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Hydrology Research Articles are Becoming More Topically Diverse

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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 equally-common 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 *Climate Change Impacts*, *Water Policy & Planning*, and *Pollutant Removal*. Topics with the largest decreases in popularity were *Stochastic Models* and *Numerical Models*. At a journal level, *Water Resources Research*, *Jour-*

nal of Hydrology, and *Hydrological Processes* 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: Topic Diversity, Interdisciplinarity, 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, diverse 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 some 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].

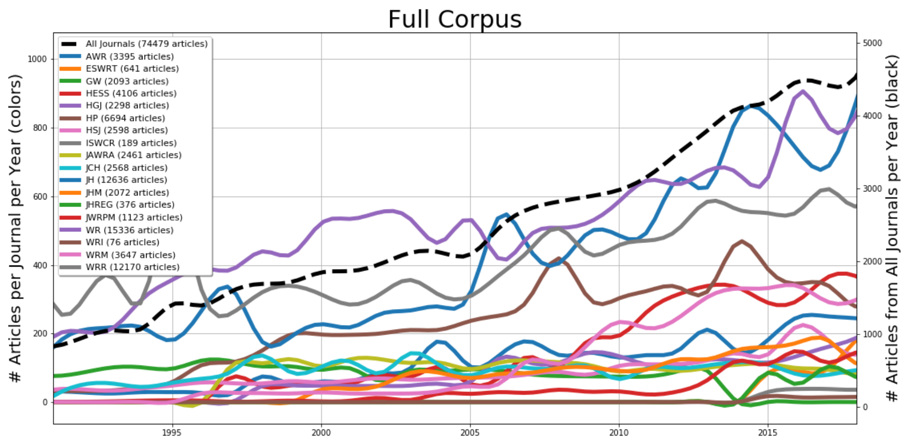

Figure 1: Number of articles published per year between 1991 and 2019 in 18 major water research journals (Source: Web of Science)

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 knowledge 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 diversity 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. it 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 diversity, including whether certain topics are explicitly 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 sequential Latent Dirichlet Allocation (LDASeq) in GenSim [35], based on Blei and Lafferty [36]'s Dynamic Topic Model (DTM), to identify dominant topics and to associate topics with individual research articles. LDASeq is described in Appendix A — this NLP method identifies topics by associating a unique set of words that frequently co-appear together in timestamped documents and assigns weights to each of those words based on their likelihood of appearance within a particular topic.

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 [37, 38]. 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

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
A	Slice of documents based on year of publication t_d
LDASeq Model Components	
K	Number of topics
K_{opt}	Optimal number of topics
α	Parameters of a Dirichlet prior on on the per-document topic distribution
β	Parameters of a Dirichlet prior on the per-topic word distribution
μ	Distribution of topics over document d
μ_d	Weight of a particular topic assigned to document d
z	list of K topics
z_d	Per-word topic vector for document d
w_d	Word collection in document d
Derived Distributions	
μ_{kj}	Weight of a particular topic k over all documents in journal j
μ_k	Average weight for topic k over all documents at time t
$\hat{\mu_k}$	Mean weight of topic k over all documents
μ_{kj}^t	Weight of topic k in journal j at time t
μ_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_{μ,H_d}	Correlation coefficient between document-topic distributions μ 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

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 topically diverse over time. We will test these hypotheses by exploring sub-topics 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 LDASeq model with 45 topics ($K_{opt} = 45$). We used a combination of objective-subjective method to choose the opitmal number of topics. Details of this process can be found in Appendix A.

2.2.1. Temporal Trends in Topic Distributions

There are multiple methods of analyzing temporal trends and distributions of topics. Griffiths and Steyvers [37] applied a disjointed time-blind topic model and rearranged documents according to their publication dates. Blei and Lafferty [36] 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 [39] introduced a non-Markov joint modeling framework where topics are associated with a continuous distribution over document timestamps. We initially tested Griffiths and Steyvers [37]'s approach of time-unaware topic modeling and post-hoc aggregation of results according to timestamp for benchmarking. Due to the sequential nature of our data, we chose dynamic topic modeling [36] approach for this study because, unlike a time-blind topic model, it provides a qualitative scope into the contents of a large textual dataset in addition to providing us with a quantitative, predictive model for our sequential corpus.

