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Improving quantitative synthesis to achieve generality in ecology

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Synthesis of primary ecological data is often assumed to achieve a notion of 'generality', through the quantification of overall effect sizes and consistency among studies, and has become a dominant research approach in ecology. Unfortunately, ecologists rarely define either the generality of their findings, their estimand (the target of estimation) or the population of interest. Given that generality is fundamental to science, and the urgent need for scientific understanding to curb global scale ecological breakdown, loose usage of the term 'generality' is problematic. In other disciplines, generality is defined as comprising both generalizability—extending an inference about an estimand from the sample to the population—and transferability—the validity of estimand predictions in a different sampling unit or population. We review current practice in ecological synthesis and demonstrate that, when researchers fail to define the assumptions underpinning generalizations and transfers of effect sizes, generality often misses its target. We provide guidance for communicating nuanced inferences and maximizing the impact of syntheses both within and beyond academia. We propose pathways to generality applicable to ecological syntheses, including the development of quantitative and qualitative criteria with which to license the transfer of estimands from both primary and synthetic studies.

Ecologists often seek to extend inferences from their studied systems to predict phenomena in different taxonomic, spatial or temporal settings[1]. Indeed, around 40% of the most cited ecology journals demand that submissions are relevant for other species, ecosystems, biomes or time periods (Appendix S1 in the Supplementary Information). In principle, this is a fair request, to prevent the literature from becoming a descriptive 'stamp collection' of case studies[2], with inferences limited to the sampled population. Ecologists have pursued many roads to generalities[3,4], including developing mathematical models to predict key population parameters[5,6], unifying conceptual frameworks to predict the importance of different mechanisms in different contexts[4,7] and coordinating globally distributed experiments to predict responses of ecological systems to perturbations[8]. A further road that has gained prominence in ecology over the past 30 years is the use of 'quantitative synthesis' to identify generalities about the strength and direction of ecological effects[9].

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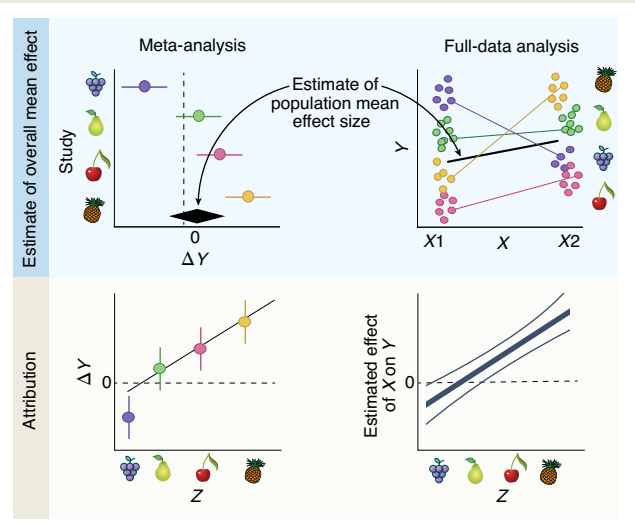
BOX 1

Current practices in quantitative synthesis

Two approaches to quantitative synthesis are widely used: (1) the meta-analysis of study-level summary statistics (hereafter 'meta-analysis'), which requires treatment-level means, standard deviations and sample sizes; and (2) full-data analyses that fit multilevel (generalized) linear mixed models to raw, site-level observations, hereafter 'full-data analysis' (see table). In health disciplines, full-data analyses are known as 'individual patient data meta-analysis', and are considered the 'gold standard'[91], owing to their potential for resolving issues regarding study-specific designs and confounding variation. The use of full-data analyses has also surged in ecology, aided by open-science policies that encourage or mandate the publication of raw data alongside articles, and initiatives that collate raw data (for example, PREDICTS[92], BioTime[93] and COMPADRE/COMADRE[94,95]). While definitions vary within and between disciplines—for example, meta-analysis may be considered a special case of multilevel modelling[96]—we use the term 'synthesis' to encompass both meta-analysis and full-data analysis, as defined in the table.



Two approaches used to synthesize primary studies, represented as different fruits, that have measured responses of some ecological variable *Y* to variable *X* and effect modification by variable *Z*. See table.

Two approaches to the synthesis of primary studies that have measured responses of some ecological variable *Y*, such as biodiversity or carbon storage, to variable *X*, and effect modification by variable *Z*

	Meta-analysis	Full-data analysis
Input data	Study-level summary statistics (mean, standard deviation, *n*) compiled across multiple studies. Primary studies may have measured outcomes in different units.	Study-level raw data compiled across multiple studies. Unit of measurement must be consistent across studies.
Study-level effect sizes	Study-level differences between categorical treatments (for example, Hedges' *g* or log response ratios), or the magnitudes of these changes against a continuous predictor (for example, correlations).	Study-level random slopes on the scale of the linear predictor.
Statistical procedure	Precision-weighting, generally using the inverse of the sum of study-level and between-study variance.	Partial pooling, wherein group (study) estimates are 'shrunk' towards the population mean as a function of the relative variance of each estimate.
Estimate of overall mean effects	Meta-estimate of mean effect (ΔY; top left in figure).	Fixed-effect estimate (top right in figure).
Estimate of between-study heterogeneity	Heterogeneity statistics, for example, I^2. Benchmarks of I^2 of 25, 50 and 75% are interpreted as small, medium and high, respectively.	Concurrent interpretation of three parameters: the variances of (1) random slopes and (2) random intercepts, and (3) the covariance of intercepts and slopes.
Attribution	Comparison of subgroup mean effects, or meta-regression of effect sizes on meaningful 'effect modifiers' or 'moderators' (*Z*; bottom left in figure).	The analyst may fit an interaction term between *X* and *Z*, and interrogate the marginal effects. Sometimes analysts perform post hoc analyses of random slopes, for example, regression on 'effect modifiers' or 'moderators' (*Z*; bottom right in figure).

