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SPECIAL FEATURE: UNCERTAINTY ANALYSIS

The current state of uncertainty reporting in ecosystem studies: a systematic evaluation of peer-reviewed literature

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Abstract. Transparency in reporting is essential to scientific progress. No report should be considered complete without a full account of uncertainties, including those due to natural variation and measurement and model error and those incurred by handling problematic data, such as outliers. We randomly selected 132 papers published in 2019 from a list of 100 scientific journals to characterize the current state of uncertainty reporting in ecosystem studies. Each paper was evaluated for the extent to which it reported measures of uncertainty in any of four topic areas common to ecosystem studies: vegetation, soils, precipitation, and surface water. We found that most papers reported a minority of the uncertainty sources we deemed relevant. Papers on surface water reported the highest fraction of uncertainty sources (averaging 47% ± 5%), followed by soils (45% ± 4%), vegetation (32% ± 4%), and precipitation (21% ± 8%). A greater fraction of relevant uncertainty sources were reported when the topics were the primary focus of the paper (44% ± 3%) than when they were not (32% ± 4%). Sampling error—the uncertainty in replicate measurements—was the source most commonly reported in studies of vegetation (84%), soil mass (56%), and surface water (76% of papers). The source of measurement error most often reported was chemical analysis, with 41% of papers on surface water and 75% of papers on precipitation reporting this source, if applicable. In contrast, only 1 of 12 papers reporting chemistry of vegetation provided information on analytical uncertainty. Fewer papers reported what methods were used for handling missing or unusable data and observations below detection limits, but it was difficult to judge whether these sources were relevant if they were not mentioned. Finally, we found that a minority of the papers made all (21%) or some (an additional 21%) of their data available in online repositories, after correcting for a failure rate of 13% of the links. Clearly, there is room for improving the completeness and transparency of scientific reporting in ecosystem studies.

Key words: biomass; ecosystem ecology; measurement error; model error; precipitation; sampling error; soils; Special Feature: Uncertainty Analysis; surface water; uncertainty reporting; vegetation.

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Introduction

Ecosystem studies are subject to many sources of uncertainty (Fig. 1), many of which are not consistently reported in the scientific literature. Natural variation, which results in sampling error in space and time, and imperfect knowledge, reflected in measurement error and model error, both contribute to the uncertainty inherent in ecological research (Harmon et al. 2007, Yanai et al. 2018). Needless to say, the failure to account for sources of uncertainty can limit the extent to which research conclusions can be evaluated and interpreted for use in broader contexts. In addition, understanding the relative magnitude of uncertainty sources makes it possible to better assign measurements to reduce uncertainty at the lowest possible cost (Yanai et al. 2010, Levine et al. 2014, Campbell et al. 2019). Efforts to increase the transparency and reproducibility of scientific research have resulted in a number of developments that are valuable to the scientific process, including increased data availability and more rigorous review of research proposals (Collins and Tabak 2014, Lyon 2016, Vannan et al. 2020). Improving reporting of uncertainty should be included among these efforts.

A recent survey of ecosystem scientists showed that researchers differ by discipline in the sources of uncertainty they most often report and the sources of uncertainty that they believe to be most relevant to their respective fields (Yanai et al. 2018). For example, soil scientists and vegetation scientists most often report natural variation, using replicate measurements, and they believe that sampling error is the most important source of uncertainty in their fields. Hydrologists, however, most often report the uncertainty of chemical analyses, although they rate other uncertainty sources, such as measurement error and filling gaps in data, as being more often important to estimates of hydrologic fluxes.

That survey of ecosystem scientists was intended, in part, to raise awareness of overlooked sources of error; questions were also directed at finding out whether researchers knew how to quantify each source of uncertainty (Yanai et al. 2018). Although the survey captured researchers' perspectives on the relative importance of uncertainty sources, we were not confident that the results accurately characterized the actual rate of uncertainty reporting. Systematic studies of the literature have been used to quantify error rates in citing scientific literature (Todd et al. 2007, Haussmann et al. 2013) and in formatting citations (Lopresti 2010). To quantify the rate at which uncertainty is reported, previous studies have evaluated all articles in a particular journal (Lechner et al. 2012) or abstracts from a particular conference (Lee 2013). This approach has also been used to quantify the frequency at which ecological studies account for imperfect detection (Kellner and Swihart 2014). A systematic evaluation of the scientific literature is the

