarchies of feature importance for ACP and ALP (Fig. 6a, b). For ACP, initial soil pH was the dominant driver (mean $|\text{SHAP}| = 0.088$), followed by exposure duration, exposure temperature, initial SOM, and MPs size. Higher pHs were associated with strongly positive SHAP values, and lower pHs corresponded to negative SHAP values (Fig. 6a). Of the categorical features, polymer composition contributed most, followed by soil source and experimental settings.

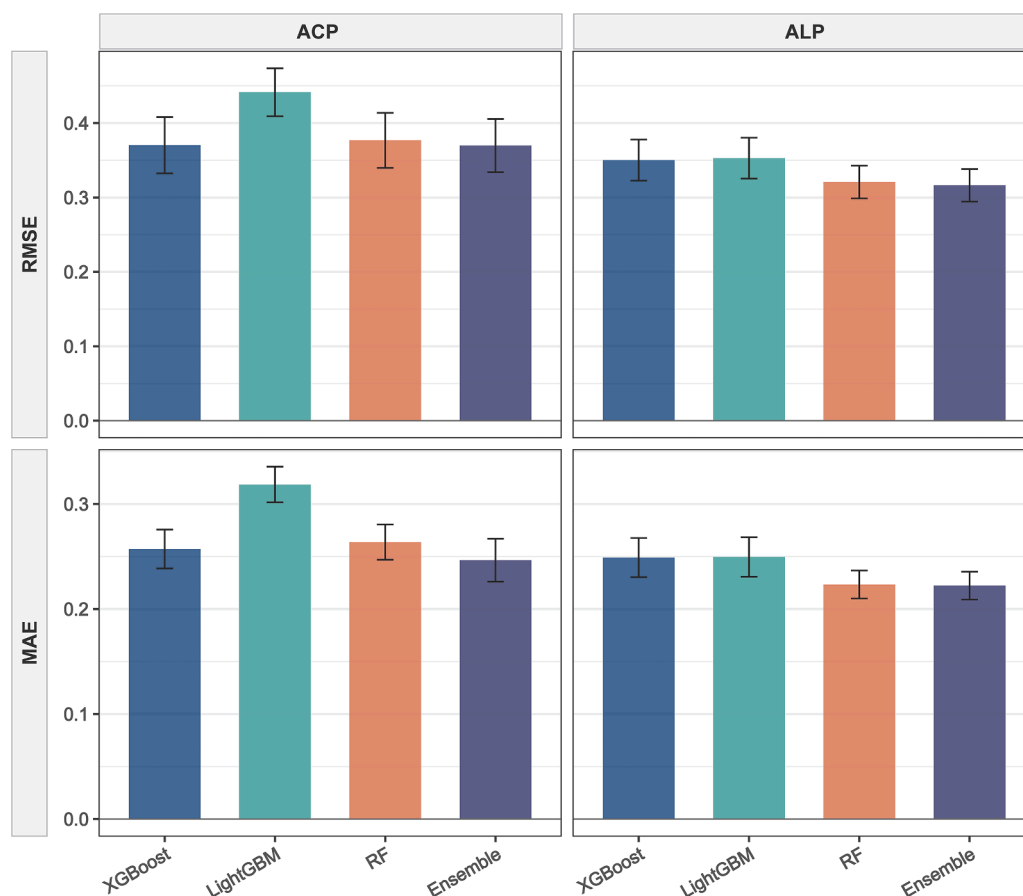


Fig. 5. Cross-validated performances of the machine-learning models for microplastic effect sizes ($\ln \text{RR}$) on the activities of soil phosphatases. Bar plots show root mean square error (RMSE) and mean absolute error (MAE) for the three algorithms (XGBoost, LightGBM, and random forest) and the stacking ensemble, applied to acid phosphatase (ACP; $n = 866$, left panels) and alkaline phosphatase (ALP; $n = 688$, right panels). Error bars represent standard errors across the ten outer cross-validation folds; ensemble bars represent held-out (nested cross-validated) stacking performance. Study-level grouping was used to prevent data leakage from non-independent effect sizes originating from shared control groups.

