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# Hydrology Research Articles are Becoming More Interdisciplinary

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**Abstract**

We used Natural Language Processing (NLP) to assess topic diversity in all research articles (~75,000) from eighteen water science and hydrology journals published between 1991 and 2019. We found that individual water science and hydrology research articles are becoming increasingly interdisciplinary in the sense that, on average, the number of topics represented in individual articles is increasing. This is true even though the body of water science and hydrology literature as a whole is *not* becoming more topically diverse. These findings suggest that the National Research Council's (1991) recommendation to increase multidisciplinarity of hydrological research has been followed. Topics with the largest increases in popularity were *Forecasting* and *Climate Change Impacts*, and topics with the largest decreases in popularity were *Hydraulics*, *Solute Transport*, and *Aquifers and Abstraction*. At a journal level, *Hydrological Processes*, *Journal of Hydrology*, and *Water Resources Research* are the three most topically diverse journals in the discipline. We also identified topics that are becoming increasingly isolated, and which could potentially benefit from integrating more with the wider hydrology discipline.

*Keywords:* Interdisciplinarity, Topic Diversity, Water Resources Science, Hydrology, Natural Language Processing, Topic Modeling

## 1. Introduction

Early emphasis on interdisciplinarity within hydrology and water resource science focused on bringing together natural scientists, engineers, and social scientists [1]. Freeze [2] identified a separation between physical and social sciences in water research and encouraged the journal Water Resources Research ($WRR$) to encourage then-limited partnerships to bolster interdisciplinarity. A report by the National Research Council [3] focused on the importance of a multidisciplinary educational base in hydrology, and encouraged multidisciplinary hydrological research as necessary to understand (and predict) the full global water cycle. Over the next decade, hydrologic sciences became central to new research topics (e.g., hydroclimatology, hydrometeorology, geobiology, hydroecology, hydrogeomorphology, ecogeomorphology, earth system dynamics, etc.) [4].

In the modern era, Montanari et al. [5] argued that the Scientific Decade 2013-2022 would focus on advanced monitoring and data analysis techniques, and that interdisciplinarity in water science could be sought through connecting economic sciences and geosciences. Montanari et al. [6] later argued that this branching tradition in hydrologic sciences has given rise to a vibrant interdsiciplinary research culture that focuses on a wide range of spatial and temporal scales, and interactions between water, earth, and biological systems. Ruddell and Wagener [7] mentioned interdisciplinarity as one of the grand challenges in hydrology education, and that it must expand beyond traditional scopes to address the evolving and unique needs of society (e.g., data and modeling driven cybereducation, developing an international faculty learning community, hydro-economics, etc.). Vogel et al. [8] described a modern interdisciplinary hydrologic science that develops deeper understanding of human-nature connections. He argued that every theoretical hydrologic model introduced previously is in need of revision to properly capture nonstationarity in nature; proposing knowledge discovery through 'Big Data' to understand the coupled human/hydrologic system. The 21st century saw a sharp rise in demand for more robust, interdisciplinary hydrologic models which account for nonstationarity associated with climate change [e.g., 9, 10, 11], and leverage large samples of available data [12]. Nearing et al. [13] argued that modern data science has the potential to transform water science given concerted effort to bring together hydrologists with data scientists, computer scientists, and statisticians.

Regardless of how we perceive open challenges in the discipline, it is important for scientists and practitioners to have some idea about whether and how the water science and hydrology science community is changing. In this study, we identify and quantify trends and interactions in and between different subtopics within the discipline. Specifically, we measure trends, diversity, and isolation of different sub-topics within the discipline, and we use these analyses to provide insight into the state of interdisciplinarity in the field. Water research articles encompass a wide range of research topics including groundwater, streamflow, climate change, eco-hydrology, biogeochemistry, water quality etc., all of which are consequential to global socioeconomic well-being. McCurley and Jawitz [14] attempted to assess interdisciplinarity in hydrology in a similar way by analyzing instances of topic keywords in article titles, however, their corpus consisted of article titles from only one journal - $WRR$, and used pre-identified keywords and topics. In this paper we look at a broad spectrum of water science and hydrology research publications (our corpus encompasses 18 high-impact journals), and use data science techniques to help (partially) automate the process of identifying distinct sub-topics in the discipline.

One of the major challenges faced by all scientific communities is the increasing volume of peer reviewed literature – Figure 1 quantifies this phenomenon in hydrology and water science. Recent advances in computational linguistics, machine learning, and a variety of application-ready toolboxes for Natural Language Processing (NLP) can help facilitate analyses of vast electronic corpora for a variety of objectives [15]. These techniques, which include information retrieval, text categorization, and other text mining techniques based on machine learning have been gaining popularity in information systems since the 1990s [16].

Topic modeling is a particular type of NLP that uses statistical algorithms to extract semantic information from a collection of texts in the form of thematic classes [17]. Topic models can be applied to massive collections of documents [18] and have been used to recommend scientific articles based on content and user ratings [19]. Topic modeling has also been used to cluster scientific documents [20], improve bibliographic search [21, 22, 23, 24, 25], and for a variety of application-specific objectives such as statistical modeling of the biomedical corpora [26], bibliometric exploration of hydropower research[17], in the analysis of research trends in personal information privacy [27], development of meta-review in cloud computing literature [28], literature review of social science articles [29], discovering themes and trends in transportation research [30], identifying contribution of authors in knowl-

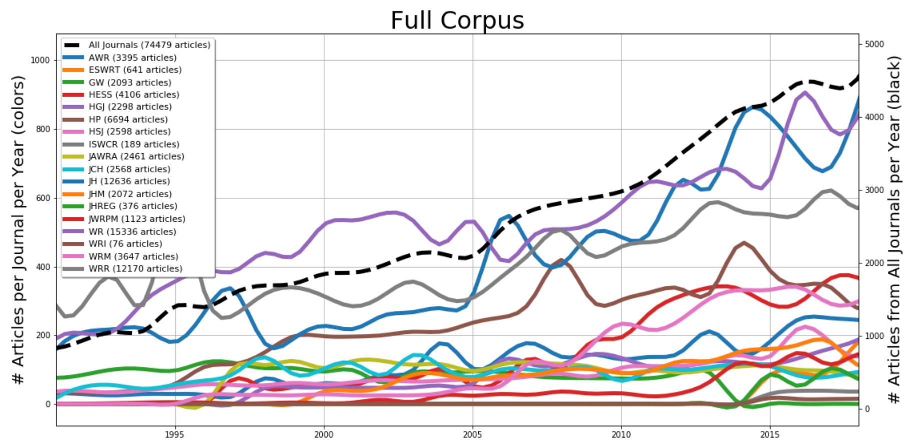



Figure 1: Number of articles published per year between 1991 and 2019 in 18 major water research journals (Source: Web of Science)

edge management literature [31], exploring the history of cognition [32], and exploring topic divergence and similarities in scientific conferences [33]. As opposed to *scientometrics* techniques [34], which have been traditionally used for ranking articles and authors based on citation data, topic modeling allows for a contextual understanding of particular scientific domains and disciplines.

Motivated by the success of topic modeling in a wide range of applications, we explore its potential to aid bibliometric exploration of peer-reviewed water science literature. In particular, we explore the question of whether peer-reviewed water science literature is increasing in interdisciplinarity with respect to sub-topics in the discipline. The specific hypotheses that we will explore are:

- Individual hydrology research papers are becoming more topically diverse i.e., interdisciplinarity is increasing at the level of individual research projects.

- The hydrology and water science corpus as a whole is becoming more topically-diverse.

- There is a difference in per-paper topic diversity between different water science journals.

- Some topics might be more or less isolated from other topics within the discipline.

We would additionally like to understand whether certain topics in water science are contributing more or less to interdisciplinary work, including whether certain topics are isolated in the community research output.

## 2. Methods

Table 1 lists notation used throughout this paper, including variables and indices related to the model and corpus. The corpus that we analyzed is described in Subsection 2.1 below. We analyzed this corpus using Latent Dirichlet Allocation (LDA) to identify dominant topics and to associate topics with individual research articles. LDA is described in Appendix A — this NLP method identifies topics by associating a unique set of words that frequently co-appear together in documents and assigns weights to each of those words based on their likelihood of appearance within a particular topic. Appendix A describes the LDA method in general and our specific implementation in detail.

### *2.1. Corpus*

Peer-reviewed abstracts offer snapshots of the historical and current trends and developments in both theoretical and applied research. In this study, we use abstracts because they are intended to be concise representations of full-texts and are used often for bibliometric analyses [35, 36]. The corpus that we use consists of abstracts from all peer-reviewed articles published in eighteen water science journals between 1991 and 2019 - this is all water science journals with a 2018 Impact Factor (IF) of greater than 0.9 (Scimago Journal and Country Rank). The list of journals and journal abbreviations, along with corresponding IFs, years of available data, and total number of abstracts, are listed in Table 2. In total, 74,479 article-abstracts were acquired from the Web of Science core collection in the form of bib files. Methods for pre-processing this corpus are described in Appendix A.