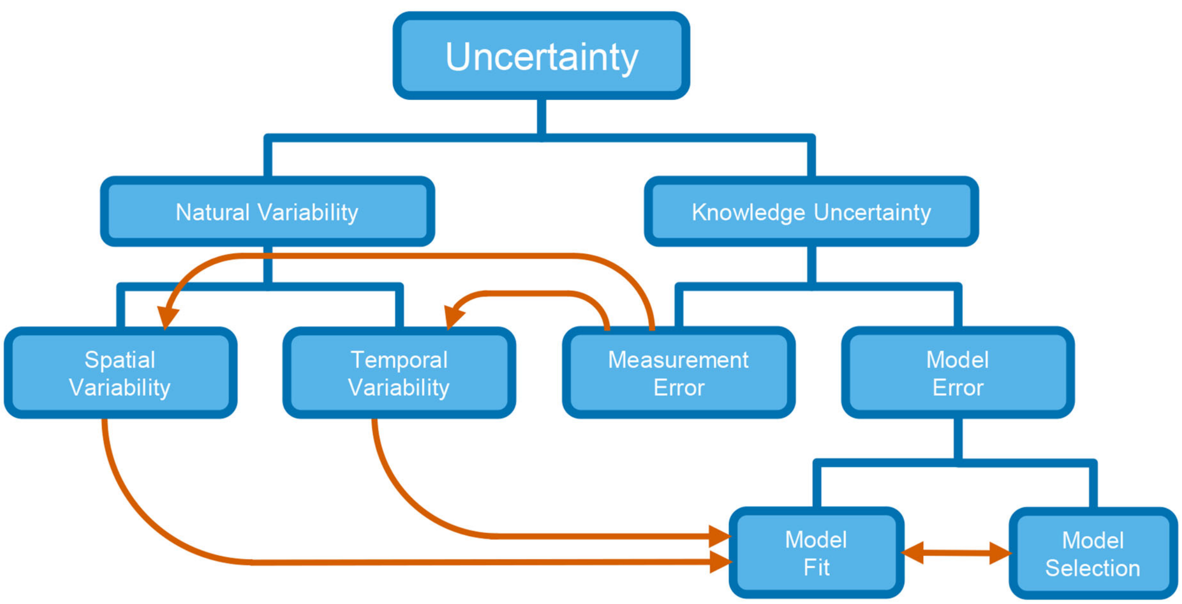

Fig. 1. Sources of uncertainty in ecosystem studies (modified from Harmon et al. 2007). Red arrows indicate sources of uncertainty that contribute to other sources of uncertainty. Reprinted from Yanai et al. (2018).

best way to discover how frequently various sources of uncertainty are reported in a given field.

Here, we report our examination of 132 randomly selected journal articles focused on ecosystem studies and published in 2019. We assessed the relevance and reporting of many possible sources of uncertainty in each article. We identified which sources of uncertainty were most frequently reported, whether researchers reported how they handled problematic data, and whether links were provided to the data. We used this information to characterize the current state of uncertainty reporting in studies of vegetation, soils, precipitation, and surface water. We also attempted to relate rates of uncertainty reporting to the location of the first author's institution, the number of authors, and the publisher. We hope that this survey will serve as a benchmark against which to test for improvements in the completeness and transparency of scientific reporting in ecosystem studies.

Methods

Data collection

We searched for a database of journals relevant to ecosystem studies and found that the categories defined by Web of Science and Scopus included many journals not relevant to our interests. We decided to make use of a database of publications of the Long-Term Ecological Research (LTER) network of the USA (https://lternet.edu/bibliography/). We ranked journals by the number of papers in the LTER database published in the last 10 yr (from 1 January 2010 through 3 September 2019). For each of the top 100 journals, we randomly selected two papers from the first issue of 2019; if the first issue failed to yield two eligible papers, we continued until 100 papers in the journal had been screened for eligibility. For journals not divided into issues, we randomly selected from the first 100 papers of 2019. To be included in our sample, papers had to report primary data collected in the field relating to vegetation, soil chemical or physical properties, or precipitation or surface water. We excluded literature reviews, opinion papers, and modeling papers that did not report data collection. To equalize the numbers of papers evaluated across the disciplines, we stopped evaluating papers reporting only vegetation after reaching 43 in this category. We continued to evaluate vegetation reports in papers also reporting soils and hydrology. Of the 100 journals we considered, 25 failed to yield any eligible papers in the first 100 articles, so they were excluded from our sample. Fifteen journals yielded only one paper. There were nine journals we passed over after we stopped selecting papers focused on vegetation.

We evaluated 132 papers; 27 papers were reviewed in multiple categories. For papers that reported information in more than one category, we determined which was the primary topic area of study. In 32 cases, the primary area of study was not one of these four categories (e.g., 5 papers focused on phytoplankton, 4 on soil microbes, and 3 on remote sensing). Two papers were deemed primary in both vegetation and soils.

Six researchers (the five authors and one additional researcher) selected papers and evaluated them. We used categories of uncertainty sources previously reported in a survey of scientists (Yanai et al. 2018). When we had difficulty deciding whether a paper belonged in our sampling frame or whether an uncertainty source was not reported or not applicable (this was more difficult than determining that it was reported), we flagged our results to be independently verified by another researcher on our team. We collected data on the sources of uncertainty reported, including sources due to natural variation, measurement error, model prediction, and model selection (Fig. 1). We did not evaluate whether uncertainty sources were quantified in accordance with international standards (JCGM/WG1 2008). We did encounter sources of uncertainty not anticipated by our categories and recorded whether these were quantified or not. We also noted whether papers reported how they identified missing or unusable values, how they filled gaps in the data, and how they dealt with observations below detection limits. We recorded the number of authors, the country of the institution of the lead author, and the country where the research took place. We collected information on the journal publisher, impact factor, and age (date of publication of the first volume). Finally, we recorded whether some or all of the data were made available electronically and noted broken links to archived data.

We used a Google Form (Appendix S1) to record our results, and these results are presented in Data S1.

Data analysis

We scored the number of times that each uncertainty source was reported, not reported, or not applicable in each of the four categories of study (vegetation, soils, precipitation, and surface water). We calculated an uncertainty score for each category for each paper, reflecting the number of uncertainty sources that were reported as a fraction of possible sources, omitting those we judged to be not applicable to the study design (Eq. 1).

$$\text{Uncertainty score} = \frac{\text{Number of uncertainty sources reported}}{\text{Number of relevant uncertainty sources}} \times 100\%. \tag{1}$$

The summary uncertainty score for a paper was the score for the primary category of study, or the average if there were multiple primary categories. We reported the frequency of the other practices we surveyed (handling missing data, values below detection, and providing access to archived data), but these results did not contribute to the uncertainty score.

We tested whether uncertainty scores were independent for the two papers sampled in a journal. For the 60 journals that provided two papers to our data set, there was little relationship between the two papers in overall score (Pearson's $r = -0.10$, $P = 0.49$). Similarly, we tested whether the uncertainty scores for multiple categories within a paper were independent. For the 27 papers in which at least two categories were scored, the pairs of observations scored within papers were not significantly correlated (Pearson's $r = 0.18$, $P = 0.39$). Thus, we treated our evaluations of papers and categories as independent in our analysis of uncertainty reporting.