Quantitative syntheses identify, appraise and combine data from individual studies or sites that have measured an effect of interest, typically via meta-analysis or multilevel modelling[10–14] (Box 1). Syntheses have been used to answer both basic and applied ecological questions by quantifying, for example, the effects of major environmental drivers such as climate change on ecological communities, the effectiveness of conservation actions, and evaluating the evidence for ecological and evolutionary theories[9]. Central to quantitative synthesis is the 'effect size' estimated for each study, representing the direction and/or magnitude of an effect, commonly measured using differences between categorical group means, or the strengths of association between variables. In the absence of theoretical models or distributed experiments, effect sizes enable scientists to combine, compare and organize extensive literature using a common measurement scale, to identify generalities across taxonomic, spatial or temporal contexts[9].

Evidence from rigorous quantitative syntheses is considered to represent one of the most methodologically robust sources for testing key ecological hypotheses, rejecting or corroborating theories and informing environmental decision-making[9–11]. Concurrently, an insidious myth persists that the very act of quantitatively synthesizing data from diverse studies is enough to warrant claims of generality about effect sizes[11–13]. Syntheses continue to proliferate in ecology[10], and are often associated with high-impact journals and media attention, for the apparently regional or global reach of their inferences[14]. At the same time, however, they can stimulate much scientific debate on biases and interpretation[14]. Here, we argue that current approaches to quantitative

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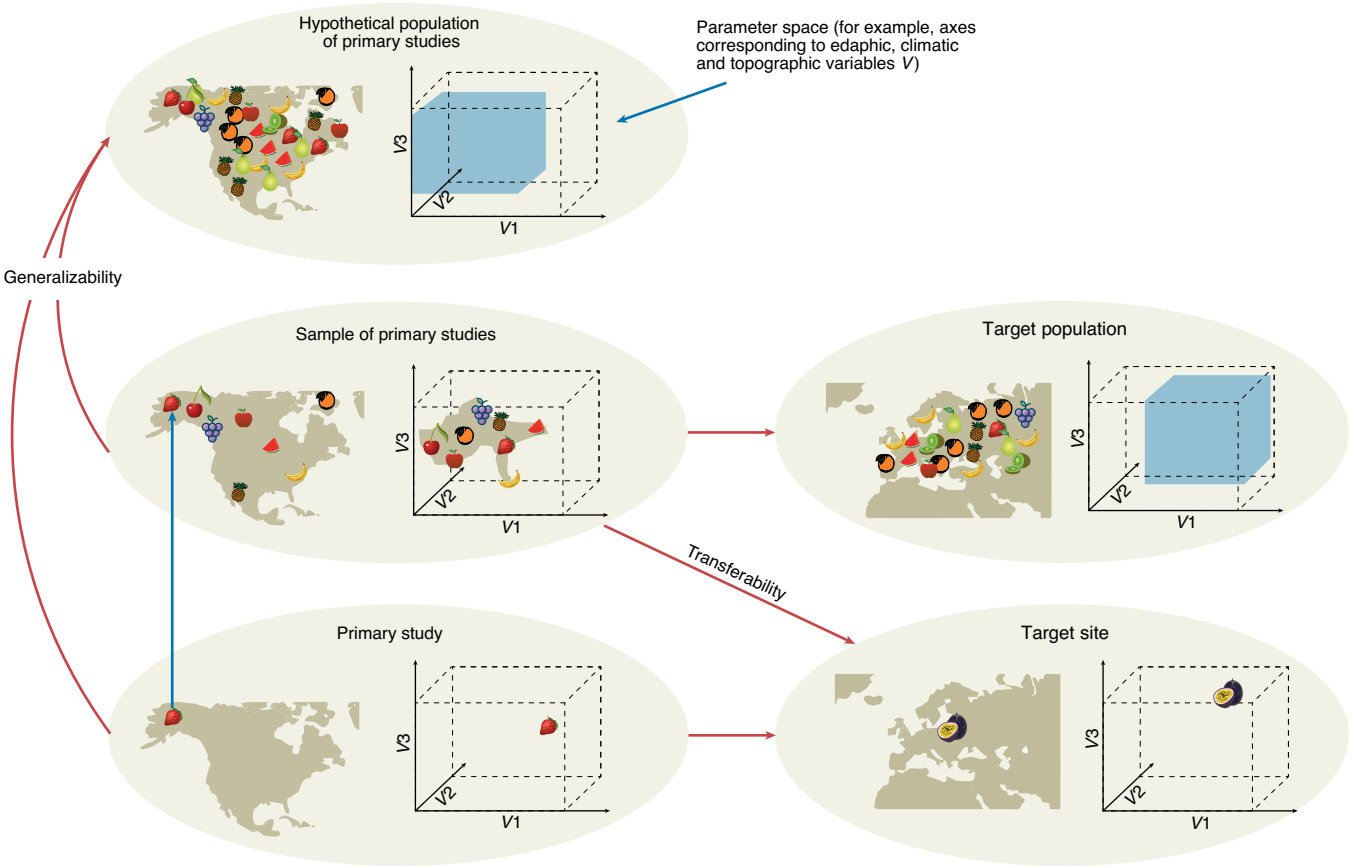