### *2.2. Analysis Methods*

To reiterate from the introduction, the hypotheses that we want to test are about whether hydrology and water science research is becoming more interdisciplinary over time. We will test this hypothesis by exploring sub-topics

Table 1: List of notation for indices, parameters and variables

| Notation | Meaning |
|---|---|
| **Corpus Parameters** | |
| $M$ | Number of documents |
| $N_d$ | Number of words in document $d$ |
| $t_d$ | Year of publication of document $d$ |
| **LDA Model Components** | |
| $K$ | Number of topics |
| $K_{opt}$ | Optimal number of topics |
| $\alpha$ | Parameters of a Dirichlet prior on on the per-document topic distribution |
| $\beta$ | Parameters of a Dirichlet prior on the per-topic word distribution |
| $\mu$ | Distribution of topics over document $d$ |
| $\mu_d$ | Weight of a particular topic assigned to document $d$ |
| $z$ | list of $K$ topics |
| $\mathbf{z_d}$ | Per-word topic vector for document $d$ |
| $\mathbf{w_d}$ | Word collection in document $d$ |
| **Derived Distributions** | |
| $\mu_{kj}$ | Weight of a particular topic $k$ over all documents in journal $j$ |
| $\mu_k$ | Average weight for topic $k$ over all documents at time $t$ |
| $\hat{\mu}_k$ | Mean weight of topic $k$ over all documents |
| $\mu_{kj}^t$ | Weight of topic $k$ in journal $j$ at time $t$ |
| $\mu_m$ | Topic distribution over entire corpus of $M$ documents |
| **Derived Metrics & Functions** | |
| $p$ | LDA model perplexity score |
| $c$ | LDA model coherence score |
| $JSD$ | Jensen-Shannon Divergence |
| $KLD$ | Kullback-Leibler Divergence |
| $I$ | Indicator function |
| $r_{k,j}$ | Correlation coefficient between topics $k$ and $j$ |
| $r_{\mu,H_d}$ | Correlation coefficient between document-topic distributions $\mu$ and their corresponding article diversity scores $H_d$ |
| $H_j$ | Shannon Diversity of journal $j$ |
| $H_d$ | Shannon Diversity per document $d$ |
| $H_d^t$ | Mean Shannon Diversity of topics in documents per year |
| $H_{dj}^t$ | Shannon Diversity of topics in documents per journal per year |
| $D_d$ | Dominance per document $d$ |
| $R_d$ | Species Richness per document $d$ |

Table 2: Repository of article-abstracts

| Journal Name | Abbreviation | IF | Years Available | Total Abstracts |
|---|---|---|---|---|
| Advances in Water Resources | AWR | 1.384 | 1991-2019 | 3395 |
| Environmental Science: Water Research and Technology | ESWRT | 1.104 | 2015-2019 | 641 |
| Groundwater | GW | 0.911 | 1991-2013 | 2093 |
| Hydrology and Earth System Sciences | HESS | 2.134 | 1997-2019 | 4106 |
| Hydrogeology Journal | HGJ | 0.940 | 1998-2019 | 2298 |
| Hydrological Processes | HP | 1.417 | 1991-2019 | 6694 |
| Hydrological Sciences Journal | HSJ | 0.913 | 1991-2019 | 2598 |
| International Soil and Water Conservation Research | ISWCR | 1.134 | 2015-2019 | 189 |
| Journal of the American Water Resources Association | JAWRA | 1.026 | 1997-2019 | 2461 |
| Journal of Contaminant Hydrology | JCH | 0.960 | 1991-2019 | 2568 |
| Journal of Hydrology | JH | 1.830 | 1991-2019 | 12636 |
| Journal of Hydrometeorology | JHM | 2.410 | 2000-2019 | 2072 |
| Journal of Hydrology: Regional Studies | JHREG | 1.378 | 2015-2019 | 376 |
| Journal of Water Resources Planning and Management | JWRPM | 1.418 | 1991-2019 | 1123 |
| Water Research | WR | 2.721 | 1991-2019 | 15336 |
| Water Resources and Industry | WRI | 1.255 | 2015-2019 | 76 |
| Water Resources Management | WRM | 1.097 | 1996-2019 | 3647 |
| Water Resources Research | WRR | 2.135 | 1991-2019 | 12170 |

within the discipline, and measuring whether individual research articles, individual journals, and the body of water science and hydrology literature as a whole is becoming more topically diverse. The analysis tools that we use to address these research questions are described below. This analysis was applied to the posterior document-topic and topic-word expectations from a trained LDA model (Appendix A) with 45 topics ($K_{opt} = 45$).

*2.2.1. Temporal Trends in Topic Distributions*

There are multiple methods of analyzing temporal trends and distributions of topics. Griffiths and Steyvers [35] applied a disjointed time-blind topic model and rearranged documents according to their publication dates. Blei and Lafferty [37] developed a sequential topic modeling approach that learns time-dynamic parameters for the document-topic and topic-word distributions constrained by linear filtering theory. Wang and McCallum [38] introduced a non-Markov joint modeling framework where topics are associated with a continuous distribution over document timestamps. We took Griffiths and Steyvers [35]'s approach of time-unaware topic modeling and post-hoc aggregation of results according to timestamps. We calculated temporal topic distributions for a given year $\mu_k$ as the proportion of all topic weights over all papers from a given year, $t$:

$$\mu_k = \frac{\sum_{d=1}^{M} \mu_d \; I(t_d - t)}{\sum_{d=1}^{M} I(t_d - t)}. \tag{1}$$

$\mu_d$ represents the weight for topic $k$ assigned to document $d$, $t_d$ is the year in which document $d$ was published, and $I$ is an indicator function such that $I(0) = 1$ and $I(x) = 0$ for $x \neq 0$. Henceforth, $I$ will carry the same meaning.

Statistical significance of these trends were assessed using standard linear regression analysis between variables. In each case, we computed the (i) Pearson correlation coefficient ($r$) as the strength of association between variables, (ii) the p-value for the t-test of the correlation coefficient against a null hypothesis of zero-trend, and (iii) the Bayes Factor (B10) as a measure of the strength of evidence toward the alternate (nonzero-trend) hypothesis.

*2.2.2. Using Topic Diversity to Measure Interdisciplinarity*

There are several common interdisciplinarity indicators of varying validity and consistency based on disciplines, multi-classification systems, similarity of research fields, and networks [39]. Leydesdorff and Rafols [40] explored some of these as citation-based indicators for interdisciplinarity of journals and found Shannon entropy [41]. Shannon entropy is also a classic diversity metric that is used - among many other things - in ecology studies to quantify the diversity of species in a given ecosystem or location [e.g., 42, 43]. Intuitively, articles are analogous to a given ecological site and topics are analogous to species.

Shannon entropy is one of the most widely used indicators of interdisciplinarity of journals and articles. Carusi and Bianchi [44] used Shannon entropy as one of the measures of interdisciplinarity in 1258 journals in the field of information and communication technology. Silva et al. [45] assessed the interdisciplinarity of scientific journals using entropy, and found that entropy-based measurement of interdisciplinarity correlates well with impact factors and citation counts. A previous study [46] conducted an interdisciplinarity assessment for Informatics journals using Topic Modeling with Shannon entropy as a diversity metric. Entropy has been used to measure interdisciplinarity of researchers and research topics [47], research proposals [48], and collaborations [49].

We therefore used the entropy based diversity metric applied to topic distributions as a primary measure of interdisciplinarity at corpus and article levels. We augmented this analysis with two other diversity indexes borrowed from ecology: Dominance and Species Richness. Dominance indices are a binary indicator of the topic with the highest distribution weight per document, and we report the mean dominance score per topic in individual documents. Species Richness is the number of individual topics appearing with non-zero weight in a given article. Dominance and richness provide insight into whether topics appear as either primary or isolated (respectively) in individual documents.