We used four separate simple linear regression models in R (lm function in the base R package) to test whether the summary scores were significantly related to the country or continent of the first author's institution, the journal publisher, or the age of the journal. The assumptions of simple linear regression were not met for the analysis of the effects of the number of authors, the 2-yr impact factor, or the 5-yr impact factor of the journal, so to test the effects of these factors, we used three separate generalized linear regression models using a binomial (logit) function (glm in the lme4 package in R).

We tested whether scores differed by category of study and whether scores were higher if the category of study was the primary focus of the paper. For this analysis, the response variable was the score for each category evaluated within each paper, not the summary score for the paper. Predictor variables were fixed categorical effects —the category of study, whether the category was primary or secondary, and their interaction —in a single simple linear regression model for analysis of variance (lm function in base R).

Results

Papers in our data set by country, number of authors, and publisher

From the 100 journals in our sampling frame, we evaluated 132 papers, with 27 papers reviewed for multiple categories, for a total of 160 evaluations (Fig. 2). By category, we reviewed 47 papers that reported information on vegetation, 54 on soils, 14 on precipitation, and 45 on surface water.

The sample included papers by lead authors from 31 countries. The country with the most papers in the sample was the USA (45), followed by China (18). Germany, Canada, and Spain had eight papers each. The UK had seven; Sweden had four; Mexico, Iran, and Australia had three papers each; and 21 countries had 1–2 papers in the sample. Papers by authors from different countries did not differ consistently in their reporting of uncertainty ($P = 0.36$). Papers by authors based in Europe (41 papers) and Asia (29 papers) had better overall uncertainty scores, with a median of 50% and 42%, respectively, than papers by authors in North America (56 papers), with a median uncertainty score of 33% ($P = 0.03$ for the effect of continent). The locations of the studies are provided in Data S1; we had difficulty analyzing these as many took place in multiple countries or in international waters.

Papers with 3–5 authors comprised more than half of the sample (72 papers). No paper had

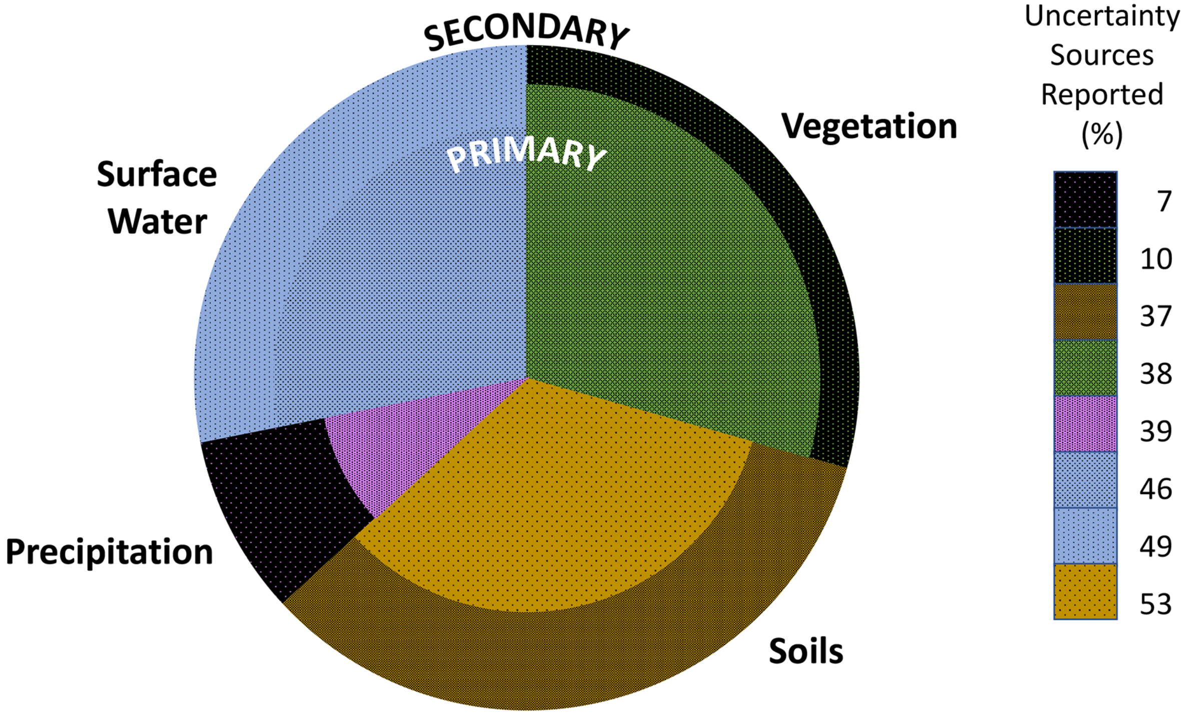

Fig. 2. The area of each section is proportional to the number of papers primarily (inner portion) or secondarily (outer portion) focused on vegetation, soil, precipitation, or surface water, with the fill pattern indicating average rates of uncertainty reporting, based on the fraction of applicable uncertainty sources reported by each paper. Some papers are represented in more than one topic area.

only one author, and 16 papers had 10 or more authors. The number of authors on the paper did not affect the overall rate of uncertainty reporting ($z = 0.79$, $P = 0.43$ in logistic regression).

Surprisingly, uncertainty scores differed by publisher. The 26 journals published by Elsevier had the highest overall scores, averaging 55%; Wiley accounted for 37 journals with an average score of 44%, and Springer accounted for 23 journals with an average of 33% ($P = 0.03$). These three publishers accounted for 65% of all the journals we studied; 16 other publishers accounted for 1–5 titles each. A test of all 19 publishers was not significant ($P = 0.17$). The journal impact factor was not related to uncertainty reporting ($P = 0.99$ for the 2-yr impact factor and $P = 0.94$ for the 5-yr impact factor), nor was the age of the journal ($P = 0.39$).