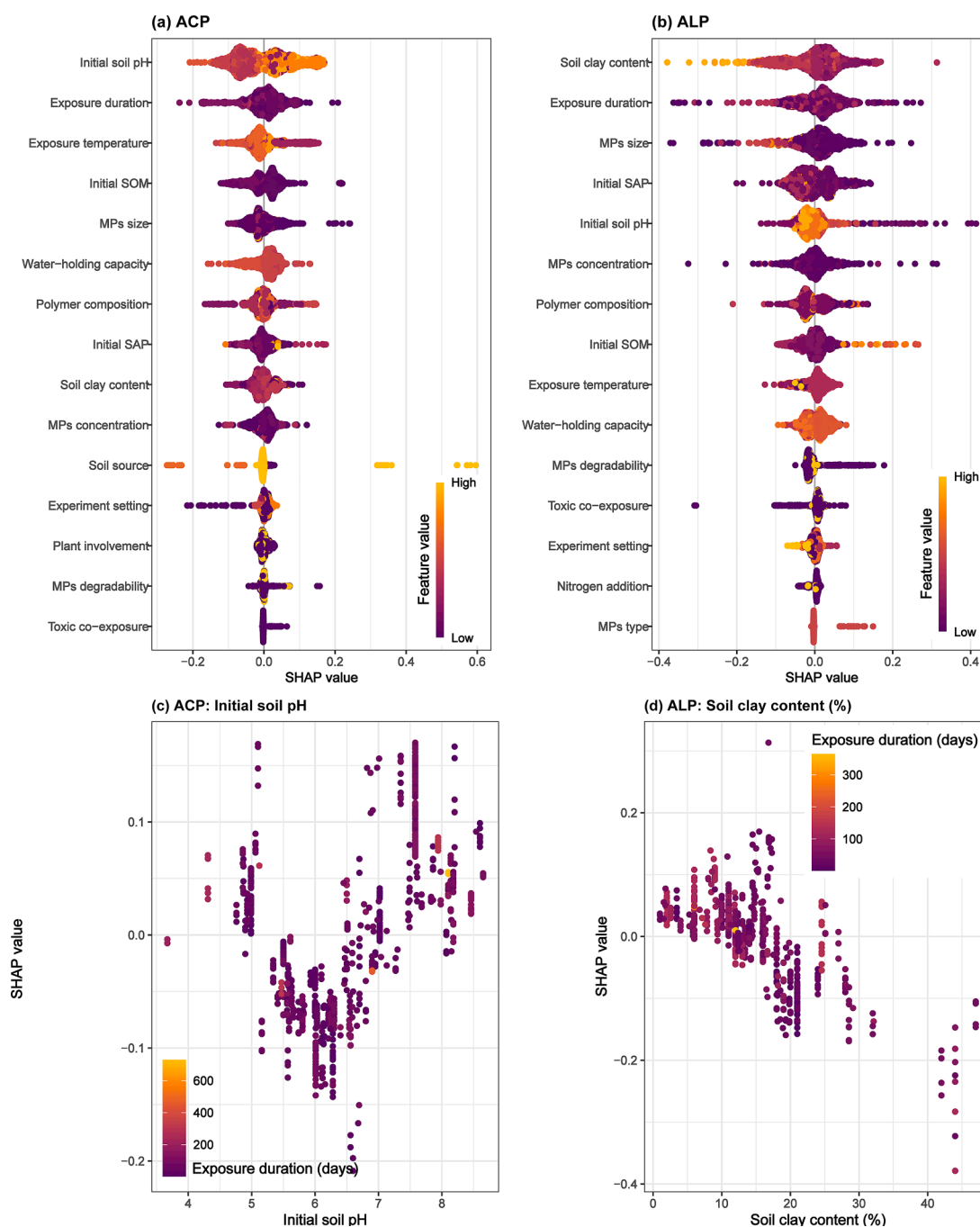


Fig. 6. SHAP (SHapley Additive exPlanations) feature importance and dependence analysis for the XGBoost models. (a, b) SHAP beeswarm plots for acid phosphatase (ACP; $n = 866$ observations from 122 experimental groups) and alkaline phosphatase (ALP; $n = 688$ from 96 groups), showing the 15 predictors ranked highest by mean $|SHAP|$ value. Each point represents one observation; the x-axis is the SHAP value (contribution to the predicted $\lnRR$) and colour encodes the feature value (yellow = high, purple = low). SHAP values of one-hot indicator columns have been summed within their parent moderator, so each row corresponds to one variable rather than one category level; for categorical moderators the colour scale encodes the level index and is therefore not ordinal. Initial soil pH is the dominant driver for ACP (mean $|SHAP| = 0.088$) and soil clay content for ALP (0.062); both ranked first across all five best-performing hyperparameter configurations. (c) SHAP dependence plot for initial soil pH in the ACP model, coloured by exposure duration, and (d) for soil clay content in the ALP model, coloured by exposure duration. Dashed lines indicate zero SHAP contribution. SHAP values quantify the attribution of variance within the compiled dataset while jointly holding all covariates.

The hierarchy of feature importance for ALP was fundamentally different (Fig. 6b). Soil clay content was the dominant driver (mean $|SHAP| = 0.062$), followed by exposure duration, MPs size, initial SAP, and initial soil pH. The beeswarm plot indicated that high clay contents were associated with negative SHAP values (i.e., reduced or negative MP effects on ALP activity).

3.5.3. SHAP dependence plots identify nonlinear interactions

The SHAP dependence plots for the highest ranked features suggested nonlinear relationships and interactions (Fig. 6c, d). For ACP, the dependence plot for initial soil pH had a nonlinear pattern: SHAP values were predominantly negative between $pH \approx 5.5$ and 6.5 , transitioned through zero around $pH 6.5-7$, and became increasingly positive above $pH 7$ (Fig. 6c); a small cluster of positive values near $pH 5$ rests on few

observations. Pairwise TreeSHAP interaction analysis (Fig. S5) supported the modulation of the pH effect by exposure duration: pH $\times$ exposure duration ranked 5th of 561 feature pairs (mean $|\text{interaction SHAP}| = 0.0138$), although the strongest ACP interaction was clay content $\times$ pH (0.0228). For ALP, clay content $\times$ exposure duration ranked 5th of 595 pairs (0.0146).