We calculated temporal topic distributions for a given year μ_k as the proportion of all topic weights over all papers from a given year, t:

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

μ_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. Relationship of Topic Diversity to Interdisciplinarity

There are several common interdisciplinarity indicators of varying validity and consistency based on disciplines, multi-classification systems, similarity of research fields, and networks [40]. Leydesdorff and Rafols [41] explored some of these as citation-based indicators for interdisciplinarity of journals and found Shannon entropy [42] as one of the indicators of interdisciplinarity. 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., 43, 44]. Intuitively, articles are analogous to a given ecological site and topics are analogous to species.

Carusi and Bianchi [45] used Shannon entropy as one of the measures of interdisciplinarity in 1258 journals in the field of information and communication technology. Silva et al. [46] also found that an entropy-based indicator of interdisciplinarity correlates well with impact factors and citation counts. A previous study [47] conducted an interdisciplinarity assessment for Informatics journals using Topic Modeling with Shannon entropy as a diversity metric. Entropy has also been used as an indicator of interdisciplinarity of researchers and research topics [48], research proposals [49], and collaborations [50]. [33] used topic entropy to compare the diversity of scientific conferences. It must be explicitly stated that while topic diversity (measured as Shannon Entropy) is an indicator of interdisciplinarity, it does not directly measure interdisciplinarity itself. Topics do not necessarily translate into explicit disciplines either - interdisciplinarity should be measured as a combination of multiple objective and subjective indicators as its definition varies according to context. We therefore used the entropy based metric applied to topic distributions to measure diversity at corpus and article levels.

2.2.3. Measuring Diversity at the Article Level

We used Shannon entropy to measure the topic diversity H_d for each article in our corpus as:

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

Where μ 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:

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

Shannon diversity is represented using the natural unit of information (nat), where 1 nat represents the information contained in an event when the probability of that event occuring is *1/e*.

2.2.4. Measuring Diversity 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 μ_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 μ_{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 μ_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, μ_{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, μ_{kj}^t, 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 μ_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 μ_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 0.2.

We identified topics that frequently appear isolated using the correlation coefficient between document-topic distributions and their corresponding article diversity scores (entropy metrics), r_{μ,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

The first step towards using the posterior expectations of the LDASeq model is 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 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 LDASeq were conceptually similar to these, however LDASeq 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). Some of these rising topic trends (e.g. 'Rainfall-Runoff', Precipitation', 'Rainfall', 'Spatial Variability') 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 within our cor-

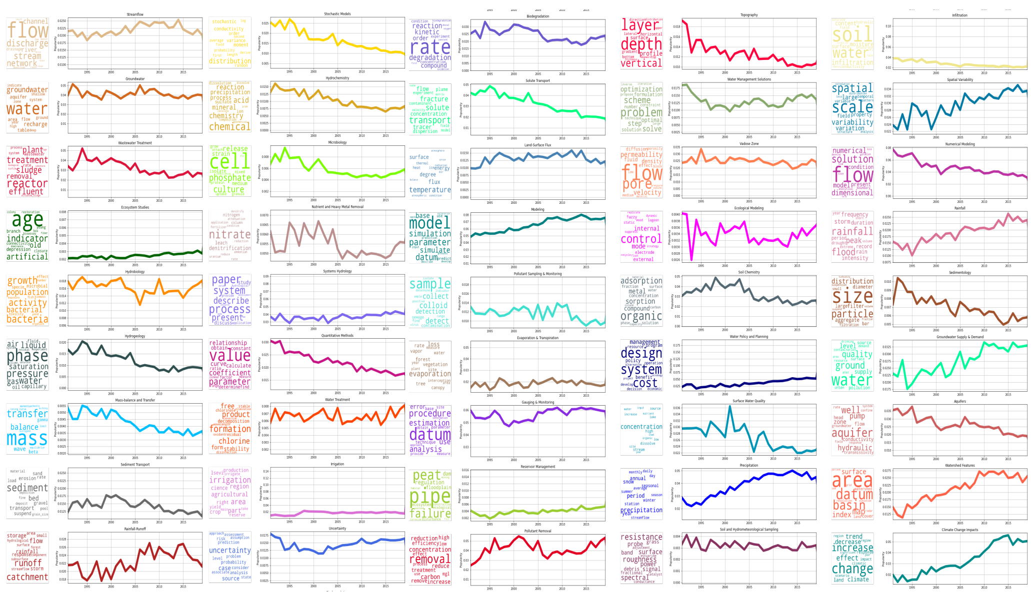

Figure 2: Wordclouds show the words most strongly associated with each topic, and the sizes of words within the wordclouds are proportional to their likelihood of appearance within individual topics. Topic trends are independent and not depicted relative to each other (see Figure 3).