Sources of uncertainty reported by topic

There were 47 papers in our sample that reported plant biomass (Fig. 3A). The source of uncertainty most often relevant was sampling error, and this source was the most often reported in our entire data set, with 32 papers reporting it of the 38 vegetation papers for which it was relevant. Sources of measurement error were rarely reported, although these were usually relevant. Specifically, biomass measurement error was reported in only 3 of 30 papers in which we judged it could have been reported; uncertainty in locating plot boundaries was reported in 1 of 17; and uncertainty in plot area was never reported. Species identification was a source of measurement uncertainty in 27 papers but was reported by only two, and uncertainty of tree status (live or dead) was reported in only one of nine relevant papers. Uncertainty in spatial and temporal patterns was less often relevant (eight and seven papers, respectively) but was reported at higher rates (four and three papers). Other sources of modeling error were even less often relevant. The confidence and prediction intervals of biomass models were relevant for

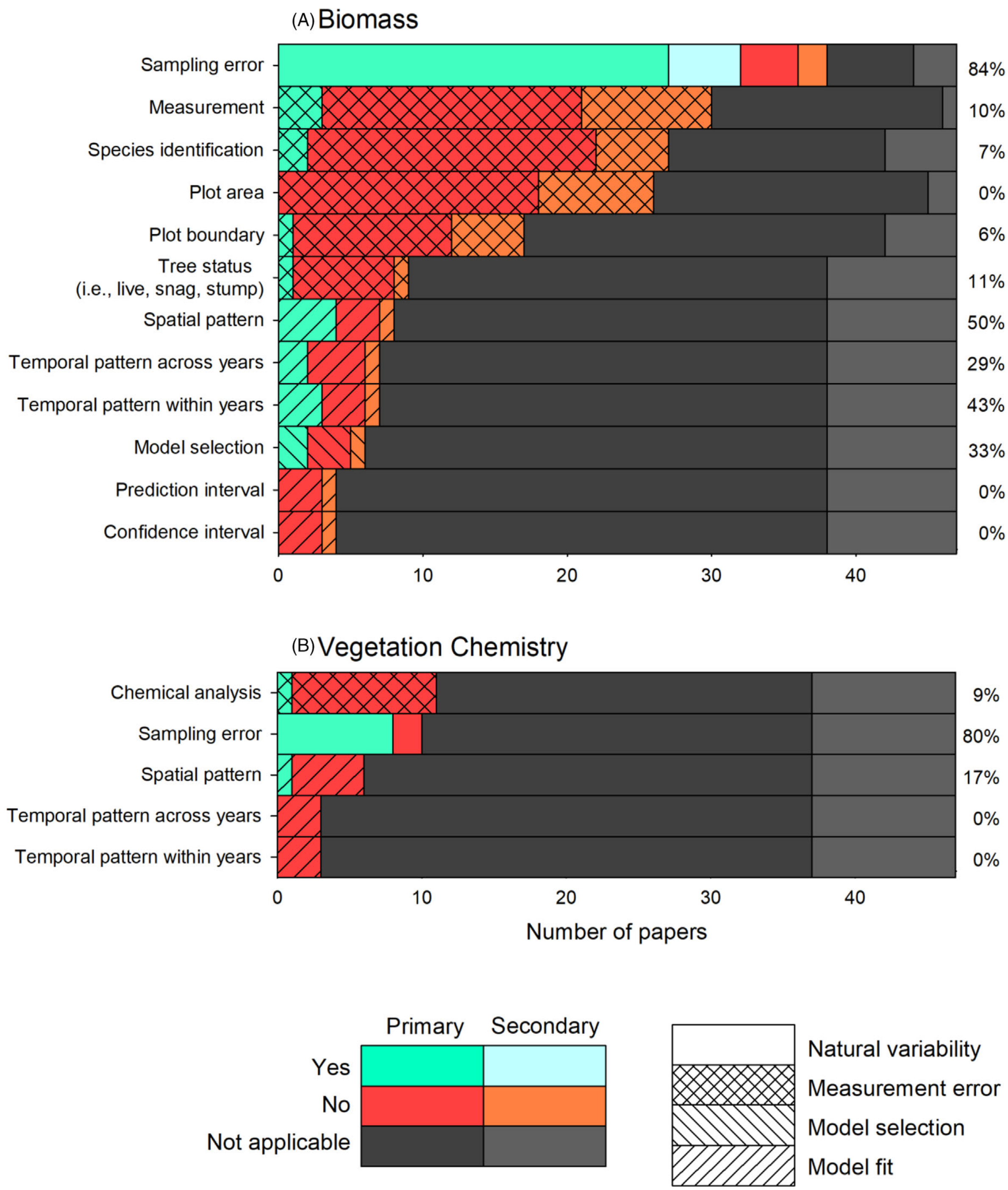

Fig. 3. Sources of uncertainty reported in studies of (A) biomass and (B) chemistry of vegetation. On the right is the portion of papers reporting each source, of those for which it was relevant. Sources are ordered by the number of papers for which they were relevant.

only four papers in our data set and were not reported by any of them, but model selection error was reported by two papers of six. Overall, papers addressing biomass reported 32% ± 4% (mean and standard error) of the sources of uncertainty that we deemed relevant.

Vegetation chemistry was less often reported (12 papers) in our survey than biomass (Fig. 3B). Of sources of uncertainty pertaining to vegetation chemistry, chemical analysis and sampling error were most often relevant. Sampling error was the only source that was commonly reported (8 of 10 papers). One paper reported uncertainty in chemical analysis (of 11 relevant papers) and one reported uncertainty in spatial pattern (of six relevant papers). None of the papers we surveyed reported uncertainty in temporal pattern across or within years for vegetation chemistry, although three papers could have done so. Overall, papers addressing vegetation chemistry had uncertainty scores of 38% ± 7%.