Fig. 1 | Generality, which we use synonymously with external validity, comprises the generalizability and transferability of estimands drawn from primary and synthetic research. Syntheses collate data from primary studies, each of which usually has a well-defined and narrow context relative to the context of the synthesis, and these studies are here each represented by a fruit of one of several types. Collated, these studies form a reference sample from a hypothetical population of studies, which together cover a broader context (here of fruits, either implicitly or explicitly defined by the researcher). Generalizability concerns the validity of an inference based on a sample that is randomly or non-randomly drawn from the target population (left column). Transferability concerns the validity of inferences based on a reference sample, when applied to either a different target population or unit (target context). Transfer across space is shown as an example, to sites in a different spatial location (middle row), or an individual target site from a different population (bottom row), which may also differ in temporal or taxonomic context to the reference sample. In both cases, the synthesized samples and the populations may have well-defined or poorly defined contexts. Here, the context of the synthesis is represented by the distribution of individual studies (fruits) within three measured or unmeasured dimensions of parameter space, for example, edaphic, taxonomic, climatic variables (*V*) that vary depending on context and may influence the outcome of a study. In our example, the hypothetical reference and target contexts overlap (within the parameter space shaded blue) despite being on different continents.

synthesis often fail to make valid inferences about the generality of effect sizes, or allow such inferences to be drawn by readers.

Assessing generality

Any assessment of generality requires two decisions: (1) what type of generality we wish to pursue, defined by the particular target context (the population or unit of observation of interest); and (2) the estimand of interest: the quantity we have estimated from a sample, based on our research question, and that we wish to predict in the target context[15,16]. Human behavioural and health disciplines tend to define generality, or more formally 'external validity', as the extent to which estimands drawn from a studied sample can be used to predict the same estimands of a broader population or other target contexts. The estimand might be a descriptive sample statistic of a variable of interest (for example, mean, variance of species richness) or a measure denoting the magnitude and/or direction of a particular effect (for example, difference in mean species richness of logged and unlogged forest stands) for a specified individual unit or population. We focus on the latter in this Review.

By contrast, generality is rarely defined in ecology, with researchers often discussing the degree to which study 'findings' or 'results' can be 'transferred', 'extrapolated', 'generalized', 'applied' or 'are relevant' to other contexts. Figure 1 summarizes two types of generality: generalizability and transferability[13,17,18]. Generalizability concerns the validity of extending an inference about an estimand from the sample to the sampled population. For example, ecologists might reasonably conclude that the mean effect of forest logging on understorey vegetation observed in a randomly selected sample of independent forest stands in a national park in central Japan represents the mean effect across all forest stands in the park. Extending inferences beyond the sampled population extends the scope of statistical inference to different sampling units or a spatiotemporally different population of units. The validity of this extension is termed 'transferability'[18,19]. For example, one might predict a similar effect of logging to that observed in central Japan for a similar forest type in the United Kingdom. The validity or bias of this transfer could be defined as the accuracy of an estimand in a target context, quantified by the difference between the transferred estimand and the 'true' estimand.

Ecologists' statements concerning generality in both primary case studies and syntheses often do not use formal definitions of generality and, in our experience, usually gloss over the assessments required to individuate both the studied context and the target context over which to transfer specific estimands of interest. In quantitative synthesis, the estimand is the target of estimation by an effect-size metric. A recurrent criticism is that combining effect sizes from very different contexts

('mixing apples with oranges') makes for questionable interpretability of overall ecological effects[20], leaving us with precise answers to vague questions[21]. We argue that the direction of progress in synthesis science needs resetting to enable the valid transfer of estimands in ecology. Determining the criteria or conditions that permit transfer to a specific target context is a research agenda in its own right. Here, we first examine current practice of quantitative synthesis, to understand whether and how it can substantiate claims about the generalizability or transferability of ecological effect sizes. We then provide guidance to enable nuanced inferences about the generalizability and transferability of estimands. While our focus is on synthetic research, the ability of syntheses to make general claims will depend on generality being precisely defined within primary studies, and therefore our recommendations extend to primary studies too. Finally, we outline a research agenda to guide both fundamental and applied ecological research towards valid generalizations and transfers.

Current practices in quantitative synthesis do not support generality

Quantitative syntheses, whether by meta-analysis or full-data analysis (Box 1), generally involve some or all of three steps: (1) the estimation of study-level effect sizes and an overall mean effect size; (2) estimation of heterogeneity statistics that describe differences in study-level effect sizes; and (3) attribution of effect-size heterogeneity to meaningful predictors (known as moderators), intended to provide a more nuanced configurative account of the overall effect. In syntheses, the estimand of interest is the effect size. Here, we review these steps to demonstrate how current practices often do not support valid inferences about the generalizability and transferability of effect sizes.

Step 1: Estimating mean effects across a sample of primary studies

Meta-analyses of primary studies typically synthesize study-level differences between categorical treatments (for example, Hedges' *g* or log response ratio LR), or the magnitudes of these changes against a continuous predictor (for example, Pearson's *z*), whereas full-data analyses are performed with raw, site-level observations using (generalized) linear mixed models. Standard statistical procedures are used to estimate a measure of central tendency in effect sizes, which corresponds to a weighted mean effect (meta-analysis) or a fixed effect estimated by the partial pooling of random slopes (full-data analysis). Weighting and shrinkage increase the precision of model parameters for meta-analysis and full-data analysis, respectively[22,23].

Implicitly or explicitly, these mean-effect-size estimates are generalized by the researcher from the sample of primary studies to some hypothetical population of studies, which is rarely defined. In the absence of its characterization, it is typically implied or assumed that the target population is either (1) exactly the study sample (in which case generalization is unnecessary) or (2) the whole population from which the study observations have been randomly and independently sampled (in which case generalization is valid). In both cases, it is assumed that the target population is implicitly defined by the inclusion and exclusion criteria of the study[19]. The validity of generalization depends on representativeness (increased by unbiased random sampling) and sample size. Often syntheses claim to be 'global' (Supplementary Fig. 1), implying that inference can be generalized to some global population of studies. Such inferences are criticized when study contexts do not comprise a random and representative sample of possible contexts across a hypothetically 'global' population, owing to taxonomic and geographic biases[24]. Samples are further distorted by language[25] and publication[26] biases (for example file-drawer effects[27]). Moreover, mean estimates can be strongly skewed by outlying effects[28].