3.5.4. ALE plots identify continuous dose-response relationships

ALE plots for the six highest-ranked numeric features of each enzyme (Fig. 7) described continuous, nonlinear relationships that the categorical subgroup analysis could not resolve. In each panel the rug marks show the distribution of observations and the shaded region marks the upper decile of the predictor range, where data are sparse and the curve is not interpreted.

For ACP, the ALE curve for initial soil pH (Fig. 7a) was not monotonic across the full range, but rose steeply above pH 7 and reached its most positive values in alkaline soils; the isolated positive values below pH 5 rest on few observations. Exposure temperature (Fig. 7b) showed elevated ALE values below approximately 20 °C and a decline to near zero by 25 °C; the minimum and subsequent rise above 25 °C fall within the sparsely sampled shaded region and are not interpreted. Soil clay content (Fig. 7c) declined to a minimum near 15–20% clay before rising in the sparsely sampled clay-rich tail. Initial SOM (Fig. 7d) fell sharply from positive values in the lowest-SOM soils to persistently negative values thereafter. Exposure duration (Fig. 7e) declined from positive values during the first weeks of exposure to values slightly below zero for longer exposures, and MP size (Fig. 7f) declined from positive values for the smallest particles to slightly negative values above approximately 500 μm .

For ALP, soil clay content (Fig. 7g) produced the largest and clearest effect: ALE values declined from strongly positive in nearly clay-free soils, crossed zero at approximately 15–20% clay, and remained negative thereafter, reaching approximately -0.2 in the most clay-rich soils. Exposure duration (Fig. 7h) rose to a maximum within the first weeks of exposure and then declined steadily, becoming negative for the longest exposures. MP size (Fig. 7i) declined modestly with increasing particle size. Water-holding capacity (Fig. 7j) was non-monotonic, with a positive maximum near 60% and negative values at the highest WHC. Initial SOM (Fig. 7k) reached a minimum near 20–25 g kg^{-1} and increased at higher concentrations, and initial SAP (Fig. 7l) declined from positive values in phosphorus-depleted soils to negative values at intermediate concentrations.

3.6. Net phosphatase response in the paired subset

ACP and ALP were measured in the same experimental unit for only 50 of the 1554 observations, the net phosphatase response was +3.70% (95% CI -6.67 to $+15.22$) and the ACP:ALP response ratio was -9.03% (-20.25 to $+3.77$), with both intervals estimated from a random-intercept model with experimental group as the grouping factor. The scarcity of paired measurement suggests that whether MP exposure shifts net P mineralization is not currently answerable from the published literature.

4. Discussion

This study has two principal findings with broad implications for understanding MP-soil interactions: (1) ACP and ALP responded to different environmental drivers, with soil pH dominating the responses of ACP and clay content dominating the responses of ALP, and (2) dose-response relationships were continuous and nonlinear between key drivers and phosphatase activity that the subgroup meta-analysis could not identify, providing a mechanistic framework for predicting the effects of MPs.

4.1. Soil pH as the primary variable affecting the responses of ACP to MPs

The identification of soil pH as the dominant driver of ACP activities (Fig. 6a) is consistent with the well-established roles of pH in regulating the function of soil enzymes and composition of microbial communities (Acosta-Martínez and Tabatabai, 2000; Eivazi and Tabatabai, 1977) and is consistent with the fundamental enzymology of ACPs. The catalytic efficiency of ACPs is directly affected by the protonation states of active-site residues, with optimal activity occurring at pH 4–6.5 and sharp decreases above pH 7 (Eivazi and Tabatabai, 1977). The SHAP dependence plot (Fig. 6c) and the ALE plot (Fig. 7a) for initial soil pH both indicated more positive values in alkaline soils, with SHAP values transitioning from predominantly negative between pH ≈ 5.5 and 6.5 to positive above pH 7. This pattern indicated that MPs had the strongest stimulatory effects on ACP in alkaline soils and no detectable stimulation in acidic soils (pH < 6.5).

Several mechanisms could account for this pH-dependent pattern. First, MPs affect soil pH in polymer-dependent directions: conventional polymers (e.g. PE, PP, and PS) generally increase pH by altering aeration and macroporosity (de Souza Machado et al., 2018b), but biodegradable polymers (e.g. PLA) decrease pH by releasing lactic acid during degradation, particularly in soils with low buffering capacity (Boots et al., 2019). In alkaline soils (pH > 7.5), where ACP is already operating well above its optimum and activity is naturally suppressed, MP-induced changes to microbial-community composition and substrate availability may induce additional ACP production as a compensatory mechanism for acquiring P under suboptimal enzymatic conditions. Second, pH affects the composition of phosphatase-producing organisms: fungi, which are major ACP producers, dominate in acidic soils, but bacteria dominate in alkaline soils (Fierer, 2017). Additional stimulation by MPs in acidic soils, where fungal ACP production is already high, may be buffered by existing pools of enzymes. MP-induced shifts in microbial communities in alkaline soils, where ACP production is lower, may disproportionately affect ACP activity. Third, pH controls the speciation of substrates of organic P and enzyme-mineral interactions by affecting the balance of electrostatic and hydrophobic forces (Staunton and Quiquampoix, 1994), in turn affecting the accessibility of both substrates and enzyme-binding sites on mineral surfaces.