Fifty-four papers in our sample concerned soils (Fig. 4), more involving soil chemistry (50 papers) than soil mass (23 papers). For soil chemistry (Fig. 4B), sampling error was the most often reported source of error (35 of 49 papers). Uncertainty in analytical chemistry was often relevant but not very often reported (9 papers of 47). Uncertainty in spatial pattern was reported in 6 of 13 eligible papers, while uncertainty in temporal pattern was less often relevant (four papers) and was reported only once. Uncertainty in the measurement of horizon depths was reported only once although we judged it relevant to 14 papers. Papers addressing soil chemistry had an average uncertainty score of 46% ± 5%.

Of the 23 papers reporting soil mass, sampling error was again the most commonly reported (Fig. 4A). Sampling error in bulk density measurements was reported in 10 of the 18 papers for which it was relevant. Other sources of uncertainty were rarely reported. Two papers reported uncertainty in soil horizon depth (of 14 relevant papers); for spatial pattern, uncertainty was reported in one of six papers. Uncertainty in temporal pattern was never reported, nor was uncertainty in coarse fraction, but these were rarely relevant. Overall, papers addressing soil mass reported 37% ± 7% of the sources of uncertainty that we deemed relevant.

There were 14 papers in our sample that reported precipitation (Fig. 5A). Precipitation volume was reported in all of these papers, of which three reported measurement uncertainty, usually rain gauge efficiency. One of the seven studies involving spatial interpolation of rain gauge data reported model selection uncertainty. Analytical uncertainty of chemical analysis had the highest rate of uncertainty reporting (three of four relevant papers). None of the sampled papers involved interpolation of precipitation chemistry; one of the three papers involving interpolation of precipitation volume reported the model uncertainty. Overall, papers reporting precipitation reported 21% ± 8% of the relevant uncertainty sources.

Surface water was reported by 45 papers in our sample (Fig. 5B). Sampling error was the most often reported source of uncertainty (31 of 41 papers for which this was relevant), followed by uncertainty in analytical chemistry (16 of 39). Watershed area is commonly needed to calculate runoff, but uncertainty in this source of measurement area was never reported in the 16 papers for which this was relevant. Uncertainty in filling gaps was reported by one paper for water volume and four for water chemistry, of 14 and 15 papers, respectively, for which these sources were relevant. Uncertainty was also reported by two papers for model selection and three papers for model fit for estimates of water flux (of 13 relevant papers) and by four papers for uncertainty in measurement of water flux, such as the relationship of stage to discharge (of 10 relevant papers). Overall, papers on surface water reported uncertainty in 47% ± 5% of the relevant sources.

The four topic areas differed significantly in rates of uncertainty reporting ($P = 0.002$; Fig. 2). Research on surface water had the highest rate (averaging 47% ± 5% of the relevant sources), followed by soils (45% ± 4%), vegetation (32% ± 4%), and precipitation (21% ± 8%). Primacy of the topic was also important ($P = 0.005$ for the main effect of primacy in ANOVA), with greater rates of uncertainty reporting for primary topics (averaging 44% ± 3% for 98 evaluations) than for secondary topics (averaging 32% ± 4% for 62 evaluations). There was an interaction of topic area and primacy of the topic ($P = 0.09$); notably, for surface water, uncertainty was not