*2.2.3. Measuring Interdisciplinarity at the Article Level*

We used Shannon Diversity to measure the interdisciplinarity per article $H_d$ for each article in our corpus as:

$$H_d = -\sum_{k=1}^{K}(\mu log(\mu)), \tag{2}$$

Where $\mu$ is the distribution of topics over document $d$. We also calculated the mean Shannon diversity in documents per year as $H_d^t$:

$$H_d^t = \frac{\sum_{d=1}^{M} H_d \; I(t_d - t)}{\sum_{d=1}^{M} I(t_d - t)}, \tag{3}$$

Finally, we calculated the Shannon diversity per article per journal per year $H_{dj}^t$ as:

$$H_{dj}^t = \frac{\sum_{d=1}^{M} H_d \; I(|j_d - j| + |t_d - t|)}{\sum_{l=1}^{K} \sum_{d=1}^{M} H_d \; I(|j_d - j| + |t_d - t|)}, \tag{4}$$

Dominance indices, $D_d$, $D_d^t$, and $D_{dj}^t$, and species richness indexes, $R_d$, $R_d^t$, and $R_{dj}^t$, were calculated in the same way as entropy metrics according to their respective definitions outlined in Section 2.2.2.

*2.2.4. Measuring Interdisciplinarity at the Journal and Corpus Level*

We calculated Shannon diversity at the corpus level and then computed these corpus indexes for both the entire corpus and for each journal. To do this, we began by calculating the K-nomial distribution over topics $\mu_j$ in a particular set of articles $j$ (either a journal or the whole corpus, although we will hereafter refer to subscript $j$ as referring to a specific journal):

$$\mu_{kj} = \frac{\sum_{d=1}^{M} \mu_d \; I(j_d - j)}{\sum_{l=1}^{K} \sum_{d=1}^{M} \mu_d \; I(j_d - j)}, \tag{5}$$

where $\mu_{kj}$ is the relative popularity of a particular topic in a particular journal as a fraction of popularity of all topics in the journal. We then calculated the total entropy of each $\mu_j$, $H_j$, as a measure of the Shannon diversity of the per-journal topic distributions:

$$H_j = -\sum_{k=1}^{K} (\mu_{kj} log(\mu_{kj})), \tag{6}$$

The popularity of a particular topic in a particular journal for a particular year, $\mu_{kj}^t$ is a fraction of the popularity of all topics in that journal and year:

$$\mu_{kj}^t = \frac{\sum_{d=1}^{M} \mu_d \; I(|j_d - j| + |t_d - t|)}{\sum_{l=1}^{K} \sum_{d=1}^{M} \mu_d \; I(|j_d - j| + |t_d - t|)}, \tag{7}$$

We used these per-year, per-journal topic distributions to construct time-series of individual topic popularity in each journal, $\mu^t_{kj}$, which allowed us to quantify the evolving diversity of topic distributions in individual journals over time.

### *2.3. Identifying Isolated and Co-occuring Topics*

We identified topics with greater or lesser degrees of isolation from other topics in water science articles in two ways: first by calculating the correlation coefficient between pairs of topics, and second by observing the statistical relationship between topic distribution weights and article diversity. The former allows us to broadly separate frequently co-occuring (i.e., exist within the same article) topics from the ones which do not frequently co-occur, and the latter allows us to identify which topics participate more or less often in articles with greater or lesser topic diversity. Intuitively, a negative statistical relationship between topic distribution weights and article diversity indicates decreasing article diversity when certain (isolated) topics are more present within an article.

The correlation coefficient between topic weights over the whole corpus $M$ for each pair of topics, $r_{k,j}$, was calculated as:

$$r_{k,j} = \frac{\sum_{d=1}^{M} (\mu_k - \hat{\mu_k})(\mu_j - \hat{\mu_j})}{\sqrt{\sum_{d=1}^{M} (\mu_k - \hat{\mu_k})^2}\sqrt{\sum_{d=1}^{M} (\mu_j - \hat{\mu_j})^2}}, \tag{8}$$

where $\mu_k$ is the weight for topic $k$ assigned to document $d$, and $\hat{\mu_k}$ is the mean weight for a topic $k$ assigned over all documents in the corpus, and $\mu_j$ is the weight for a topic $j$ assigned to document $d$, and $\hat{\mu_j}$ is the mean weight for topic $j$ assigned over all documents in the corpus. We only report correlations greater than 0.1.

We identified topics that frequently appear isolated using the correlation coefficient between document-topic distributions and their corresponding article diversity scores (entropy metrics), $r_{\mu,H_d}$. Topics that frequently occur in documents with low diversity scores are considered to be 'isolated'.

## 3. Results and Analysis

### *3.1. Naming the Topics*

We identified and named $K = 45$ topics by first looking at the topic-word distributions (the set of words most likely to appear within a particular

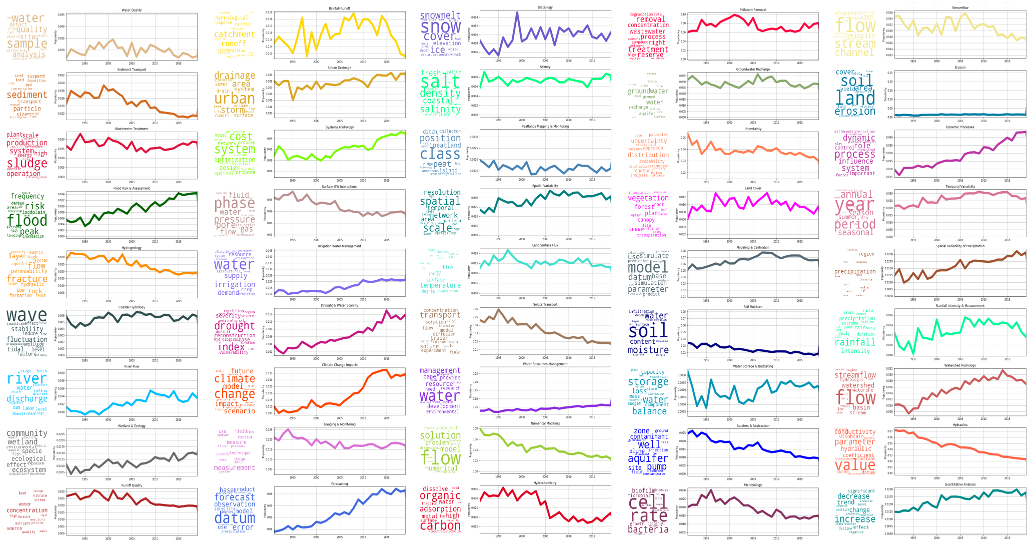


Figure 2: Wordclouds show the words most strongly associated with each topic, and the sizes of words within the wordclouds are proportional to their likelihood of appearance within individual topics. Topic trends are independent and not depicted relative to each other (see Figure 3).

topic), and the per-document topic distributions (from the titles of 100 articles most closely associated with each topic). We reinforced our choices of topic names with an informal survey sent to four qualified hydrologists outside of our research group. Figure 2 illustrates the topic-word distributions of $K = 45$ topics in the form of wordclouds, along with our chosen topic names.

This topic naming analysis was similar to what was done by McCurley and Jawitz [14], who looked at topic diversity in *WRR* papers as described in the introduction. Those authors assigned seven topics in hydrology prior to their analysis: catchment-hydrology, hydro-geology, hydro-meteorology, contaminant hydrology, socio-hydrology, and hydro-climatology. Our post-hoc identified topics extracted using LDA were conceptually similar to these, however LDA was able to extract a larger and more nuanced set of topics through unsupervised learning.

*3.2. Temporal Trends of Topics in the Full Corpus*

The popularity of each topic changes with time, and these trends are also shown in Figure 2. Some topics demonstrated statistically significant rising trends in popularity (table 3). At least several of these rising trends might be attributed to researchers increasingly leveraging the availability and accessibility of hydrology related data, both in terms of breadth and depth. Other topics demonstrated statistically significant downward trends (table 3). The remainder of topics do not demonstrate any significant trend.