The dominance of pH for ACP is consistent with global-scale observations. Margalef et al. (2017) identified that the concentration of organic P was the strongest predictor of basal phosphatase activity across 379 global observations, with organic P availability negatively correlated with pH. Acosta-Martínez and Tabatabai (2000) reported that ACP activity was uniquely negatively correlated with pH among 14 soil enzymes in limed soils, confirming its exceptional sensitivity to pH. Our findings extend this observation by demonstrating that this pH control also governs how exposure to MPs modulates ACP activity. Liu et al. (2023) exclusively analyzed non-biodegradable MPs and reported a 4.3% increase in ACP activity in acidic soils and a 5.5% decrease in alkaline soils. This finding contrasts with our finding of stimulation being strongest in alkaline soils, but the discrepancy is likely attributable to the different scopes of the two analyses. Liu et al. (2023) focused solely on non-biodegradable MPs, whereas our study included both conventional and biodegradable polymers. Biodegradable MPs (e.g. PLA) acidify soil by releasing organic acids during degradation, and their inclusion in our study added observations in which differences in pH and the responses of ACP interacted differently from conventional MPs.

4.2. Clay content as the dominant driver of the responses of ALP to MPs

The identification of soil clay content as the dominant driver of the responses of ALP is consistent with decades of research on enzyme-mineral interactions in soils. Burns (1982) proposed a “homeostatic level” of enzymatic activity controlled by enzyme-organo-mineral interactions, wherein extracellular enzymes adsorb to clay surfaces by a