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Figure 3 shows the relative popularity of topics over time plotted on 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 within our corpus (over -50%) are “Stochastic Models” (-62%), “Numerical Modeling” (-61%), “Solute Transport” (-56%). Conversely, the topics that gained the most (over +50%) are “Climate Change Impacts” (+155%), “Water Policy & Planning” (+143%), “Pollutant Removal” (+117%), “Watershed Features” (+72%), “Irrigation” (+60%), “Modeling” (+57%), “Precipitation” (+57%), and “Rainfall” (+55%). These changes in the popularity of topics can be, perhaps, interpreted as shifting focus of researchers who publish their works within the journals in our corpus. Climate change, water policy, water management, irrigation studies, and rainfall are all general topics which are increasingly a part of the global zeitgeist. In addition to leveraging the availability of data, water researchers are responding to the needs of the time.

3.3. Are Articles becoming More Topically Diverse?

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 = 0.95, p-value = 1.36e-14, B10 =

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

Rising Trends

Topic	p-val	BF10
Rainfall-Runoff	1.24E-04	253.82
Water Policy and Planning	2.42E-04	139.38
Precipitation	1.92E-04	171.40
Spatial Variability	8.20E-05	367.25
Rainfall	1.30E-04	242.14
Groundwater Supply & Demand	5.12E-09	2.50E+06
Watershed Features	5.61E-13	1.13E+10
Climate Change Impacts	1.06E-14	4.47E+11
Ecosystem Studies	4.46E-03	10.74

Falling Trends

Topic	p-val	BF10
Wastewater Treatment	4.86E-07	3.85E+04
Hydrogeology	1.41E-10	6.86E+07
Mass-balance and Transfer	1.94E-10	5.11E+07
Stochastic Models	1.34E-14	3.58E+11
Hydrochemistry	2.21E-11	3.79E+08
Microbiology	1.52E-07	1.11E+05
Quantitative Methods	5.38E-16	7.05E+12
Surface Water Quality	2.35E-06	9.13E+03
Numerical Modeling	3.54E-10	2.93E+07
Sedimentology	5.51E-08	2.83E+05
Aquifers	6.43E-10	1.69E+07

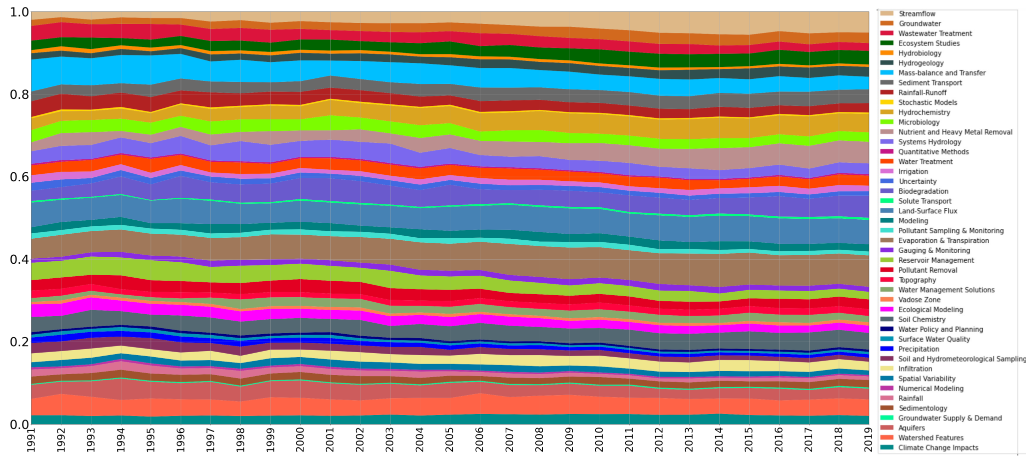

Figure 3: Temporal variation of topic popularity relative to each other.

3.39e+11, indicating a statistically significant trend at any reasonable significance threshold.