With at least a qualitative evaluation of possible sources of bias, such syntheses nevertheless have value. Indeed, as the authors of one study[29] argue, "it is not representativeness of the study subjects that enhances the generalisation, it is knowledge of specific conditions and an understanding of mechanism that makes for a proper generalisation". Accordingly, the main issue is failure to characterize the reference or target contexts, even if they are narrow in scope (for example, a limited geographic area or number of taxonomic groups studied). Rather than representativeness, a greater cause for concern is the biases introduced through the uncritical application of synthesis methods, originally developed for orthogonal medical and social studies[30,31]. For example, in serving to increase the precision of estimated mean effects, the weighting and shrinkage imposed by under-parameterized meta-analytic and multilevel models can amplify any within-study biases[30]. This is owing to non-random variation in scale across studies, yielding precise yet inaccurate effect-size estimates[30]. Ecological studies employ a range of study and analytical designs[30,32] variously factoring confounding variability in or out. A meta-analyst typically equates the different covariate configurations and study designs of primary studies when estimating effect sizes from treatment group means, and so introduces differing degrees of omitted variable bias and internal validity among the included primary studies.

Step 2: Estimating heterogeneity

The mean effects reported by a synthesis cannot be properly interpreted without an analysis of heterogeneity, or inconsistency, among effect sizes[33]. For meta-analysis, the I^2 statistic represents the percentage of variance between effect sizes that cannot be attributed to sampling error[34]. For full-data analyses, heterogeneity can be assessed using measures of random-slope variance[35,36]. Reviews have found that a large proportion of meta-analyses in ecology and evolution do not report heterogeneity statistics[35,37] and/or present aggregated mean effects that can conceal variability even within relatively homogeneous subgroups[38]. Yet heterogeneity is critical to interpreting mean effects[34]. For example, consider that a mean effect of zero biodiversity change with land use change can be achieved under two circumstances: (1) effect sizes are all zero (homogenous; low between-study variance); or (2) effect sizes are very different but centred on zero (heterogeneous; high between-study variance), with high heterogeneity signalling a need to explore the nature or drivers of the variation. It is important to present the range and variability of effect sizes alongside main effect interpretation, using, for example, orchard plots[36] (for instance, as in refs. [39,40]) and density plots (as in refs. [38,41]).

Ecological syntheses that estimate between-study variability often report very high heterogeneity (I^2 values ~90%)[42] and random-slope variances[43]. Average effect sizes with high heterogeneity have questionable meaning. While meta-analysis of a set of similar experiments on a single species has a clear interpretation, interpreting a meta-effect across species and biogeographic contexts may be questionable[44]. Even Glass, an early proponent of meta-analysis[45], suggested that while meta-analysis is able to provide a "big fact", it cannot give more "sophisticated answers; they aren't there"[46]. The key point here is that while average effects are often assumed to yield generalities, averages of highly heterogenous effect sizes are neither generalizable nor transferable by themselves.

Step 3: Attributing variation to meaningful predictors

The next, and arguably the most useful, step is to attribute effect-size variation to meaningful predictors, and reach beyond the scope of individual studies to evaluate what Cooper[47] called "review-generated evidence". In meta-analysis, this is achieved by subgroup analyses that estimate and compare mean effects across meaningful groupings of studies, and the meta-regression of effect sizes against 'effect modifiers', or 'moderators'. In full-data analyses, attribution is either done by fitting more complex models that contain interaction terms between study-level or site-level covariates (for example, that comprise an environmental gradient), or post hoc, through regressions of random slopes on effect modifiers[48].

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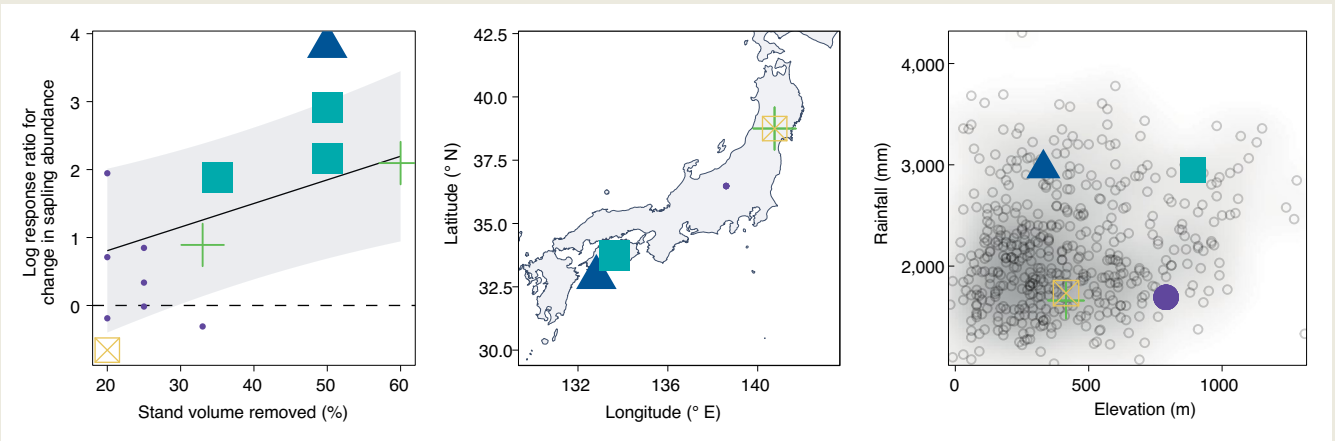
BOX 2

Example CoG statement for synthesis of plantation thinning effects on broadleaved sapling abundance

Summary of study: A recent study[55] synthesized the effects of stand-level forest management interventions on biodiversity in Japan. Here, we present effect sizes representing the effect of plantation thinning on broadleaved tree regeneration, for plantations dominated by either *Cryptomeria japonica* (sugi) or *Chamaecyparis obtusa* (hinoki) distributed across Japan. For each comparison, a log response ratio was estimated to represent the proportionate difference in broadleaved sapling abundance between replicates of thinned and unthinned stands. Effect sizes were meta-regressed on thinning intensity, measured as the percent of stand volume removed. A positive effect of stand thinning on sapling abundance increased with thinning intensity (left panel in figure). Further details are available in Appendix S2 in the Supplementary Information.