Table 3: Rising and falling temporal trends of topics (only statistically significant trends are reported)

| Rising Trends | | | |
|---|---|---|---|
| **Topic** | $r$ | **p-value** | **BF10** |
| Dynamic Processes | 0.91 | 1.22E-12 | 5.49E+09 |
| Drought & Water Scarcity | 0.90 | 1.77E-07 | 4.67E+08 |
| Watershed Hydrology | 0.90 | 6.66E-12 | 1.49E+09 |
| Forecasting | 0.86 | 1.13E-09 | 1.00E+07 |
| Wetland & Ecology | 0.77 | 5.39E-07 | 3.50E+04 |
| Flood Risk & Assessment | 0.66 | 7.30E-05 | 4.09E+02 |
| Spatial Variability of Precipitation | 0.59 | 6.20E-04 | 6.02E+01 |
| Falling Trends | | | |
| **Topic** | $r$ | **p-value** | **BF10** |
| Hydraulics | -0.97 | 3.27E-19 | 6.77E+15 |
| Solute Transport | -0.95 | 9.35E-16 | 4.23E+12 |
| Aquifers & Abstraction | -0.94 | 3.85E-14 | 1.35E+11 |
| Numerical Modeling | -0.94 | 9.80E-14 | 5.69E+10 |
| Hydrogeology | -0.88 | 1.00E-10 | 9.41E+07 |
| Surface-GW Interactions | -0.87 | 2.44E-10 | 4.14E+07 |
| Water Quality | -0.86 | 1.13E-09 | 1.00E+07 |
| Hydrochemistry | -0.85 | 1.29E-09 | 8.94E+06 |
| Microbiology | -0.84 | 6.19E-09 | 2.10E+06 |
| Uncertainty | -0.70 | 1.40E-05 | 1.78E+03 |
| Sediment Transport | -0.57 | 1.00E-03 | 3.70E+01 |

Figure 3 shows the relative popularity of topics over time plotted on

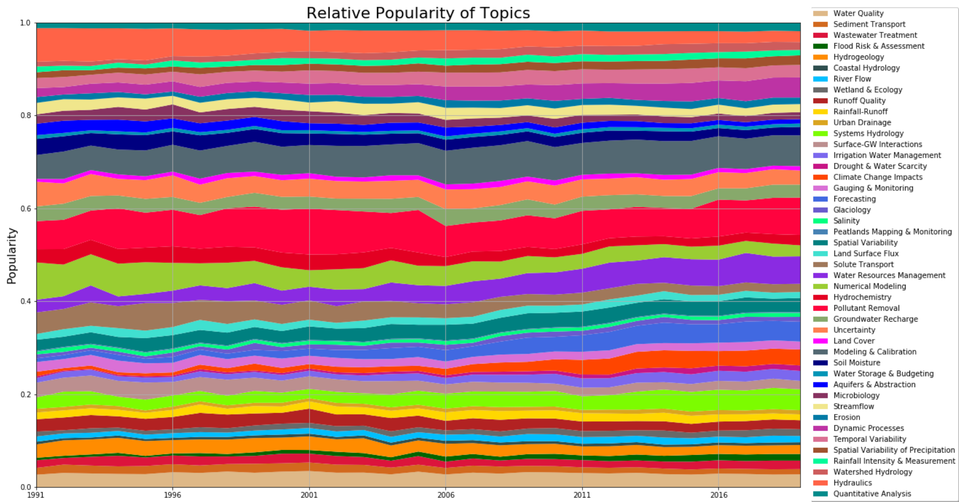



Figure 3: Temporal variation of topic popularity relative to each other.

the same scale (Figure 2 shows the same topic trends but not normalized). Considering the relative popularity of topics in 1991 vs. 2019, topics that lost the most popularity are "Hydraulics" (-68%), "Solute Transport" (-62%), "Aquifers & Abstraction" (-61%). Conversely, the topics that gained the most are "Forecasting" (+450%), "Climate Change Impacts" (+247%), "Drought & Water Scarcity" (+233%), "Dynamic Processes" (+123%), "Water Resources Management" (+117%), and "Irrigation Water Management" (+113%).

### *3.3. Are Articles becoming More Interdisciplinary?*

The corpus-wide mean per-article diversity metrics (Shannon entropy, richness, and dominance) are shown in Figure 4. Our findings indicate the average diversity of topics within individual water science articles is increasing overall. Regression-based trend analysis for the Shannon diversity metric time from the entire corpus are: $r$ = 0.94, p-value = 6.79e-14, B10 = 7.68e+10, indicating a statistically significant trend at any reasonable significance threshold. The mean richness of topics $r_d$ i.e., the mean number of topics per article also increased over time (R = 0.96, p-value = 1.89e-16, B10 = 1.76e+13), while mean dominance $D_d$, demonstrates a statistically

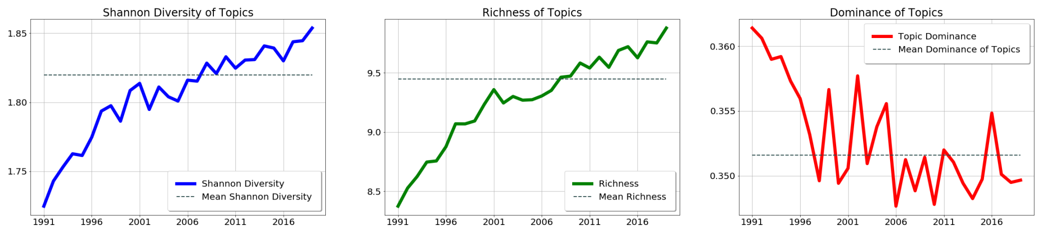



Figure 4: Mean per-article diversity, species richness and topic dominance per year. The dashed lines represent the mean per-article diversity, species richness, and topic dominance over the entire corpus.

decreasing trend (R = -0.71, p-value = 1.70e-05, B10 = 1.55e+03), meaning the average highest topic distribution weight per article is decreasing.

### *3.4. Which Journals Are Contributing to Per-Article Interdisciplinarity?*

To understand which journals are contributing to the trend of increasing diversity of topics in individual research articles, we calculated the mean diversity of articles per year for each of the eighteen journals as shown in Figure 5. As before, we used linear regression to assess the significance of temporal trends in these per-journal time series.

$WRR$ demonstrates the strongest rise (as an individual journal) in the mean diversity of topics per article published between 1991 and 2019 (R = 0.96, p-value = 5.92e-16, BF10 = 5.79e+12). Other significant drivers of the overall rise in per-article diversity within this corpus are $AWR$ (R = 0.84, p-value = 1.59e-08, BF10 = 8.61e+05), $JCH$ (R = 0.75, p-value = 4.00e-06, BF10 = 5.06e+03), and $JH$ (R = 0.74, p-value = 8.00e-06, BF10 = 3.01e+03). Journals which demonstrate moderate rises in per-article diversities are $HP$ (R = 0.51, p-value = 5.08e-03, BF10 = 8.76), $WR$ (R = 0.57, p-value = 1.40e-03, BF10 = 29.29), and $WRM$ (R = 0.61, p-value = 2.01e-03, BF10 = 22.30). $GW$(R = 0.48, p-value = 2.30e-02, BF10 = 2.91), $JWRPM$ (R = 0.41, p-value = 3.10e-02, BF10 = 2.13), $JAWRA$ (R = 0.36, p-value = 9.60e-02, BF10 = 0.97), $HSJ$ (R = 0.25, p-value = 0.19, BF10 = 0.53), and $HGJ$ (R = 0.29, p-value = 0.20, BF10 = 0.59) do not demonstrate any significant trend at a significance level of $\alpha = 0.01$. Average diversity of articles published in $HESS$ (R = -0.38, p-value = 9.60e-02, BF10 = 1.15) decreased. The rest of the journals do not have publication records long enough for trend analysis.

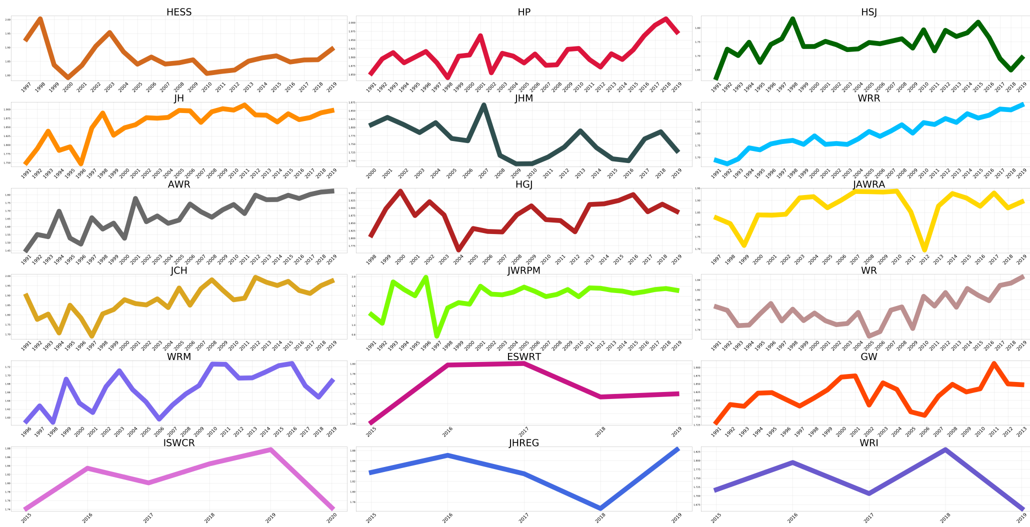



Figure 5: Mean per-article diversity (Shannon entropy) per-journal over time

### *3.5. Is the Whole Corpus becoming More Interdisciplinary?*

Figure 6 shows the temporal variability of topic entropy (diversity) over time for the entire corpus (dashed black line) and for each individual journal (solid colored lines). This differs from the average per-article diversity metrics reported in the previous subsection in that these metrics are calculated over the topic distributions averaged over all papers in the corpus (journal). Whereas the per-article diversity metrics measure interdisciplinarity of (presumably) individual research projects, the corpus metrics measure the diversity of topics overall in a journal or corpus and measure the mixture of topics at community level rather than at the level of individual research projects.