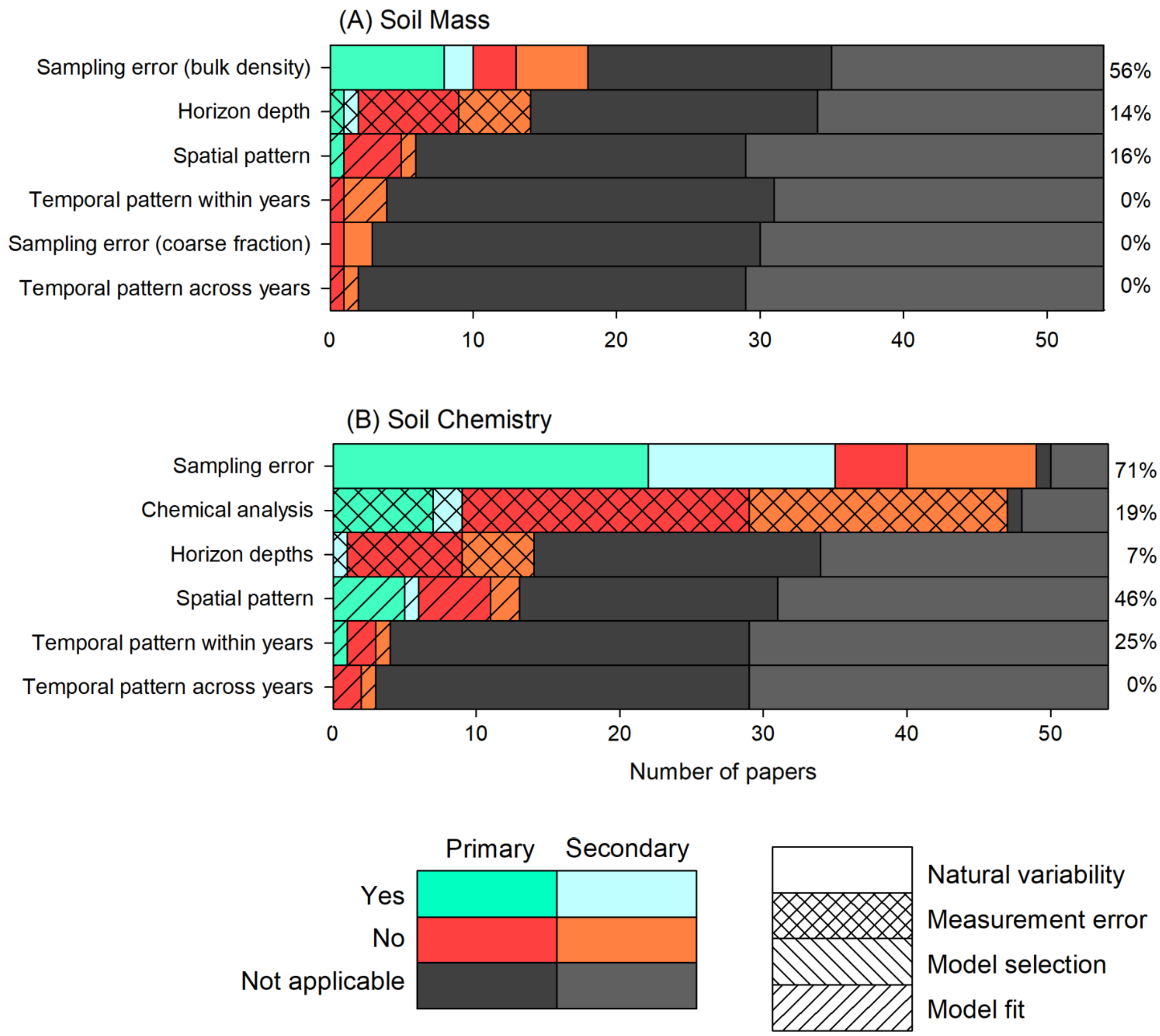

Fig. 4. Sources of uncertainty in studies of soil (A) mass and (B) chemistry. On the right is the portion of papers reporting each source, of those for which it was relevant. Sources are ordered by the number of papers for which they were relevant.

reported at higher rate in papers that addressed this topic as a primary area of interest (46% ± 6%) than in those with surface water as an area of secondary interest (49% ± 8%).

Practices for handling problematic data

We recorded whether papers reported practices for handling problematic data (Fig. 6). In many cases, the lack of information about such practices may reflect an absence of problematic data. Thus, "not mentioned" may not represent a failure to report a source of uncertainty, and we did not use our assessments of reporting of these practices in computing the overall uncertainty scores.

Concentrations below analytical detection limits were mentioned by only nine papers, four on surface water and five on soils. One paper used half the detection limit and the rest were evenly divided between omitting the values and replacing them with zeros, which have the effect of overestimating and underestimating means, respectively.

Outliers and unusable values were mentioned by 31 papers. The most common method for identifying them was the use of expert judgment

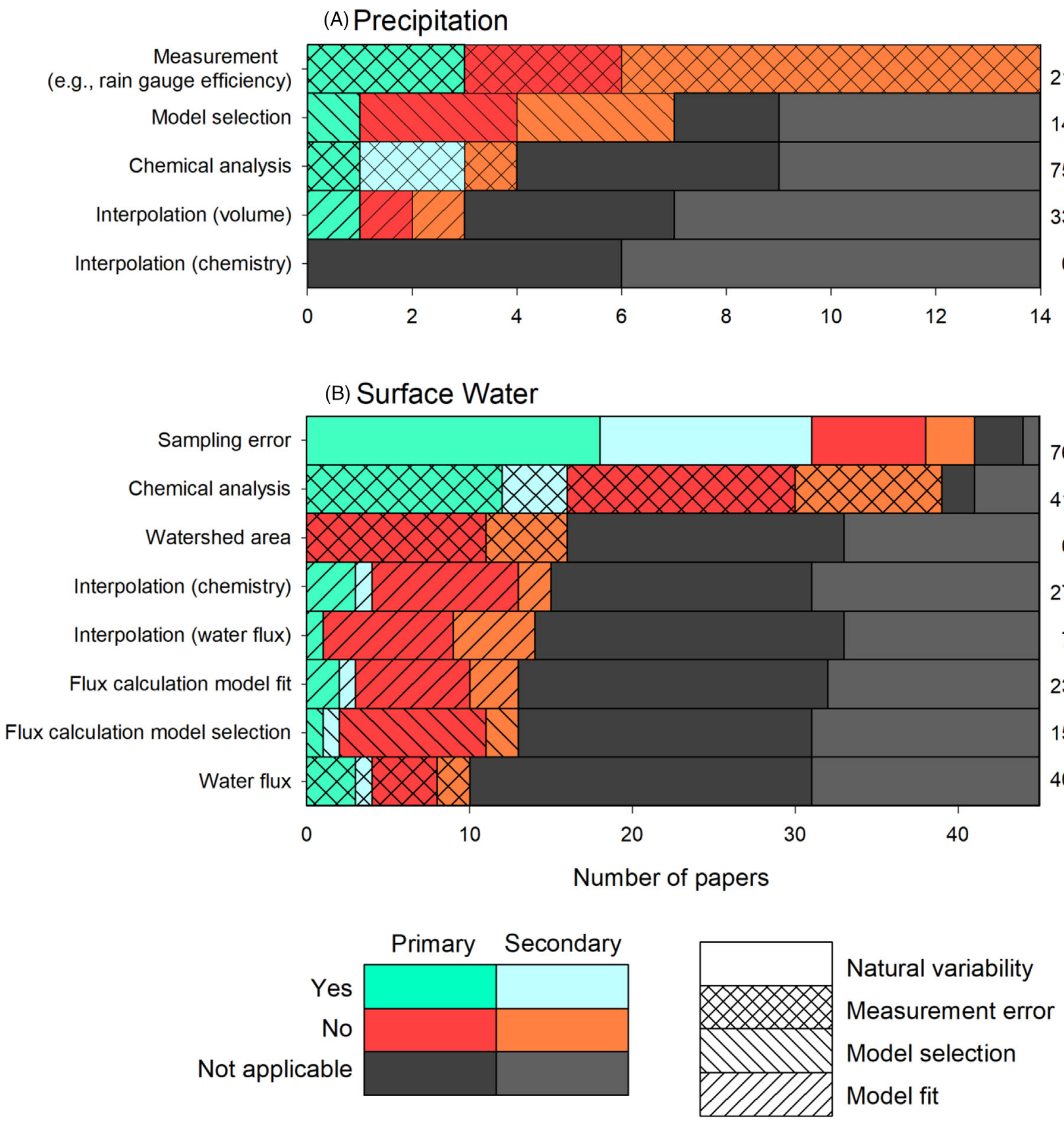

Fig. 5. Sources of uncertainty reported in studies of (A) precipitation and (B) surface water. On the right is the portion of papers reporting each source, of those for which it was relevant. Sources are ordered by the number of papers for which they were relevant.