Constraints on generality (CoG): Reductions in sugi and hinoki stand volumes by greater than 30% are likely to increase sapling abundance in young, even-aged plantations between 20 and 41 years old, located across warm-temperate Japan (middle and right panels in figure). For these closed-canopy forests, the positive effect of thinning on sapling abundance should increase with thinning intensity, up to 60%. Further studies are required to establish whether positive effects remain or indeed become stronger after 60%, because planted trees might have indirect effects on broadleaved regeneration: clear-cutting (100% reductions) can lead to dominance of herbs and/or shrubs, which inhibit the regeneration of broadleaved tree species[57]. In the studies collated, stands had been surveyed between two and seven years after line or selective thinning. Positive effects may not be evident after longer periods, as recruitment to older age classes may not persist following rapid canopy closure, and repeated thinning may be required to ensure the survival of regenerated seedlings.

Positive effects of thinning on broadleaved tree regeneration should hold for plantations with intact broadleaved seed banks, which are major sources of seedlings recruited after disturbance in conifer plantations[58], and for sites located in highly forested landscapes. We caution against transferring the positive effect of thinning to landscapes with little forest cover, because recruitment has been shown to decline with distance to forest[58], with seeds of more than 60% of tree species in warm-temperate forests of Japan dispersed by forest-dwelling birds[59]. We speculate that these positive effects will extend to closed-canopy plantations in other temperate regions where light availability is the most limiting resource for understorey plants, but caution that the positive effect of thinning will probably not extend to older plantations with more complex age structures and open canopies, that is, to stands with forest floors that are not light-limited, or to stands in regions with high densities of deer (*Cervus japonicus*) that limit regeneration[60], or where thinning is known to enhance single-species dominance or invasive species establishment (for example, giant bamboo (*Phyllostachys* sp.) in warm-temperate Japan)[61].



Left: effect sizes representing the effects of plantation thinning on abundance of saplings depend on thinning intensity, showing grey-shaded 95% confidence intervals in the regression based on between-study and within-study uncertainty; values above the horizontal dashed line signify higher abundance in thinned than unthinned stands. Point colour and shape combinations correspond to study identifiers, while point size is proportional to estimated weights. Middle: spatial distribution of study sites in Japan. Right: distribution of studies in parameter space according to mean annual rainfall and elevation. Coloured study locations are overlain on parameter space occupied by plots dominated by sugi or hinoki surveyed in a national forest inventory[56] (grey shading corresponds to plot density; see Appendix S2 in the Supplementary Information for details).

Attribution attempts to make inferences about the degree of transferability of an effect size, with moderators specifying the conditions under which effects can be transferred. No single reference study or sample of studies will transfer perfectly to another target context, due to inherent contextual and study-design differences. Attribution should force us to define the populations to which we wish to transfer our effect sizes (subgroups of studies, levels of predictors in a meta-regression). Target contexts are typically coarsely parameterized, however, and researchers usually estimate overall effects across broad and heterogeneous subgroupings. Obviously, subgrouping and model complexity are limited by sample size, and data availability/reporting by primary studies[49]. Attribution is prone to bias and spurious effect modification when there is covariation amongst study-design attributes (for example, replication), random effects and effect modifiers[30]. Because the effect modifiers that implicitly represent target contexts are often poorly characterized or heterogeneous, this limits the transferability of meta-estimates to any single setting[11].

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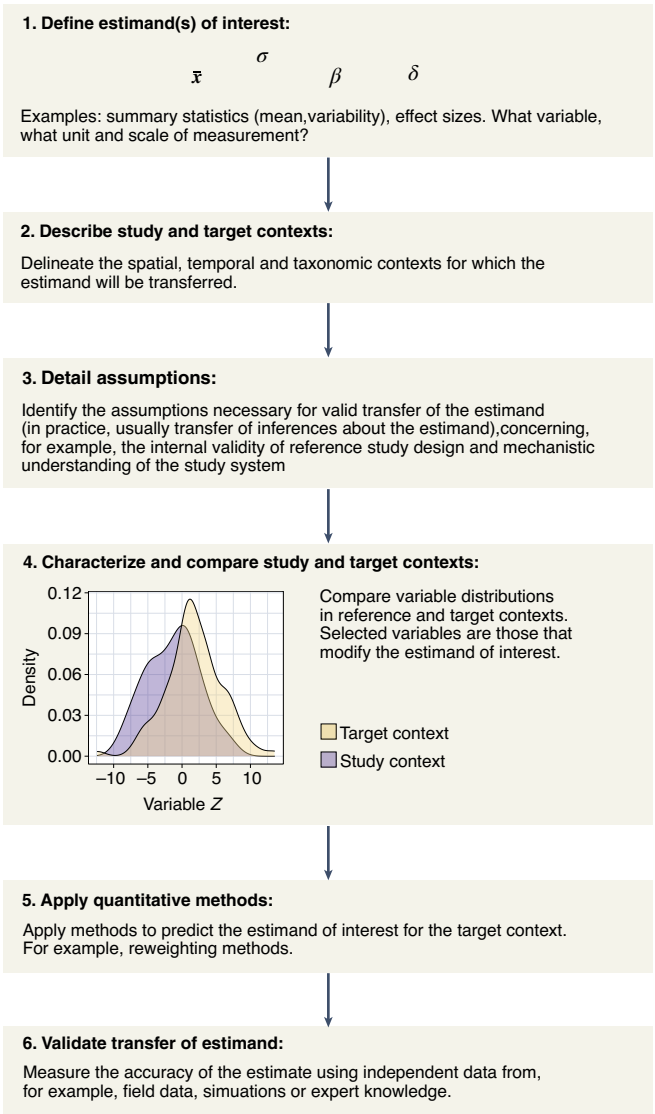