The diversity for the entire corpus rose from the 1990s and peaked around 2009, since then, the entropy of the entire corpus has remained steady or slightly decreased. However, no definite trend exists overall (R = -0.17, p-value = 0.37, BF10 = 0.34). This shows the increasing article-level interdisciplinarity does not translate to overall corpus interdisciplinarity.

*HP* (3.7 nats) is the most interdisciplinary journal in our corpus, followed by *JH* (3.65 nats), *WRR* (3.5 nats), and *HESS* (3.45 nats) – more details and a figure are given in the next subsection 3.6. (Figure 6 shows per-journal topic diversity trends; there were statistically significant upward trends in *JHM* (R = 0.65, p-value = 1.00e-04, BF10 = 300.90), *HGJ* (R = 0.59,

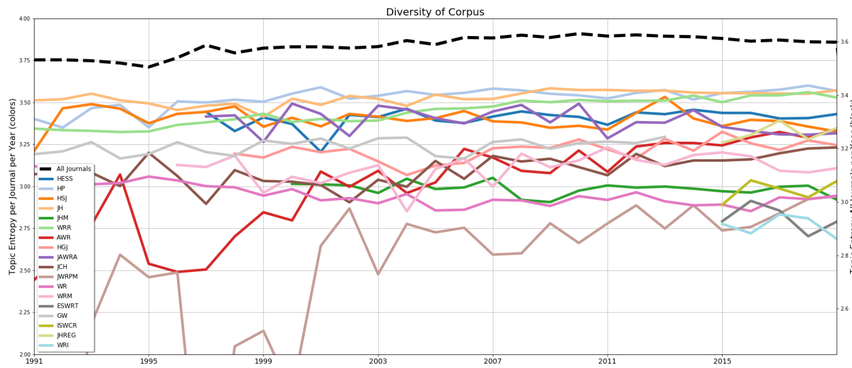



Figure 6: Temporal variation of the diversity of each journal, as measured by the entropy of that journal's topic distribution in a particular year.

p-value = 7.00e-04, BF10 = 56.13), *HESS* (R = 0.53, p-value = 2.50e-03, BF10 = 17.55), and *JAWRA* (R = 0.51, p-value = 3.70e-03, BF10 = 12.49). Other journals did not demonstrate any significant trend in entropy over time.

### *3.6. Overall Journal Diversity*

The stacked bar plots in Figure 7 show the relative fraction of topic representation in each journal, with the total height of each bar representing the journal's topic entropy. *HP*, *JH*, and *WRR* are the three most diverse journals overall in our corpus. The overall Shannon Diversity per journal decreases for more specialty journals – i.e., journals which focus on subsurface topics - *GW*, *HGJ*, atmospheric science topics - *JHM*, water quality related topics - *JCH*, and water management topics - *WRM*, *JWRPM*. Journals with a fairly recent publication history – i.e., *ESWRT*, *ISWCR*, *JHREG*, and *WRI* had lower overall diversity compared to the rest of the corpus, which is expected.

### *3.7. Identifying Isolated Topics*

To reiterate from Section 2.3, we approached the problem of identifying isolated topics in our corpus by (i) looking at the correlations (both positive and negative) between pairs of topics to understand which topics co-appear frequently, and (ii) quantifying relationships between article interdisciplinarity and corresponding topic weights.

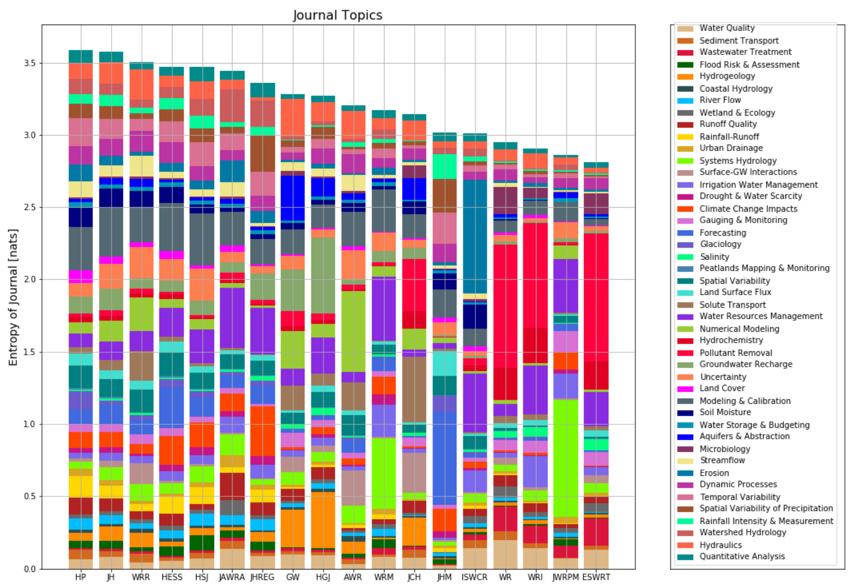



Figure 7: Total bar height represents the overall diversity of topic distributions of each journal for the whole study period. The stacked color bars represent the fraction of papers representing each individual topic in that journal.

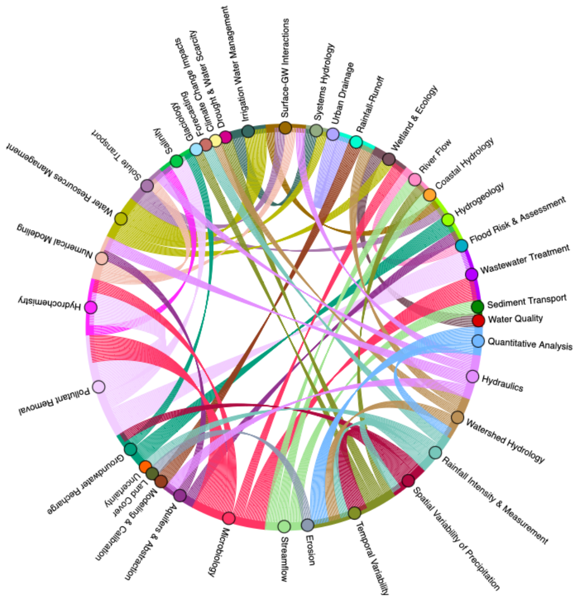
### 3.7.1. *Co-appearing Topics*

An intuitive way to depict inter-topic correlations $r_{k,j}$ are chord-diagrams. $r_{k,j}$ correlation coefficients measure relationships between per-paper topic weights, meaning that a higher $r_{k,j}$ value indicates papers that contain word groups associated with topic $k$ also tend to contain word groups associated with topic $j$. Positive correlation coefficients between pairs of topics indicate some degree of co-appearance of these topics in research articles, and vice-versa. Positive and negative inter-topic correlations are shown in Figure 8, where the width of each chord represents the overall correlation between a pair of topics. For ease of viewing, positive correlations are only plotted for $r_{k,j}$ > 0.10 and negative correlations $r_{k,j}$ < -0.10. While inter-topic correlation plots for the entire corpus lends us a snapshot of co-appearing and disjointed topics, they also assist in segregating isolated topics.

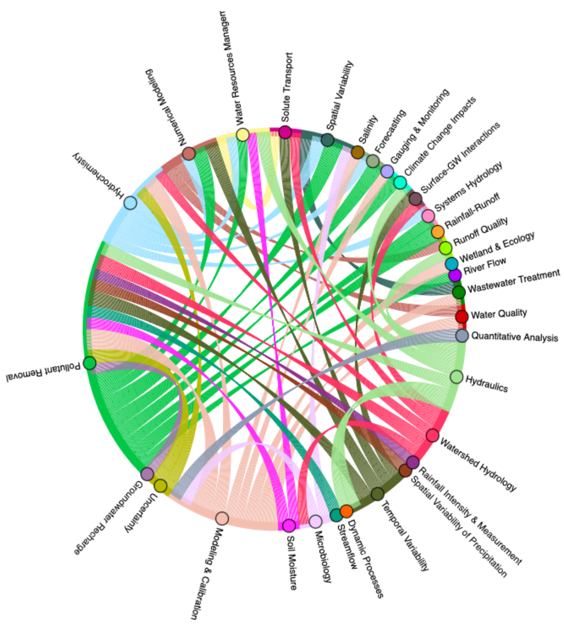
### 3.7.2. *Positive Inter-Topic Correlations*

The largest positive inter-topic correlations are observed between "Pollutant Removal" & "Hydrochemistry" ($r_{k,j} = 0.38$), "Pollutant Removal" & "Wastewater Treatment" ($r_{k,j} = 0.32$), "Pollutant Removal" & "Microbiology" ($r_{k,j} = 0.31$), and "Water Resources Management" & "Irrigation Water Management" ($r_{k,j} = 0.27$). "Modeling & Calibration" is most correlated with "Rainfall-Runoff" ($r_{k,j} = 0.17$). This relationship is concurrent with the hydrological community's historical focus on calibrating rainfall-runoff models at various scales [50]. The "Rainfall-Runoff" topic also correlates with "Urban Drainage" ($r_{k,j} = 0.14$), and "Watershed Hydrology" ($r_{k,j} = 0.15$).