To gain an intuitive interpretation of this change in diversity, we applied another metric from ecological/biological sciences - ENS(Effective Number of Species). In our case, we will call it ENT(Effective Number of Topics), where $ENT = e(H_d)$. As an example, if $ENT = x$ for mean per-article diversity H_d^t for year(t), H_d^t is equivalent to articles containing x count of equally-common topics. In our corpus, the mean effective number of topics (ENT) per article steadily rose from 13.62 in 1991 to 15.29 in 2019. This means a 4.44% rise in mean per article topic diversity translates to 12.26% rise in the number of equally-common topics per article between 1991 and 2019. This rising ENT can also be interpreted intuitively as an indicator

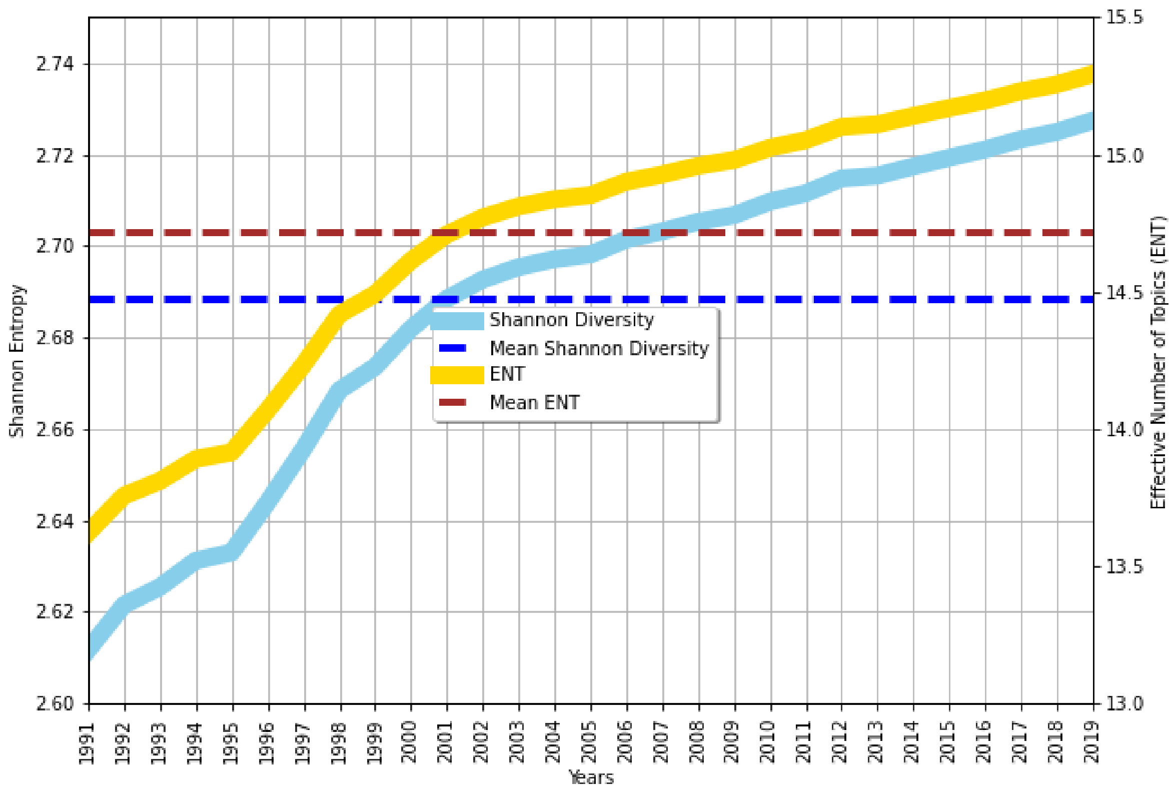

Figure 4: Mean per-article diversity (left axis) and ENT per year (right axis). The dashed lines represent the mean per-article diversity and ENT over the entire corpus.

of water researchers creating new knowledge, and also, absorbing knowledge from topics within other disciplines through interdisciplinary collaborations and education.

3.4. Which Journals Are Contributing to Per-Article Diversity?

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.

Water Resources Research WRR demonstrates the strongest rise (as an individual journal) in the mean diversity of topics per article published between 1991 and 2019 (R = 0.92, p-value = 2.39e-12, BF10 = 2.77e+09). Other journals with overall rise in per-article diversity within our corpus are Advances in Water Resources AWR (R = 0.69, p-value = 5.69e-05, BF10 = 513.33), Water Research WR (R = 0.67, p-value = 9.14e-05, BF10 = 336.08), Journal of Contaminant Hydrology JCH (R = 0.67, p-value = 1.05e-05, BF10 = 297.751), and Journal of Hydrology JH (R = 0.57, p-value = 1.57e-03, BF10 = 27.06). While these results do not directly translate to a rise of interdisciplinarity within these journals, they most certainly indicate increasing diversification of topics. This increasing diversification can be driven by multiple factors, which again includes researchers creating new and absorbing knowledge from other disciplines.