Fig. 2 | Transferring an estimand to a target context. A schematic illustrating the six steps involved in transferring an estimand to a target context.

Pathways to generality with ecological synthesis

We have demonstrated that ecology currently lacks frameworks with which to generalize or transfer estimands from quantitative syntheses. Generalization is rarely achievable given that samples are typically non-random and heterogeneous in ecology[50]. In this section, we propose three actions that can be taken immediately by ecologists to facilitate greater nuance in communicating the transferability of the estimands. We then detail four urgent research agendas required to improve the validity of estimand transfers.

Three actions for communicating the transferability of estimands

Action 1: Define the estimands and target contexts in a 'Constraints on generality' statement. Psychology researchers have called for journals to require 'Constraints on generality' (CoG) statements in the discussion sections of empirical articles, encouraging authors to draw conservative inferences, rather than make broad generalizations about undefined or ill-defined target contexts. CoG statements describe and justify target contexts, and specify assumptions the authors consider necessary for the estimand to validly transfer to other contexts[51,52]. They discourage exaggerated generality claims. CoG statements function to help both researchers and readers transfer estimands to specific target contexts. We provide an example in Box 2.

A CoG statement can explicitly define the estimand to be transferred, the target context and any boundary conditions to which findings can be confidently applied, distinguishing between so-called 'known' and 'speculative' inferences[51]. Context parameterization might be quantitative (for example, stating climatic, edaphic and topographic ranges) or qualitative (for example, insects in coniferous forests of central Japan, but not all animals over the globe). Variables include those that might alter the importance of a mechanism through which a causal effect operates[53]. Context parameterization permits both researchers and readers to implement what social scientists term the 'proximal similarity model' sensu Campbell 1986[54]. This model involves conceptualization of potential target contexts as a gradient of similarity, from most closely similar to least similar. Proximal similarity supports transferability to those populations that are spatially, temporally and taxonomically most alike (that is, most proximally similar to) those in the focal study[13].

Researchers could make statements about the predicted estimand in a specific target context, for example, the magnitude and sign of an effect on a specified outcome, and how estimands might change along a given gradient under specified conditions, and state whether the target gradient extends beyond the range of the reference population's parameter space. Researchers could articulate assumptions underlying the predictions (for example, what conditions must hold, such as site historical factors), as well as potential ecological and/or societal impacts of an assumption being violated.

We see an opportunity for reviewers to be involved in improving CoG statements. If the onus is only on authors to specify generality, these statements risk being arbitrarily subjective and marginalized to a perfunctory 'limitations' section. Reviewers could serve two roles in this regard. First, at the stage of submitting their evaluation, reviewers could be asked a short-response question about what they perceive the generalizability and transferability of the empirical findings to be. If the statements of the authors and reviewers diverge notably, this would indicate to the editor a lack of clarity in the manuscript about generality or necessary context. For journals that provide peer-review reports alongside published papers, the reviewers' perceptions of generality could provide additional insights to readers. Second, reviewers can serve a role, again through a short-response question, in discouraging authors from exaggerating generality, especially in the title and abstract.

Action 2: Move beyond static representations of ecological relationships. Researchers could work harder to meaningfully communicate contingency, uncertainty and transferability of estimands to different audiences, including researchers and practitioners. In both primary and synthetic studies, the usual current practice is to display outputs of analyses as two-dimensional static plots, typically holding other covariates at their mean values[62]. Given the conditional character of ecological relationships, estimated using nonlinear link functions and linear models with interaction terms, such two-dimensional plots are often ineffective at displaying the range and variability of estimands[63]. Possible alternatives include interactive graphics that enable readers to explore underlying data points from full-data syntheses, and the prediction of marginal effects for user-specified covariate values (for example, ref. [64]). For example, a recent study[65] produced an interactive web application to help psychology researchers visualize interaction effects and communicate the statistical integrity of analyses (https://connorjmccabe.shinyapps.io/interactive/). For meta-analysis, 'dynamic meta-analysis' software has been developed, whereby effect sizes can be filtered and weighted, and results can be recalculated, using subgroup analysis, meta-regression and recalibration[66], which could be extended to alternative weighting schemes that incorporate generality criteria[31,67]. EviAtlas is an example of open source software

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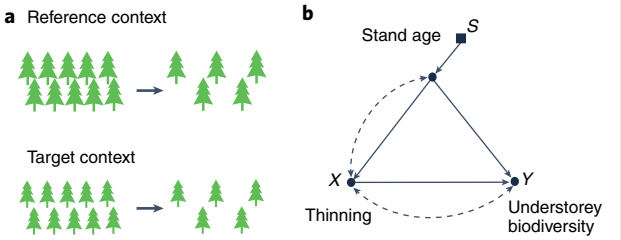
BOX 3

Selection diagram approach for identifying contextual variables and assumptions, and transport formulae to enable transfer of an estimand



Selection diagram approach for the effect of forest thinning on understorey biodiversity (adapted from ref. [82]). In **a**, we consider the problem of transporting experimental results between two locations. We have conducted a randomized experiment in a location (reference context) to estimate the causal effect of forest thinning (treatment X) on understorey biodiversity (outcome Y) for every stand age group ($Z=z$), denoted $P(y|do(x),z)$. We now wish to transport the results to forests in another location (target context), but we find the distribution $P(xyz)$ to be different from the one in the target context (call the latter $P^*(xyz)$). In particular, the average age of the trees is significantly lower than that in the reference context. How do we estimate the causal effect of X on Y in the target context, denoted $R=P^*(y|do(x),z)$?