Positive correlations also exist between "Rainfall Intensity & Measurement" and "Spatial Variability of Precipitation" ($r_{k,j} = 0.11$), "Rainfall Intensity & Measurement" and "Temporal Variability" ($r_{k,j} = 0.11$), and "Rainfall Intensity & Measurement" & "Forecasting" ($r_{k,j} = 0.13$). These co-appearing topics pertain to the effect of spatiotemporal variability of rainfall on hydrologic indicators [51], and scale dependencies in rainfall studies and forecasting [e.g., 52, 53, 54]. Notable correlations exist (perhaps predictably) between "River Flow" and "Streamflow" ($r_{k,j} = 0.12$), "River Flow" and "Temporal Variability" ($r_{k,j} = 0.11$), and "River Flow" and "Flood Risk & Assessment" ($r_{k,j} = 0.11$). Flood risk assessments rely extensively on river flow parameters [55]. Similarly, many studies have focused on the impacts of global climate change on watersheds, and subsequently, natural hydrosystems [e.g., 56, 57, 58], which is reflected by a notable co-appearance of "Climate Change Impacts" and "Watershed Hydrology" ($r_{k,j} = 0.11$) in our




Positive Correlations




Negative Correlations

Figure 8: Inter-topic correlations: positive correlations in the left subplot and negative correlations in the right subplot. Only correlations $|r_{k,j}| > 0.10$ are shown.

corpus. “Quantitative Analysis” co-appears with “Watershed Hydrology” ($r_{k,j} = 0.11$).

“Erosion” correlates significantly with “Land Cover” ($r_{k,j} = 0.11$). Land cover changes have been linked to erosion in watersheds in previous studies [e.g., 59, 60, 61]. “Water Resources Management” predictably demonstrates correlations with “Systems Hydrology” ($r_{k,j} = 0.12$), “Irrigation Water Management” ($r_{k,j} = 0.27$), and “Wetland & Ecology”($r_{k,j} = 0.14$). These four topics often appear together in literature that focuses on integrated water resources management [e.g., 62, 63, 64].

“Salinity” & “Pollutant Removal” ($r_{k,j} = 0.19$), “Salinity” & “Hydrochemistry” ($r_{k,j} = 0.13$), and “Salinity” & “Groundwater Recharge” ($r_{k,j} = 0.10$) are likely to appear together. Topics pertaining to water biology and chemistry i.e. “Microbiology”, “Wastewater Treatment”, “Pollutant Removal”, and “Water Quality” frequently appear together in our corpus (as discussed before, this group of topics have the highest intertopic correlations). Pairs of subsurface and related research topics - “Groundwater Recharge” & “Hydrogeology” ($r_{k,j} = 0.21$) and “Aquifers & Abstraction” & “Hydrogeology” ($r_{k,j} = 0.14$) also demonstrate significant relationships. “Numerical Modeling” and “Hydraulics” ($r_{k,j} = 0.16$) are correlated, which is expected because open channel hydraulics often use numerical modeling techniques [65]. “Numerical Modeling” also often (plausibly) appears alongside “Surface-GW Interactions” ($r_{k,j} = 0.12$), “Solute Transport” ($r_{k,j} = 0.13$), and “Aquifers & Abstraction” ($r_{k,j} = 0.11$). Numerical models have been historically used in groundwater flow and transport studies [66]. These positive correlations summarize water science topics which communicate with other topics. In the next subsection we look at topics in our corpus that are insular from each other.

### *3.7.3. Negative Inter-Topic Correlations*

Anti-correlations indicate that there are set of vocabulary in the water science literature that are largely not shared between sub-communities. Topics such as “Pollutant Removal”, “Hydrochemistry”, “Modeling & Calibration”, “Numerical Modeling” and “Hydraulics” are negatively correlated to a wide variety of other topics. “Modeling & Calibration” rarely appears with “Pollutant Removal” ($r_{k,j} = -0.20$), “Hydrochemistry” ($r_{k,j} = -0.14$), “Gauging & Monitoring” ($r_{k,j} = -0.10$), and “Wetland & Ecology” ($r_{k,j} = 0.12$). “Hydrochemistry” rarely appears with “Uncertainty” ($r_{k,j} = -0.11$), “Watershed Hydrology” ($r_{k,j} = 0.12$), “Systems Hydrology” ($r_{k,j} = -0.10$), “Forecasting" ($r_{k,j} = -0.11$), "Spatial Variability" ($r_{k,j} = -0.13$), and "Water Resources Management" ($R_{k,j} = -0.11$). "Hydraulics" is negatively correlated with "Pollutant Removal" ($r_{k,j} = -0.12$), "Runoff Quality" ($r_{k,j} = -0.11$), "Water Resources Management" ($r_{k,j} = -0.13$), and "Irrigation Water Management" ($r_{k,j} = -0.11$). These negative correlations indicate potential for expanding avenues of collaborative research.

These negative inter-topic correlations between topics help us identify the most insular (isolated) topics in our corpus by complementing our findings, as we discuss in section 3.7.4.

*3.7.4. Topic Isolation*

The most insular topics in our corpus tend to reduce the paper-wise diversity when they appear in an article (meaning they are less likely to appear alongside a wide variety of other topics). We refer to these topics as being 'isolated'. It is important to remember that these topics are actually collections of words (Figure 2), and thus topic isolation means that there is a subsection of water science literature that uses a particular vocabulary that is somehow disconnected from other portions of the community.

Statistical relationship between mean per-article Shannon Diversities $H_d$ and their corresponding topic distribution weights $\mu$ are shown in Figure 9. Topics that demonstrate a negative relationship with per-article diversity ($r < 0$) are 'isolated'. These eleven topics were (in decreasing order of isolation) "Pollutant Removal" ($r_{\mu,H_d} = -0.23$), "Numerical Modeling" ($r_{\mu,H_d} = -0.17$), "Uncertainty" ($r_{\mu,H_d} = -0.16$), "Systems Hydrology" ($r_{\mu,H_d} = -0.16$), "Forecasting" ($r_{\mu,H_d} = -0.15$), "Water Resources Management" ($r_{\mu,H_d} = -0.14$), "Modeling Calibration" ($r_{\mu,H_d} = -0.07$), "Hydraulics" ($r_{\mu,H_d} = -0.04$), "Climate Change Impacts" ($r_{\mu,H_d} = -0.03$), "Solute Transport" ($r_{\mu,H_d} = -0.02$), and "Surface-GW Interactions" ($r_{\mu,H_d} = -0.02$).

Figure 10 shows the temporal behavior of these isolated topics. Topics that have become less isolated with time include: "Hydraulics" ($r = 0.94$, p-value = 2.52e-14, BF10 = 1.92e+11), "Numerical Modeling" ($r = 0.94$, p-value = 3.13e-14, BF10 = 1.57e+11), "Solute Transport" ($r = 0.89$, p-value = 3.60e-10, BF10 = 2.83e+07), and "Uncertainty" ($r = 0.75$, p-value = 2.00e-06, BF10 = 8783.52), indicating an increasing co-appearance with a wider variety of other topics in individual articles. Opposite trends (increasing isolation) were observed for "Forecasting" ($r$ = -0.94, p-value = 5.38e-14, BF10 = 9.51e+10), "Systems Hydrology" ($r$ = -0.74, p-value = 5.00e-06,