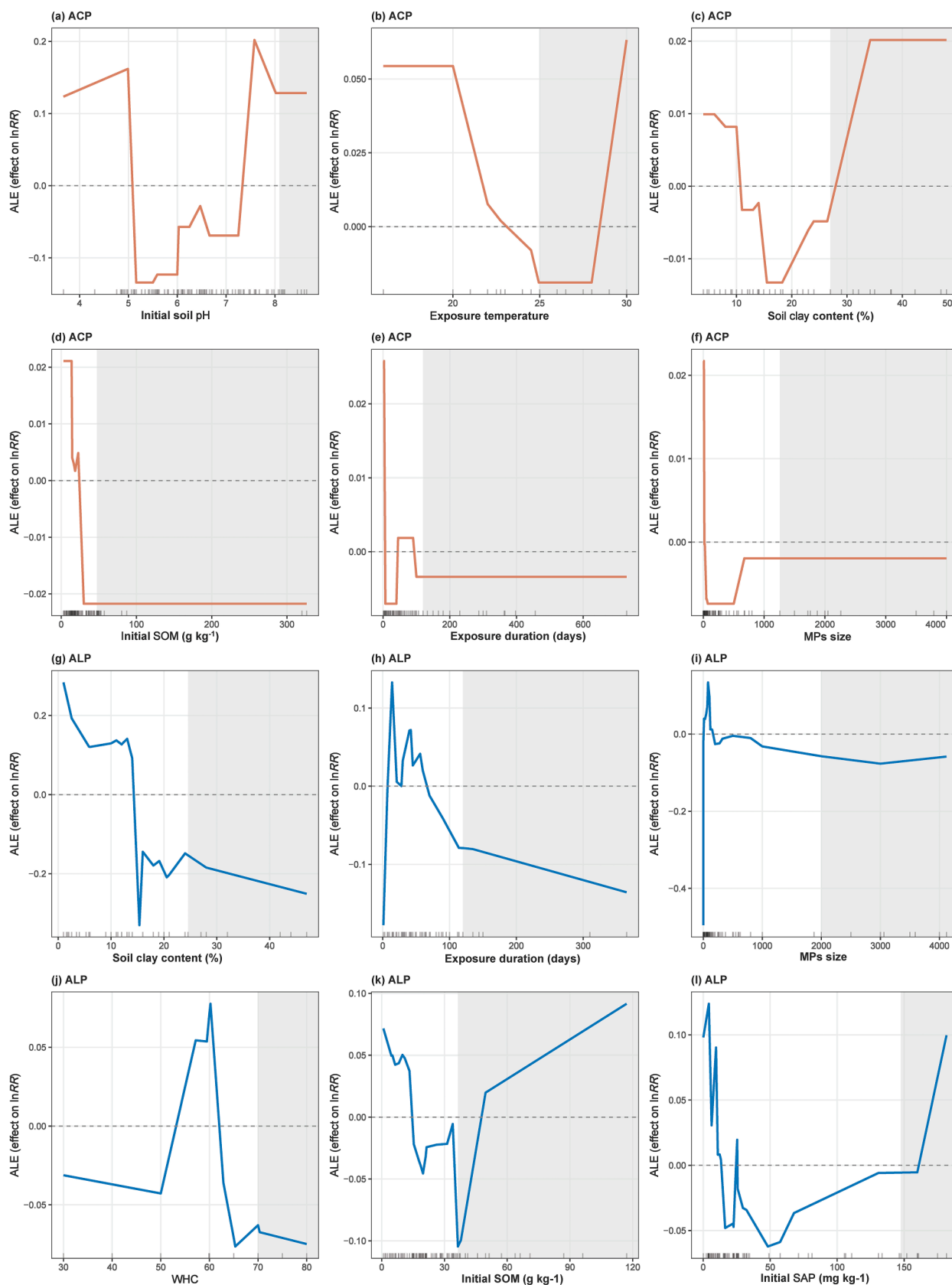


Fig. 7. Accumulated local effects (ALE) plots for six numeric features of each enzyme, selected among the highest-ranked predictors by mean $|SHAP|$ and by the availability of a continuous ALE grid across the observed range. (a–f) Acid phosphatase (ACP): (a) initial soil pH, (b) exposure temperature, (c) soil clay content, (d) initial soil organic matter (SOM), (e) exposure duration, and (f) MP size. (g–l) Alkaline phosphatase (ALP): (g) soil clay content, (h) exposure duration, (i) MP size, (j) water-holding capacity, (k) initial SOM, and (l) initial soil available phosphorus (SAP). Dashed horizontal lines indicate no effect. Rug marks show the distribution of observations; shaded regions mark the upper decile of each predictor range, where data are sparse and the curves are not interpreted.

dual mechanism: adsorption simultaneously reduces catalytic activity by conformational changes but increases the longevity of enzymes by protecting them against proteolysis and decomposition (Nannipieri et al., 2012). This protective mechanism is particularly relevant for ALP because ALP is primarily a free extracellular enzyme in the soil where mineral stabilization determines its functional half-life, unlike ACP, which has a substantial intracellular plant-root component (Allison, 2006). Soil phosphatase activity integrates functionally distinct enzyme pools: enzymes within viable microbial cells and plant roots, free extracellular enzymes in the soil solution, and extracellular enzymes stabilised by adsorption to clay minerals and humic substances (Burns, 1982; Nannipieri et al., 2012; Burns et al., 2013). Because ACP derives from both plant and microbial sources and retains a substantial intracellular component, a larger fraction of measured ACP activity is less directly exposed to surface sorption and denaturation at microplastic interfaces than is the case for ALP, which is almost exclusively a microbially derived extracellular enzyme dependent on mineral association for persistence.

The ALE plot for soil clay content (Fig. 7g) indicated a strongly negative relationship with the ALP effect size: ALE values decreased from positive at low clay contents to markedly negative above approximately 15–20% clay. This pattern suggests that MPs may stimulate ALP activity in sandy, clay-poor soils but that this stimulatory effect

diminishes or reverses in clay-rich soils. A simple buffering interpretation is not sufficient here: stabilisation of the enzyme pool by mineral surfaces would predict responses approaching zero in clay-rich soils, not the negative responses observed. Two mechanisms are consistent with the observed direction. First, in clay-poor soils extracellular ALP is weakly stabilised and the enzyme pool turns over rapidly, so the additional surfaces and labile carbon introduced with MPs can raise net enzyme production, whereas the same input has little scope to raise activity where a large, mineral-stabilised pool already sets a high baseline. Second, clay minerals and MP surfaces compete for the same extracellular enzyme and substrate pools: co-sorption of ALP and of MP-derived leachates and plasticiser additives onto clay surfaces can reduce the catalytically accessible enzyme fraction through conformational change, producing net suppression rather than protection. We note that the clay subgroup contrast was not statistically significant ($Q_M = 4.430$, $p > 0.05$), that the >32% clay category comprised 28 of 511 observations with measured clay (5.5%), and that clay was unreported for 25.7% of ALP observations; the clay–ALP relationship rests primarily on the machine-learning analysis.