In **b**, the selection diagram conveys the assumption that the only difference between the two populations is factors determining age distributions of trees shown as $S \rightarrow Z$, while age-specific effects $P(y|do(x),Z=z)$ are invariant across forest contexts. Dashed arcs (for example, $X \dashleftarrow\dashrightarrow Y$) represent the presence of latent variables affecting both X and Y. Under these assumptions, the causal effect in the target context, R, can be estimated using a transport formula as follows: $R = \sum_Z P^*(y|do(x),z)P^*(z) = \sum_Z P(y|do(x),z)P^*(z)$. It combines experimental results obtained in the reference context, $P(y|do(x),z)$, with observational aspects of target context, P^*z, to obtain an experimental claim, $P^*(y|do(x))$, about the target context. By formalizing this graphically and formulaically, we are forced to define what we must assume about other confounding variables besides stand age, both latent and observed, for our formulae to have validity.

for producing interactive visualizations of systematic map databases[68]. These applications could be embedded within online publications, which increasingly support interactive graphics and code[69,70].

Action 3: Quantify the 'transfer domain' for full-data syntheses. In addition to quantitative context parameterization (action 1), researchers could identify the 'transfer domain' that delineates the parameter space to which effect sizes can be validly transferred (given CoG statements and assumptions), also known as the 'applicability domain', in predictive modelling across disciplines including chemistry[71], material science[72] and environmental science[73]. For full-data syntheses of large datasets, cross-validation techniques could be used, wherein model parameters are estimated using 90% of the primary studies (training set) and model predictive performance evaluated using the remaining 10% (test set). After repeating on different combinations of primary studies in training and test sets, studies for which effect sizes are not predicted well would be considered outside of the transfer domain. To identify the boundary conditions, one could identify the characteristics of studies that are unpredictable. Employing cross-validation for meta-analysis will change the focus from the most precise estimate and its statistical significance to how well estimands transfer to different contexts.

Four agendas for developing a science of generality applicable to synthesis

Here, we propose four research agendas to guide the development of both quantitative and qualitative assumptions that underpin the generalizability and transferability of estimands for scientists and policymakers. We identify six key steps (Fig. 2) that could help to formalize the assumptions that underpin transfer of estimands to specific contexts in ecology[74].

Develop qualitative and quantitative criteria with which to evaluate transferability of an estimand (for scientists)

After specifying an estimand for a target context of interest (Fig. 2, steps 1 and 2), researchers could develop qualitative criteria or quantitative indicators with which to appraise the transferability, or assumptions that (if met) justify the transfer of an estimand of interest (step 3). These criteria can be used to enhance CoG statements (action 1) and guide the appraisal of primary studies that are used in quantitative syntheses. Criteria could comprise descriptors of dissimilarity between the reference and target contexts (their covariate distributions), study-design attributes (for example, replication, spatial interspersion), analytical design attributes (for example, model complexity, statistical matching), modelling choice (for example, machine learning) and the mechanistic nature of the causal relationships. Ideally, these criteria and assumptions would be identified at the beginning of a study, to guide its design, rather than at the end[75]. While high-level categories of appraisal criteria are likely to be useful to guide the analysis and interpretation of primary and synthetic studies, exact criteria will be specific to the ecological question and estimand of interest.

Health disciplines have developed objective criteria with which to judge the external validity of primary studies for a defined target context, for example refs. [76–78]. For instance, the Population–Intervention–Environment–Transfer Model of Transferability helps different audiences to judge the transferability of a health intervention, according to characteristics of the studied population (socio-demographic, attitudinal), intervention (internal validity of study), environment (public perception, climate) and transfer (feasibility of intervention)[77]. These have been recently extended to syntheses[75,79]. For example, the 'Transfer approach'[75] supports collaboration between researchers and stakeholders during the review process to systematically and transparently consider factors that may influence the transferability of medical systematic review findings. To support the identification of important contextual variables with which to define reference and target contexts and evaluate the validity of potential transfers, the use of 'selection diagrams' can help identify important conditioning variables and study-design attributes that might influence the transferability of causal effects. Two previous studies[74,80] proposed the use of these graphical representations of causal relationships, which formally articulate commonalities and differences in the form of unobserved factors capable of causing differences in causal effects between reference and target contexts. This approach is a useful tool for identifying important conditioning covariates and detailing the assumptions and tests that are required to develop qualitative

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BOX 4

Glossary of terms

Accuracy/bias
The distance of an estimate from the value it is estimating, with a large distance signifying low accuracy/high bias.

Boundary conditions
The regions of the parameter space that describe a context, within which an inference is valid.

Causal inference
An evidence-based conclusion about the causal, driving effect of a particular phenomenon.

Effect modification
An effect magnitude and/or direction that varies with the values of another effect, and vice versa.

Estimand
The target of estimation, characterized by a response variable of interest (for example, species richness), an independent variable of interest (for example, forest logging), a summary measure (for example, the standardized mean difference in species richness between the populations of logged and unlogged stands: $[\mu_1 - \mu_2]/\sigma$), the target population or unit of interest (for example, planted forest stands within a national park).

External validity
Here referred to as 'generality'. The capacity for a sample estimand to apply to a specified target population. Two types are distinguished: generalizability and transferability.