(25 instances); in six cases, statistical filtering was used.

Methods for handling missing or unusable values were described by 28 papers. Approaches used included linear interpolation, regression modeling, statistical modeling, omitting unusable values, and replacing missing data with values from literature or comparable sites.

Availability of data

Of the 132 papers we examined, 24% provided links to all the data and 48% provided links to at least some of the data (Fig. 7). However, because eight of those links were ineffective, the true rates of data availability were 21% providing all the data and 42% providing at least some of the data.

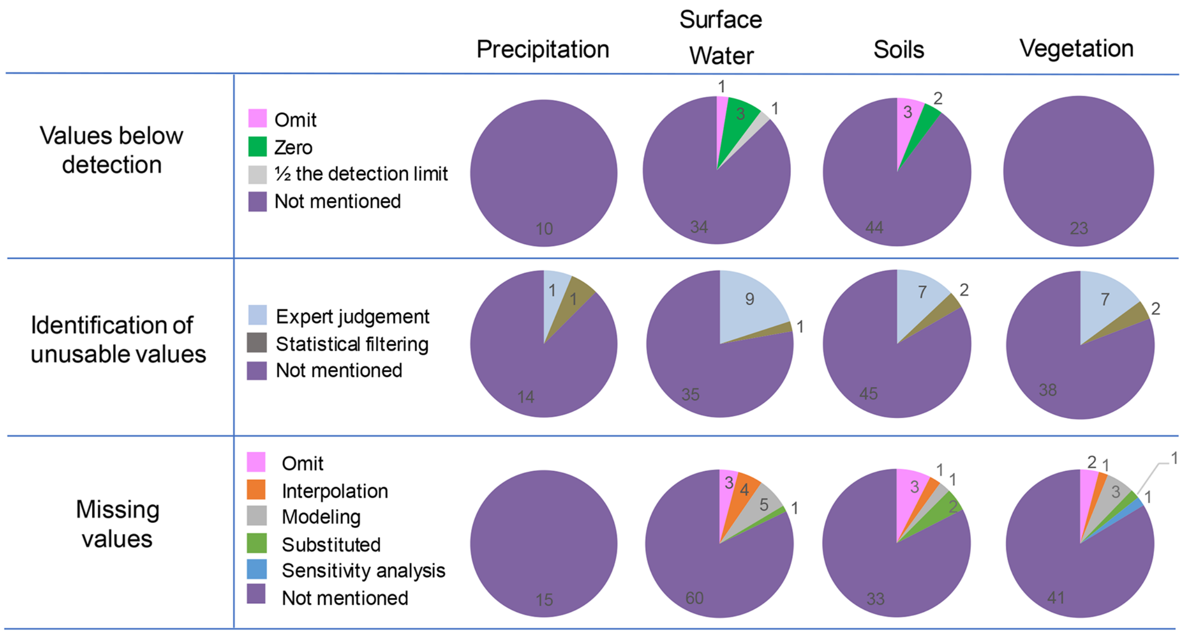

Fig. 6. Practices for handling problematic data in the four topic areas we reviewed, indicating the number of papers that used a given practice. Some papers are represented in more than one topic area, and some papers used more than one practice within a topic area.

Discussion

Rates of uncertainty reporting by type of source and topic area

Sampling error, characterized by replicate measurements, was the most commonly reported source of uncertainty, by far, in every discipline (Figs. 3–5). For biomass, vegetation chemistry, and soil chemistry, rates of reporting this source of uncertainty exceeded 80%; for soil mass and surface water, they were somewhat lower (67% and 77%). This result was not surprising, as sampling error is considered the most important source of uncertainty, according to a previous survey of ecosystem scientists (Yanai et al. 2018). Measurements of precipitation are not normally considered replicates, but are used to characterize spatial pattern, and we did not rate precipitation studies for sampling error.

Measurement errors were most commonly reported for analytical uncertainty in water chemistry, the highest rate being for precipitation (75%, based on a sample of four papers for which this source was relevant) and surface water (41%, based on 31 papers). Similarly, uncertainty in analytical chemistry was the most reported source of measurement error in papers reporting soil chemistry (25% of 28 papers). Surprisingly,

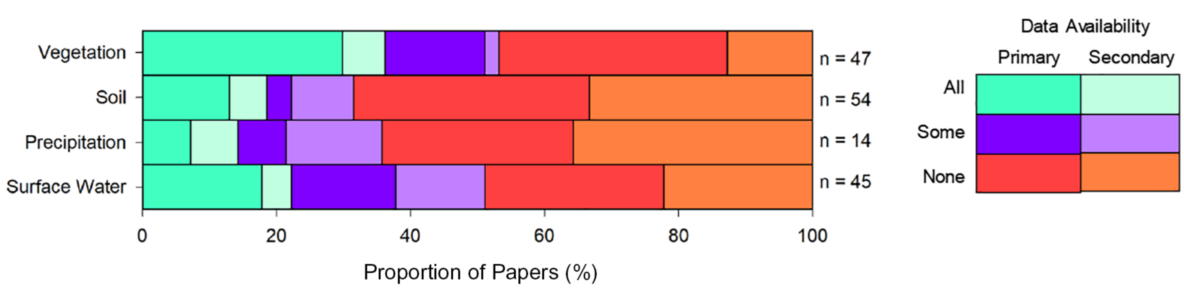

Fig. 7. The proportion of papers in each category that provided links to all, some, or none of the data. On the right is the number of papers in each topic area. Some papers are represented in more than one topic area.

only one paper of the 12 reporting vegetation chemistry (8%) reported uncertainty in chemical analysis. This information is routinely provided by the laboratories that carry out chemical analyses, but evidently, scientists in the role of author and reviewer are not consistently demanding that this information be passed on.