Journals which demonstrate moderate rises in per-article diversities are Water Resources Management WRM (R = 0.46, p-value = 0.026, BF10 = 2.68), and Hydrogeology Journal HGJ (R = 0.43, p-value = 0.05, BF10 = 1.59). Journal of Water Resource Planning & Management $JWRPM$ (R = 0.28, p-value = 0.15, BF10 = 0.62), Journal of the American Water Resources Association $JAWRA$ (R = 0.11, p-value = 0.64, BF10 = 0.29), and Hydrological Processes HP (R = 0.02, p-value = 0.94, BF10 = 0.24) do not

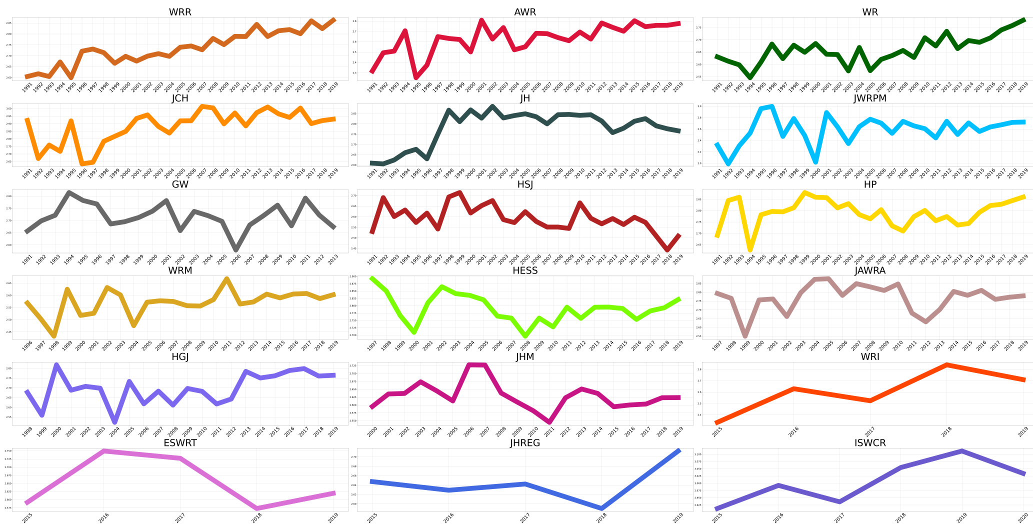

Figure 5: Mean per-article diversity (Shannon entropy) per-journal over time

demonstrate any significant trend at a significance level of $\alpha = 0.01$. Average diversity of articles published in Hydrologic Sciences Journal HSJ (R = -0.46, p-value = 0.01, BF10 = 4.11), Hydrology & Earth System Sciences $HESS$ (R = -0.36, p-value = 0.09, BF10 = 1.00), and Journal of Hydrometeorology JHM(R = -0.30, p-value = 0.21, BF10 = 0.59) decreased. The rest of the journals do not have publication records long enough for trend analysis. The declining per-article diversity trends could mean that these journals are increasingly favoring a particular set of topics or that researchers working on certain topics are favoring these journals.

3.5. Is the Whole Corpus becoming More Topically Diverse?

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 diversity 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 very slightly in the late 1990s and, since then, the entropy of the entire corpus has remained steady or slightly decreased. However, no definite trend exists overall (R = -0.43, p-value = 0.02, BF10 = 0.69). This emphasized the disentanglement of per-article diversity from corpus diversity - showing that, increasing article-level diversity does not necessarily translate to overall corpus diversity.

We used Figure 6 to also visualize the per-journal topic diversity trends. Statistically significant upward diversity trends can be seen for Advances in Water Resources AWR (R = 0.79, p-value = 2.68e-07, BF10 = 6.59e+04), Water Resources Research WRR (R = 0.713, p-value = 1.39e-05, BF10 = 1824.36), Journal of Water Resources Planning & Management $JWRPM$ (R = 0.69, p-value = 3.73e-05, BF10 = 745.97), and Hydrogeology Journal HGJ (R = 0.52, p-value = 0.01, BF10 = 5.13). Journals which demonstrated statistically significant downward trends were Water Research WR (R = -0.64, p-value = 1.70e-04, BF10 = 191.81) and Hydrological Sciences Journal HSJ (R = -0.59, p-value =8.04e-04, BF10 = 48.40). Other journals did not demonstrate any significant trend in entropy over time. Here again, evidences