The difference in the dominant drivers between ACP (pH) and ALP (clay content) has important implications for understanding the differential vulnerability of P-cycling enzymes to MP contamination (Fig. 8). The difference suggests that the responses of ACP are primarily affected

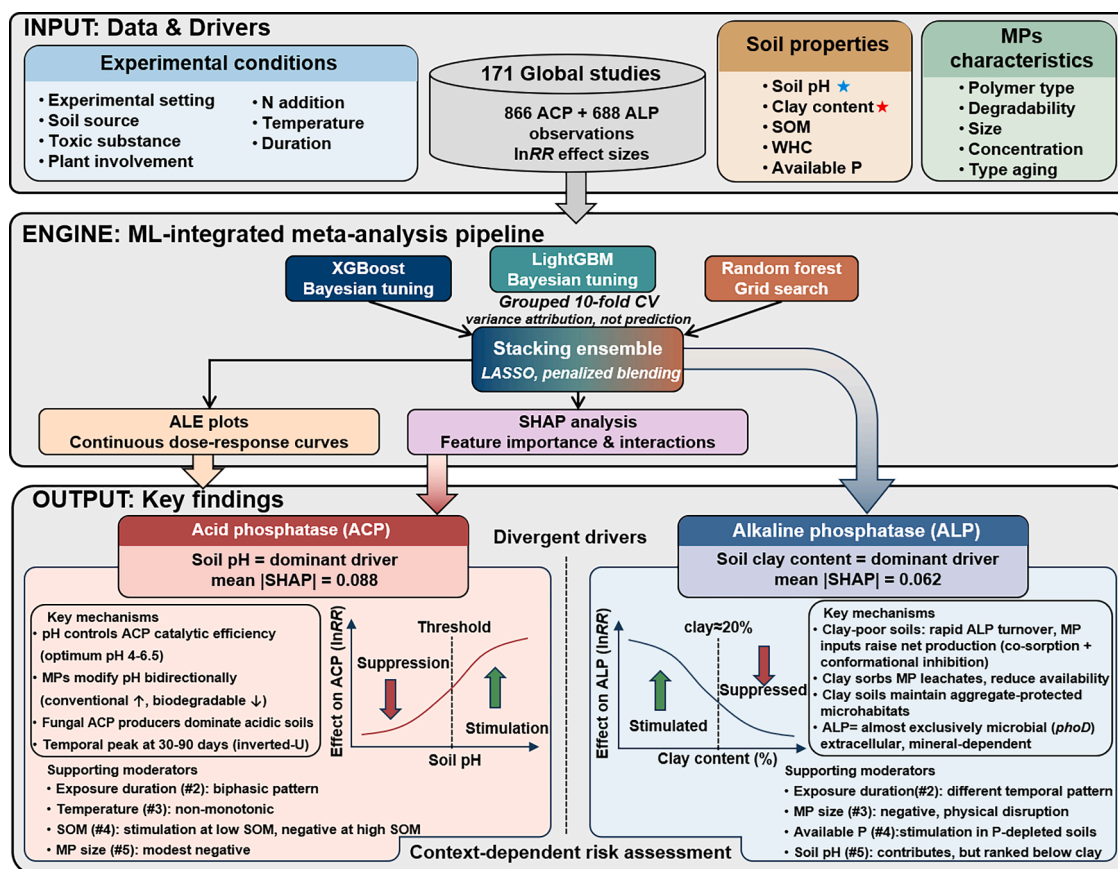


Fig. 8. Conceptual framework summarizing the meta-analysis approach integrated with machine learning and its principal findings. The Input box illustrates the three categories of predictor variables extracted from 171 global studies (866 ACP observations and 688 ALP observations): experimental conditions, soil properties, and microplastic characteristics. The Engine box depicts the analytical pipeline, in which the XGBoost, LightGBM, and random-forest models are independently tuned using Bayesian optimization and grid search under grouped 10-fold cross-validation, then integrated using a LASSO-penalized stacking ensemble. Model interpretation proceeds to the SHAP analysis, which quantifies feature importance and interactive effects at the level of individual observations, and to ALE plots, which characterize continuous, marginal dose–response relationships for the highest-ranked numeric features. The Output box summarizes the key findings: soil pH is the dominant driver of the responses of ACP, and soil clay content is the dominant driver of the responses of ALP. The framework demonstrates that the responses of ACP are governed primarily by biochemical (pH-dependent catalytic) constraints, whereas the responses of ALP are governed by physical (mineral-mediated stabilization) constraints. *phoD*, bacterial gene encoding an extracellular alkaline phosphomonoesterase, used here as an indicator of the genetic potential for alkaline phosphatase production.

by biochemical constraints on enzymatic function (pH-dependent catalytic efficiency), whereas the responses of ALP are primarily affected by physical constraints on the persistence of the enzymes (mineral-mediated stabilization). This distinction indicates the ecological differences between the two classes of enzymes: ACP includes both intracellular (plant root) and extracellular components that are relatively protected from environmental perturbation, but ALP is almost exclusively extracellular and thus more dependent on interactions with mineral surfaces for functional persistence (Burns, 1982; Burns et al., 2013; Nannipieri et al., 2012).

4.3. Temporal dynamics and the pattern of biphasic response

Exposure duration was the second most important feature for both ACP and ALP, and the ALE plots suggested different temporal patterns of response for the two enzymes (Fig. 7e, h). These patterns are consistent with a biphasic model in which short- to intermediate-term MP exposure stimulates enzymatic activity through novel carbon inputs, microbial activation and substrate priming (Feng et al., 2023), whereas prolonged exposure leads to inhibition through cumulative additive leaching, progressive restructuring of the microbial community toward MP-adapted taxa, and depletion of labile substrates (Deng et al., 2025; Rillig et al., 2024). We note that our data are consistent with this model but do not test it: exposure duration is a between-study contrast here, not a within-experiment time series.