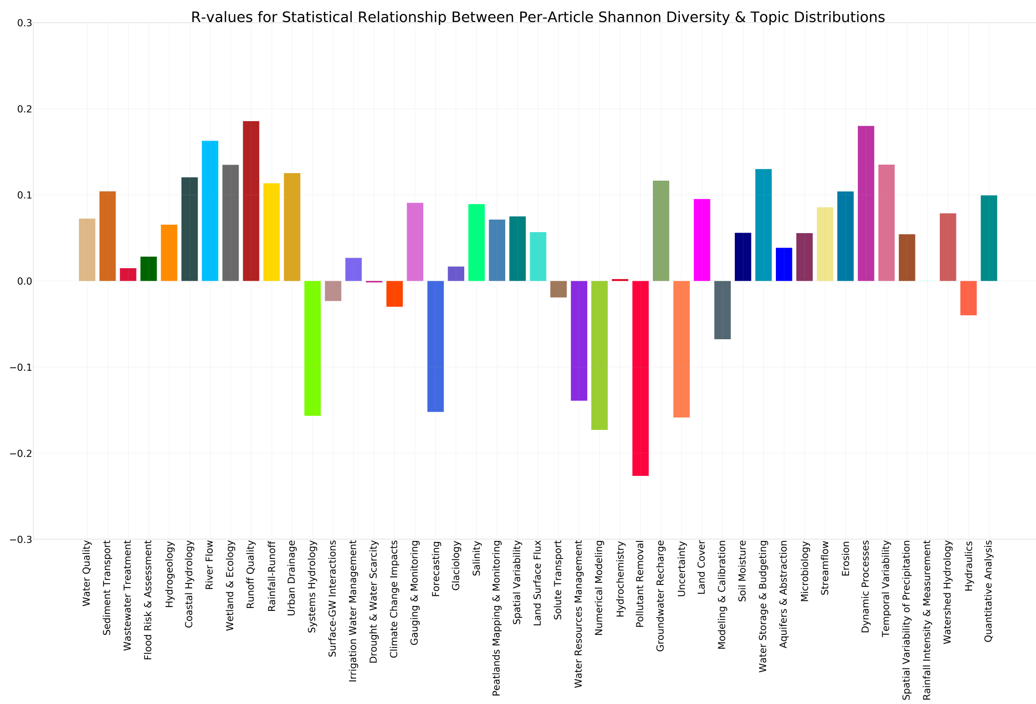



Figure 9: Pearson correlation coefficients for statistical relationships between per-article Shannon diversity metrics and per-topic distribution weights.

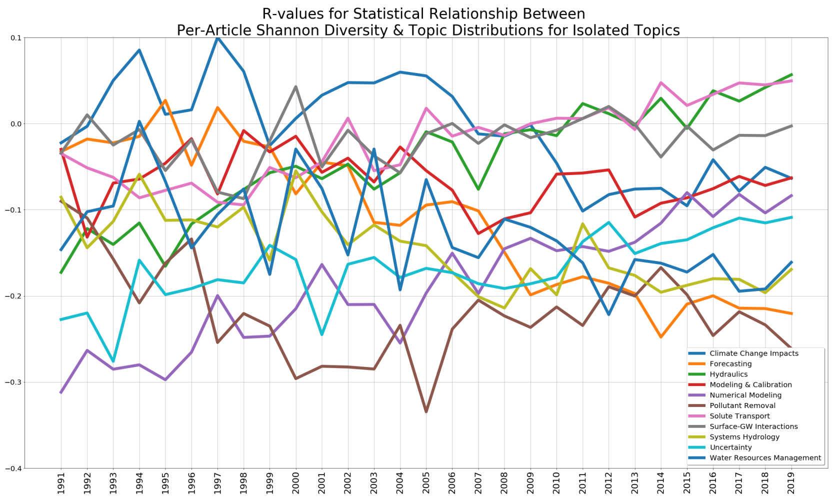



Figure 10: Trends of Pearson correlations between per-article Shannon diversity and topic distributions for isolated topics.

BF10 = 4250.94), "Climate Change Impacts" ($r$ = -0.70, p-value = 2.00e-05, BF10 = 1329.65), "Water Resources Management" ($r$ = -0.58, p-value = 9.70e-04, BF10 = 40.97). Topics with increasing isolation are more likely to be dominant topics when they appear in articles. "Pollutant Removal" ($r$ = -0.32, p-value = 8.70e-02, BF10 = 0.41), "Modeling & Calibration" ($r$ = -0.29, p-value = 1.19e-01, BF10 = 0.73), and "Surface-GW Interactions" ($r$ = 0.28, p-value = 0.14, BF10 = 0.64) do not demonstrate any significant trend.

## 4. Conclusions & Discussion

We use semantic-based topic diversity to quantify two types of interdisciplinarity in hydrology and water science articles: (i) within individual articles and (ii) across corpora (both within individual journals and within a corpus of all water science journals with a 2018 IF greater than 0.9). We tested the hypotheses that interdisciplinarity was increasing in both respects and found evidence to support one of those hypotheses but not the other. Individual researchers appear to be broadening their scope across different subtopics in the discipline (i.e., per-paper topic diversity is increasing – Figure 4), and while individual topics are changing in popularity over time (Figure 3), the water science and hydrology corpus as a whole is not increasing, nor decreasing, in diversity (Figure 6).

The primary findings of this study are (see the four hypotheses outlined in Section 1):

1. At an article level, the average (Shannon) diversity of topics in individual research papers is increasing over the entire corpus ($r$ = 0.94, p-value =4.00e-11, B10 = 7.68e+10).
2. At a corpus level, the average (Shannon) diversity of topics in the whole corpus is neither increasing nor decreasing ($r$ = -0.17, p-value = 0.37, BF10 = 0.34).
3. At a journal level, the most topically-diverse water science journals are $HP$ (3.70 nats), $JH$ (3.65 nats), $WRR$ (3.50 nats), and $HESS$ (3.45 nats). Certain journals are increasing in their average per-article topic diversity ($WRR$, $AWR$, $JCH$, $JH$), and one journal is decreasing in its average per-article topic diversity ($HESS$).
4. At a topic level, certain topics are more semantically isolated than others. The most semantically isolated topics are: "Pollutant Removal", "Numerical Modeling", and "Uncertainty".

Our interpretation of these findings is as indication that water science research is becoming more interdisciplinary. If it were the case that both per-paper diversity and the overall corpus diversity were increasing, it would be difficult to disentangle these effects, however because the topic distribution in the discipline overall has been relatively stable over the past ~30 years, the increasing trend in per-paper topic diversity indicates a bottom-up effect driven by changing efforts, attitudes, and vision by individual researchers and - perhaps - of increasingly interdisciplinary education, as called for by National Research Council [3].

The ability to automatically detect distinct sets of vocabularies (as topics) is a strength of unsupervised topic modeling, however it is important to remember that any results from an analysis of topic model outputs is related to the bags-of-words that define the topics. Diffusion of vocabulary is - again, in our opinion - a sign of bottom-up, expanding interaction within the community.

### 4.1. Future Outlook

The volume of scientific research in general is growing rapidly. This makes it difficult for researchers to be confident about fully understanding the state of the science, and also makes it challenging to expand into new research topics since so much background information is available for synthesis. We expect that in the future machine learning methods like Topic Modeling will be an integral part of the tool set available to help scientists synthesize scientific literature. While this paper provides multi-level (per-paper, per-journal, and whole-corpus) contextual insights into the current state of interdisciplinarity in water research, we envision that similar NLP-based efforts might help us address problems related to semantically synthesizing diverse bodies of water science and hydrological literature. There have been several biobliometric analyses of hydrology literature [e.g., 67, 68, 69, 70, 14], however NLP has the potential to allow for faster, and more contextual analyses of larger corpora.

## 5. Acknowledgements

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## Appendix A. Preprocessing the Corpus

Performance of topic modeling is influenced by the quality of input training data. Article-abstracts were preprocessed into a canonical format for efficacious feature extraction [71]. To prepare the data, we used separate temporally-segregated dataframes of abstracts and metadata from each journal. All sets of data were processed through identical multi-layered cleaning routines. We used Spacy and NLTK Python libraries to filter non-semantic elements such as stopwords, punctuation, and symbols, and in addition we manually identified and removed unwanted elements that were common in our article abstracts (the cleaned abstracts are available in the repository linked in the Data and Code Availability statement at the end of this article).

In the next step, we formed bi-grams and segmented texts by tokenizing with whitespaces as word boundaries. This was followed by lemmatization, to extract semantic roots from conjugations, etc. Using this corpus, we created a map between words and integer identifiers. We then converted this dictionary into a bag-of-words format, making the corpus ready for ingestion by an LDA model implemented in *Gensim* - a Python library for NLP [72].

### *Appendix A.1. Topic modeling with Latent Dirichlet Allocation*

LDA builds on another more traditional topic modeling approach (Latent Semantic Analysis) [73], and captures the intuition that text documents exhibit multiple topics in different proportions. Documents are represented as mixtures of topics (per-document topic distributions) and each topic is characterized by a distribution over words (per-topic word distributions).