Measurement errors are generally believed to be less important than sampling error (Yanai et al. 2018), but this assumption is difficult to evaluate for sources that are not reported. While quality control procedures are common in analytical laboratories, measurements taken in the field rarely undergo much scrutiny. In the case of biomass measurements, uncertainties in plot area measurement, plot boundary relocation, species identification, and tree status were rarely reported (0–11% of up to 30 papers). Measurement errors could explain reported changes of up to 25% in plant cover or species composition, according to a review of 59 studies of observer error in vegetation surveys (Morrison 2016). Measurement errors were more commonly reported by hydrologists, with 25% of papers reporting uncertainty in precipitation volume measurements (e.g., rain gauge efficiency) and 40% of papers reporting uncertainty in surface water flux measurements (e.g., stage–discharge relationships). Uncertainty in watershed area, which was relevant to 16 papers, was never reported—nor was the uncertainty in plot area for vegetation measurements, which was relevant to 26 papers. When the same area is measured over time, as is often the case in long-term monitoring, errors in the area monitored do not detract from trend detection but do result in consistently biased estimates.

Some sources of model error are more commonly reported than measurement error, though not as commonly as sampling error; none of these exceeded a 50% reporting rate. When reporting spatial or temporal pattern, fit statistics were reported by just a handful of papers in each discipline, but since many papers did not report such patterns, the rates of uncertainty reporting ranged up to 43%. Similarly, there were a few papers in which models were used to fill gaps in hydrologic data, with uncertainty reported in 6–30% of cases. Uncertainty in model selection is easily ignored, but this source was considered in four papers in our survey, two in vegetation and two in surface water.

Comparison to other studies

Most of the papers we evaluated (54%) quantified fewer than half of the uncertainty sources that we judged applicable; uncertainty scores averaged 42% and the median was 40%. Other systematic evaluations of published papers found that most do not adequately address the sources of error under investigation. In a review of 537 studies of species abundance and distribution, only 24% accounted for imperfect detection (Kellner and Swihart 2014). Similarly, spatial uncertainty was accounted for by only 23% of papers published in 2007 by a prominent landscape ecology journal, although 47% acknowledged it was an issue (Lechner et al. 2012). Taken together, these systematic studies of the scientific literature suggest that many sources of error in ecological and ecosystem studies commonly go unreported.

Our survey of randomly sampled papers from scientific journals reveals much lower rates of reporting of uncertainty sources than we found in a survey of scientists in 2015–2016 (Yanai et al. 2018). This is not a logical impossibility: An author could correctly reply "yes, I report this source of uncertainty," even if this source had been reported in only one of a dozen papers in which it could be reported; those papers, however, would show an 8% rate of reporting for such an author (1 of 12). It is also possible that the scientists we surveyed may not have understood our questions in the way we meant them and thus not answered them correctly. For example, we reached out to the 25 respondents to the survey who said that they reported uncertainty due to filling gaps in runoff, offering to cite their examples in another paper we were working on at that time (See et al. 2020). Most did not respond, and of the four who did respond, we obtained one quantitative and one qualitative estimate of this source of uncertainty. One respondent admitted that he had no such estimate. We believe that assessing the state of uncertainty reporting by having a single team of experts evaluating a random sample of journal articles provides a more meaningful and repeatable result than asking scientists to self-report.

Data availability

A minority of papers we surveyed provided access to the data they were analyzing. The capacity to archive data is a relatively recent development, and not all funding sources require that data be made available; clearly, judging from the results of this study, not all journals do, either (McCain 1995). A 2017 survey involving 1372 members of the American Geophysical Union found that 91% of respondents would use data shared by others, but many would place conditions on sharing their own data; responses varied by discipline (Tenopir et al. 2018).

Providing links to archived data is not a guarantee that the data will remain accessible. We found eight broken links in the 63 papers that provided them. This is worse than was found in a survey of top journals conducted in 2005, in which papers published 2 and 5 yr previously had failure rates of 5% and 10%, respectively, in sharing supplemental materials (Evangelou et al. 2005). A study of 655 supplementary data links in biomedical journals estimated that 10% of links were already broken at the time of publication (Anderson et al. 2006). The fact that 13% of the links we tested were broken just a year after publication is discouraging.

The future of uncertainty reporting

We hope that this study will help raise consciousness about uncertainty reporting among researchers, reviewers, journal staff, and funding agencies. Providing access to data and code has become more common, though it is not yet universal; quantifying uncertainty, similarly, should become a routine requirement of scientific reporting. Currently, few journals mention uncertainty reporting in instructions to authors, with Hydrological Processes being a notable exception.

We intend our survey results to serve as a benchmark for future reference. If awareness is increasing of the value of quantifying uncertainty and of the methods for conducting uncertainty analysis, then a future survey of this type should find higher rates of uncertainty reporting than we found in 2019. It would also be possible to survey the literature from earlier points in time to document progress to date. Please contact us if you would like to coordinate efforts on such a project—this topic makes a good introduction to sources of uncertainty for graduate students or advanced undergraduates.

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Supporting Information

Additional Supporting Information may be found online at: http://onlinelibrary.wiley.com/doi/10.1002/ecs2.3535/full