Liu et al. (2023) reported that short-term exposure to MPs (≤ 30 days) increased soil respiration by 50.2%, but exposure for 30–100 days decreased enzymatic activity by 3.3%. Deng et al. (2025) found that microbial communities were unaffected in the short term but were substantially restructured under prolonged exposure to MPs, with enrichment of MP-adapted taxa such as *Proteobacteria* and *Actinobacteria*. Our analysis suggested that exposure duration had a broadly consistent but enzyme-specific temporal effect across studies, although the specific trajectory differed between ACP and ALP. The inverted-U pattern for ACP was apparent in the subgroup analysis, with peak stimulation at 30–90 days (Fig. 2i), and pH $\times$ exposure duration ranked among the strongest pairwise interactions for ACP (Fig. S5), consistent with pH modulating the temporal trajectory of the ACP response.

4.4. Nonlinear dose–response relationships and ecological thresholds

The ALE plots indicated continuous, nonlinear relationships between environmental factors and the responses of the phosphatases. The ALE curve for SOM is counterintuitive: ACP responses to microplastics became increasingly negative as SOM increased, whereas the greater microbial diversity and functional redundancy typical of high-SOM soils would be expected to confer resistance to perturbation, that is, an effect approaching zero rather than a negative one. We therefore do not interpret this pattern as buffering. Several mechanisms could produce the observed relationship. In low-SOM soils, microplastic-derived carbon may act as a supplementary substrate and prime microbial activity, elevating phosphatase production (Feng et al., 2023). In high-SOM soils, abundant dissolved organic matter may compete with extracellular phosphatases for sorption sites on microplastic surfaces, or microplastic–organic matter complexes may concentrate co-sorbed contaminants into localised inhibitory microenvironments. These explanations are not mutually exclusive, and our synthesis cannot discriminate among them; the underlying mechanism remains unresolved and warrants targeted experimental investigation in which SOM quantity and quality are manipulated independently under controlled MPs loading.

The ALE curve for MP concentration (Fig. S6) was non-monotonic within the concentration range containing the large majority of observations (93% of ALP observations below 50 g kg^{-1}), with a total ALE range of 0.37 lnRR units, and we do not interpret the sparse high-concentration region ($>50 \text{ g kg}^{-1}$, 7% of observations). Our synthesis therefore does not support a simple monotonic or saturating

concentration–response relationship, and we do not read these data as evidence of hormesis. Determining whether biphasic dose–response dynamics operate for soil phosphatases will require experiments that sample concentrations systematically within the environmentally relevant range, rather than the sparse and unevenly distributed doses available in the published literature.

We emphasise that this synthesis cannot predict phosphorus export. No observation in our dataset measured leaching, runoff or receiving-water concentration, and the transport step from soil solution to surface water is governed by hydrology, connectivity and management factors entirely outside our dataset. What the synthesis can provide is source-area prioritisation. The driver hierarchy identified here indicates which soil types are functionally most responsive to MPs loading, clay-rich soils for the ALP pathway, alkaline soils for the ACP pathway, and therefore where monitoring effort is most likely to be informative when MPs inputs via biosolids, reclaimed-water irrigation or plastic mulching are a management concern. Converting these response functions into quantitative loads to receiving waters will require coupling them with measured runoff and leaching fluxes, which we identify as the priority next step.

4.5. Limitations and future directions

Several limitations of this study should be acknowledged. First, a large proportion of the variation in lnRR remained unexplained, likely attributable to factors not reported in the primary studies, such as the composition of soil microbial communities, the specific surface area of the MPs used, the degree of weathering, and the load of sorbed contaminants. Two reporting gaps limit mechanistic closure most severely. (1) post-treatment available P is almost never reported alongside phosphatase activity, so the step from an enzyme response to a change in the available-P pool cannot be tested; paired pre- and post-treatment P reporting is the single highest-priority addition this literature could make. (2) too few studies report *phoD* abundance or 16S diversity indices alongside phosphatase activity to support the covariate-rich modelling used here, which prevents the enzyme response from being linked to the microbial pool producing it. Second, the nature of meta-analytic data precludes causal inference; the driver hierarchies identified by the SHAP analysis represent predictive importance rather than established causal mechanisms, although their consistency with independent experimental evidence lends confidence to the interpretation. Third, the current literature remains dominated by short-term, single-polymer laboratory-incubation studies at MPs concentrations exceeding those typical of field settings, potentially limiting the ecological reality of identified thresholds. Primary studies increasingly adopt standardized reporting protocols and environmentally realistic experimental designs, so future syntheses may resolve a larger fraction of the observed heterogeneity. Fourth, despite the publication-bias diagnostics (funnel plots and Egger's test), MP research may still be subject to a reporting bias toward significant or negative effects, as studies finding no effect of MPs on enzyme activity may be less likely to be published, potentially skewing the aggregated effect sizes. Fifth, ACP and ALP respond in opposite directions along different edaphic gradients, ACP stimulation is strongest in alkaline soils (Fig. 4e), whereas ALP suppression is concentrated in clay-rich soils (Fig. 6b and Fig. 7g), which precludes a definitive conclusion about net P mobilization and underlines the need for primary studies to report both enzymes in the same experimental unit, and the ACP:ALP ratio, for integrated risk assessment. The most important limitation concerns predictive transfer. Under study-level cross-validation, none of our models predicted effect sizes in withheld studies better than the overall mean. We report this explicitly rather than relying on in-sample fit. It implies that the moderators routinely reported in this literature are insufficient to forecast MP effects, and that the SHAP-based driver hierarchy should be read as a description of the assembled evidence, not as a predictive model. This is itself a finding about the state of the field: with $I^2 \approx 99\%$ and heavy reliance on short-term, single-