We can build an intuition of this model as follows. It is assumed that the per-document topic distributions of all documents in a corpus share a common Dirichlet prior (parameterized by parameters $\alpha$), and that the per-topic word distributions also share a (different) common Dirichlet prior (parameterized by parameters $\beta$). The distribution over a particular word $w$ in a document $d$ with topic distribution $\mu_d$ can be understood as [74]:

$$p(w|\mu_d, \beta) = \sum_{k=1}^{K} p(z_k|\mu_d)p(w|z_k, \beta), \tag{A.1}$$

where $z_k$ is a particular topic from $K$ total topics. Treating the per-document topic distribution as latent and integrating over all $N_d$ words in each document $d$ and over all $M$ documents in corpus $D$ gives:

$$p(D|\alpha, \beta) = \sum_{d=1}^{M} \int_{\mu_d} p(\mu_d|\alpha) \left( \prod_{n=1}^{N_d} p(w_{dn}|\mu_d, \beta) \right) d\mu_d \tag{A.2}$$

The above is an intuition only. In actuality, LDA assumes a generating model (i.e., a model of how the corpus was produced) that samples each $\mu_d$ once for each word in a corpus, which means that each document contains a mixture of topics, which is why each document has its own topic distribution (called a per-document topic distribution). This means that each document $d$ can be associated with an $N_d$ vector of topics, $\mathbf{z_d}$, - one topic assignment (out of $K$ total topics) for each word in the document. This generating model is described in more detail by [74] and others.

Training the LDA model involves estimating the per-document topic distributions, $\mu_d$, and the per-document topic vectors, $\mathbf{z_d}$, given the words in a document, $\mathbf{w_d}$, and the Dirichlet priori parameters: $p(\mu_d, \mathbf{z_d}|\mathbf{w_d}, \alpha, \beta)$. This can be done using a variety of methods, including Gibbs Sampling [35], variational expectation-maximization (VEM) [74], and others. Overfitting is generally not a major issue for unsupervised learning with LDA, which is a Bayesian model.

Here, we use an LDA implementation in the Python *Gensim* package with VEM. We train our models with the number of passes set to 5000 and chunksize (number of documents in a batch) set to 100. We used a parallelized implementation of LDA in *Gensim* to train individual models with topic sizes ranging from $K = 10$ to $K = 80$; each model trained using 40 shared-memory cores on a single node of a high performance cluster. Using these settings it takes on the order of a few hours to train a single model: between 3-15 hours per model on our particular machine, depending on $K$.

### *Appendix A.2. Choosing an Optimal Number of Topics*

Ideally it is desirable to maximize the number of topics identified by LDA to increase variety and "depth" in terms of how the model partitions subtopics in the discipline. In practice, a number of topics, $K$, above some (unknown) optimal number of topics, $K_{opt}$, increases the occurrence of common words among different topics, resulting in compromised quality of topics [75]. We therefore adopted a hybrid quantitative/qualitative approach for deciding the optimal number of topics, $K_{opt}$.

#### *Appendix A.2.1. Data-Driven Approach to Choose an Optimal Number of Topics*

We used a combination of perplexity $p$ and coherence $c$ scores to evaluate model performance over a range of different numbers of topics. Details on how coherence and perplexity are calculated, and their underlying algorithms are given in Appendix A.3.

We trained LDA models using identical hyperparameters for different numbers of topics from $K = 10$ to $K = 80$, logging the coherence $c$ and perplexity $p$ scores for each value of $K$. The goal of this multi-model training routine was to acquire a range of values of $K$ within which $K_{opt}$ was likely. The resulting scores are plotted in Figure A.11. Coherence (higher is better) peaked at around $K = 25$ with substantial noise around that value, and there was no clear optimum in perplexity (lower is better). Therefore, to determine $K_{opt}$ we additionally qualitatively considered a range of $K = 25$ to $K = 50$ (see next subsection).

#### *Appendix A.2.2. Qualitative Approach to Choosing Optimal Number of Topics*

Qualitative perception of topics is a common step in essentially all topic modeling research [e.g., 30, 76, 17] and allows for data-driven evaluation metrics to be supported by manual validation. We assessed the quality of topics for various values of $K$, looking for increasing or decreasing occurrence of similar words within certain topics and backtracking into the dataframe

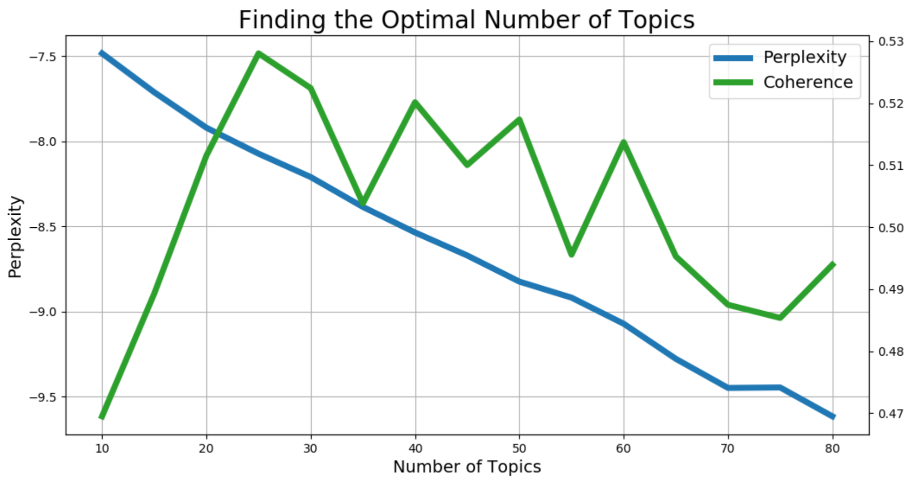


Figure A.11: Variation of topic coherence $c$ and perplexity $p$ based on LDA models trained for a range of topic numbers ($K = 10$ to $K = 80$). Lower perplexity and higher coherence indicate a better model. These values guide our subjective analysis for choosing $K_{opt}$

to observe the titles of documents associated with each topic. We drew on our prior experience in hydrology to make these assessments, and also solicited input from several other professional hydrologists. We used the aforementioned range of values of $K$, and this subjective assessment to choose $K_{opt} = 45$.

*Appendix A.3. Perplexity and Coherence*

Perplexity is a popular metric for evaluating language models [77]. Perplexity is an information theory metric that measures something like how surprised the model might be on the introduction of new data [78]. Formally defined by [74], perplexity for a collection of $M$ documents is:

$$p = exp\left\{-\frac{\sum_{d=1}^{M} log\, p(w_d)}{\sum_{d=1}^{M} N_d}\right\} \tag{A.3}$$

Perplexity is a decreasing function of the probability assigned to each per-document word distribution. Lower perplexity indicates a better model.

Topic coherence $c$ is a measure of similarity in semantics between the high probability words in a certain topic. We use *Gensim's* built-in topic coherence model, which is an implementation of the method described by

[79]. Calculating topic coherence is a four-stage process involving segmentation of word subsets, probability calculation, confirmation measure, and aggregation.

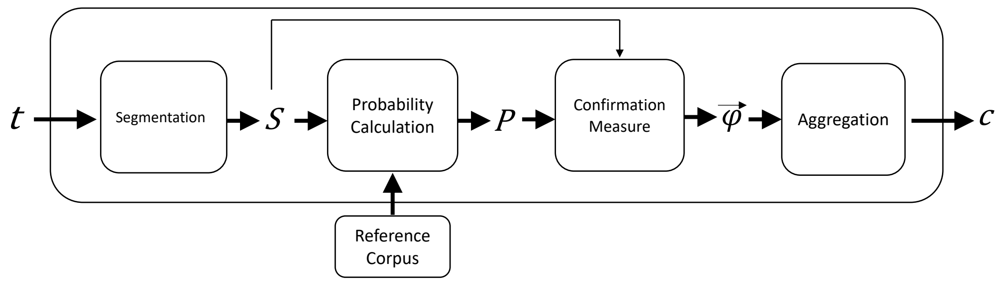


Figure A.12: Illustration of the four stages of the unified topic coherence framework. In stage 1, input words $t$ are segmented into smaller sets $S$. Probabilities of occurrence $P$ of words are calculated based on the reference corpus in the second stage. In the third stage, $P$ and $S$ are ingested to measure $\varphi$ between pairs of words $S$. Coherence $c$ is calculated in the final step.

Figure A.12 [adapted from 79] illustrates these four steps. $t$ represents an input collection of words, and the first stage creates a set of different kinds of segmentation of words $S$ from $t$, since coherence measures the fitting together of words or a set of words. Secondly, probabilities of occurrence of words $P$ are calculated based on reference corpus. Confirmation measure ingests both $P$ and $S$ to yield the agreements $\varphi$ of pairs of $S$. In the final step, the aforementioned scores are aggregated to compute coherence $c$.