Generalizability
Concerns the validity of extending an inference about an estimand from the sample to the population from which it is drawn. Generalizability could be defined as the accuracy of a sample estimand, in terms of its difference from the true population estimand.

Internal validity
The degree to which observed covariation between a dependent and an independent variable can be interpreted as a causal effect.

Precision
The distribution of replicate estimates around their mean, with a tight distribution signifying high precision. In the absence of systematic bias, greater precision leads to higher accuracy.

Primary study
A study that gathers new data on a particular population (distinguished from a secondary study, such as a synthesis of primary studies).

Sampled population
The set of observational units of a distributed variable that define the scope of inference of the testable hypotheses. Statistical analyses require random and independent sampling from the population of interest, which means that the population needs defining at the design stage. The outcome of statistical testing (for example, detection of a trend) applies to the sampled population, not to the sample(s). Thus, confidence intervals around a sample mean describe the range of plausible values of the population mean given the sample.

Shrinkage
A fundamental property of multilevel models, also known as 'borrowing strength', wherein individual group (for example, study-level) estimates are shrunk towards the overall population mean. Data nuances will determine the relative amount of strength borrowed per study, but in general, shrinkage is a function of the relative variance of each estimate, and is greater for groups with extreme values and lower replication[89]. As with weighting in meta-analyses of effect sizes, shrinkage functions to reduce the variance of cross-study estimates.

Transferability
The validity of extending an inference about an estimand to different sampling units or a different population of units. Transferability could be defined by the accuracy of a predicted estimand for a target population or observation, quantified by the difference between the transferred estimand and the 'true' estimand.

Weighting
Considered a hallmark of formal meta-analysis, the precision-weighting of each effect size by the inverse of its variance ensures that more precise studies make a larger contribution to the meta-estimate. Weighting serves only to increase the precision of the meta-estimate and the power of tests, not the accuracy of meta-estimation[90]. In the presence of bias, it can lead to precisely wrong estimates[30].

indicators and tests of transferability (example in Box 3). See Box 4 for a Glossary of terms.

Develop quantitative methods to transfer estimands (for scientists)

Ecologists could develop methods to transfer estimands to different target contexts, once the reference and target contexts have been parameterized. A recent study[81] reviewed the numerous quantitative approaches that have been developed in primarily health-related disciplines to: (1) evaluate the validity of transferring an estimand to a specified target context, based on a set of assumptions (Fig. 2, step 3) and the quantitative dissimilarity of the study and target contexts (Fig. 2, step 4); and (2) use 'external validity bias adjustment' methods to adjust an estimand for a target context (Fig. 2, step 5). For example, a pair of studies formalized a range of 'transport formulae' associated with selection diagrams that enable the recalibration of average population-level effect sizes for a well-defined target context, for example, through re-weighting observations in the reference population in proportion to distributions of conditioning covariates in the target context[18,82] (example in Box 2). The choice of method for estimand adjustment may be restricted by data availability (for example, summary-level versus individual-level data) and mechanistic understanding of the target system.

Validation of quantitative transfers (Fig. 2, step 6), and of the methods developed to enable transfer, will only be possible with independent

studies and data using cross-validation (action 3), although they are often unavailable or insufficient for a target context. Transfer methods and understanding need development as a discipline. In the meantime, data gaps might be filled by making use of continental scale, fine-resolution data from environmental monitoring programmes that span multiple environmental contexts, such as the National Science Foundation's National Ecological Observatory Network (https://www.neonscience.org) and national forest inventories. In the absence of validation data for target contexts, transferability could be estimated by contrasting predictions with existing expert knowledge, by simulations, or by performing controlled, distributed experiments[8].

Conduct interdisciplinary research that seeks to understand how multiple stakeholders perceive generalizability and transferability (for scientists and practitioners)

Scientists need to communicate the transferability, contingency and uncertainty of ecological effects in a meaningful and practicable way. This requires an understanding of how perceptions of transferability and uncertainty are formed by different audiences, including scientists, practitioners and policymakers[83,84]. Interdisciplinary research is required to understand how different attributes affect the perceived transferability of ecological effects (using, for example, surveys, workshops). These might include: (1) audience attributes (for example, sector, experience); (2) study context (biogeography, climatic conditions); (3) study-design attributes (for example, design, scale, replication); and (4) presentation attributes (for example, graphical presentation of results). Next, we can use this understanding to determine how uncertainty and contingencies are unambiguously communicated, by trialling different methods of translation, and to improve CoG statements.

Conduct adaptive research that feeds into syntheses (for scientists and science funders)

Research funding is usually based on competition between individual proposals, with an emphasis on novelty. Distributed experiments have become popular in many disciplines[85] as an approach that aims at generality by repeating an experimental design in multiple locations (for example, Nutrient Network[8], Marine Global Earth Observatory[86] and ManyLabs in psychology[87]). In practice, such distributed experiments are poorly resourced, depending on freely offered endeavours of dedicated researchers for setup and maintenance. Large-scale, multinational and long-term funding to institutions for collaboration could transform this approach, to sample across the range of contextual variables as orthogonally as possible. Importantly, the results could inform extensions to these studies, or a new set of studies, in accordance with the concept of 'adaptive experimentation'[88]. This would lead to syntheses that inform transferable research designs in an iterative manner, rather than 'making do' with what has gone before. This idea replaces the current paradigm of individual-level competitiveness and novelty with institutional-level collaboration and scope for generality, and it provides a framework for individual scientists to develop their talents in collaborative teams.

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R.S. conceived the idea and developed a first draft with J.M.B., R.E.O., S.N., C.P.D., M.R. and C.T.C. contributed to idea development and paper writing.

Competing interests

The authors declare no competing interests.

Additional information

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