polymer laboratory incubations, between-study variation is dominated by factors that primary studies do not report.

5. Conclusion

In summary, this global synthesis shows that MPs systematically stimulate acid phosphatase activity (+9.89%) while exerting non-significant but strongly context-dependent effects on alkaline phosphatase (+1.40%), and that the two enzymes are governed by divergent edaphic controls: soil pH for ACP and clay content for ALP. Both pooled estimates subsume extreme between-study variation ($I^2 > 99\%$) and should be read as central tendencies rather than as generalizable point estimates. Because phosphatase-mediated organic-P mineralization sets the size of the dissolved P pool available for diffuse export, and because wastewater-derived biosolids and reclaimed-water irrigation are major MP-delivery pathways, these results position soil enzyme activity as an upstream control on non-point-source phosphorus loading and connect the management of urban water and sludge streams to nutrient mobilization in agricultural catchments.

Identifying clay-rich soils as the setting in which the alkaline phosphatase pathway is most strongly suppressed, and alkaline (pH > 7.5) soils as the setting in which acid phosphatase is most strongly stimulated, provides a spatially transferable screening criterion for where MP inputs are most likely to perturb phosphatase-mediated P mineralization. Because the two enzymes respond in opposite directions and along different edaphic gradients, the net effect on total P mineralization remains unclear: in the small subset of observations in which both enzymes were measured in the same experimental unit ($n = 50$), neither the net phosphatase response nor the ACP:ALP response ratio differed significantly from zero. Water-resource managers should therefore read this result as identifying where each phosphatase pathway is most vulnerable, not as a direct index of phosphorus export potential. The interpretable stacking-ensemble pipeline demonstrates a transferable workflow for integrating heterogeneous contaminant datasets into decision-relevant assessments, but it characterizes soil-side response functions only; closing the soil-to-water mass balance will require coupling these functions with measured runoff and leaching fluxes to convert the risk indicators identified here into quantitative loads to receiving waters.

CRedit authorship contribution statement

Yangzhou Xiang: Writing – original draft, Visualization, Validation, Formal analysis, Data curation, Conceptualization. **Josep Peñuelas:** Writing – review & editing, Conceptualization. **Matthias C. Rillig:** Writing – review & editing, Conceptualization. **Bin Yao:** Writing – review & editing, Resources, Project administration, Conceptualization. **Ying Liu:** Writing – review & editing, Resources, Conceptualization. **Yang Luo:** Writing – review & editing, Methodology, Data curation. **Xuqiang Luo:** Writing – review & editing, Project administration, Investigation, Funding acquisition, Conceptualization. **Yuan Li:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the Natural Science Foundation of China (32260725), the Guizhou Provincial Basic Research Program (Natural Science) General Program (QKHJC MS(2025)079), and Guizhou Provincial University Key Laboratory of Advanced Functional Electronic

Materials (QJJ[2023]021). Matthias C. Rillig acknowledges funding from the project μ Plastic (031B0907A) from the Bundesministerium für Bildung und Forschung. Josep Peñuelas was supported by the Spanish Government grants PID2020115770RB-I, PID2022-140808NB-I00, and TED2021-132627 B-I00 funded by MCIN, AEI/10.13039/501100011033 European Union Next Generation EU/PRTR. The authors thank Davey L. Jones (Bangor University) for his valuable comments and suggestions on an earlier version of this manuscript.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.watres.2026.126840](https://doi.org/10.1016/j.watres.2026.126840).

Detailed machine-learning methods including data preprocessing pipeline (Section S1.1), hyperparameter optimization (Section S1.2, Table S1), grouped cross-validation design (Section S1.3), stacking ensemble construction (Section S1.4), SHAP computation details (Section S1.5), and ALE plot computation (Section S1.6); hyperparameter optimization results and stacking ensemble composition (Section S2); PRISMA flow diagram (Figure S1); geographic distribution of sampling locations (Figure S2); funnel plots for publication bias assessment (Figure S3); sensitivity analysis forest plots (Figure S4); trim-and-fill model results (Table S2); and the 171 data resource references used in this meta-analysis (Notes S1).

Data availability

Data will be made available on request.

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