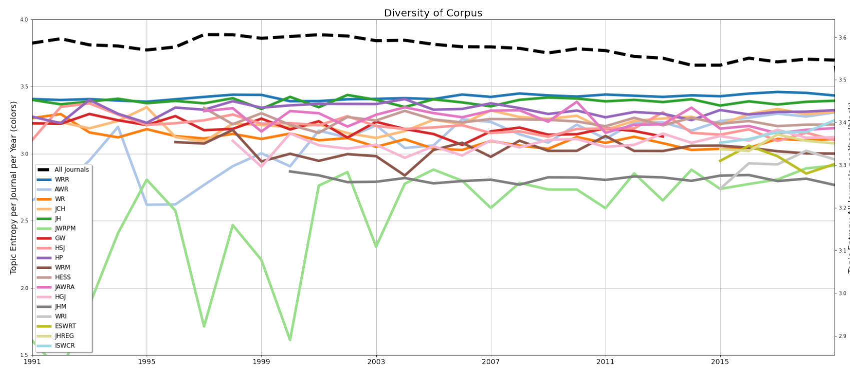

Figure 6: Temporal variation of the diversity of each journal, as measured by the entropy of that journal's topic distribution in a particular year.

of disentanglement between per-article diversity and overall corpus diversity can be seen at a journal level.

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. Water Resources Research WRR (3.45 nats), Journal of Hydrology JH (3.40 nats), Hydrological Processes HP (3.35 nats), and Journal of the American Water Resources Association $JAWRA$ (3.25 nats) are the most topically diverse journals in our corpus. We can again intuitively interpret these values in terms of ENT, meaning that these journals have published the highest numbers of equally-common topics within the entire dataset. The overall Shannon Diversity per journal decreases for more specialty journals – i.e., journals which focus atmospheric science top-

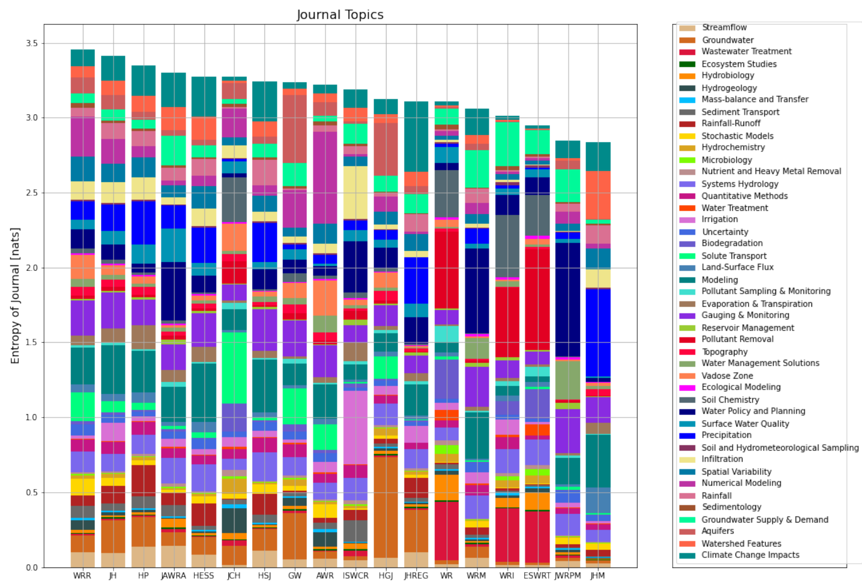

Figure 7: Total bar height represents the overall diversity of topic distributions of each journal for the whole study period. The stacked color bars represent the fraction of papers representing each individual topic in that journal.

ics - Journal of Hydrometeorology JHM and water management topics - Water Resources Management WRM, Journal of Water Resources Planning & Management $JWRPM$. Journals with a fairly recent publication history – i.e., Environmental Science: Water Research and Technology $ESWRT$, International Soil and Water Conservation Research $ISWCR$, Journal of Hydrology: Regional Studies $JHREG$, and Water Resources and Industry 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 diversity and corresponding topic weights.

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 $r_{k,j}$ > 0.20 and negative correlations $r_{k,j}$ < -0.20. 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 and Negative Inter-Topic Correlations

Positive Correlations or likelihood of co-occurrence can be observed for a range of topics, e.g. between “Rainfall” and “Streamflow”, “Rainfall” and

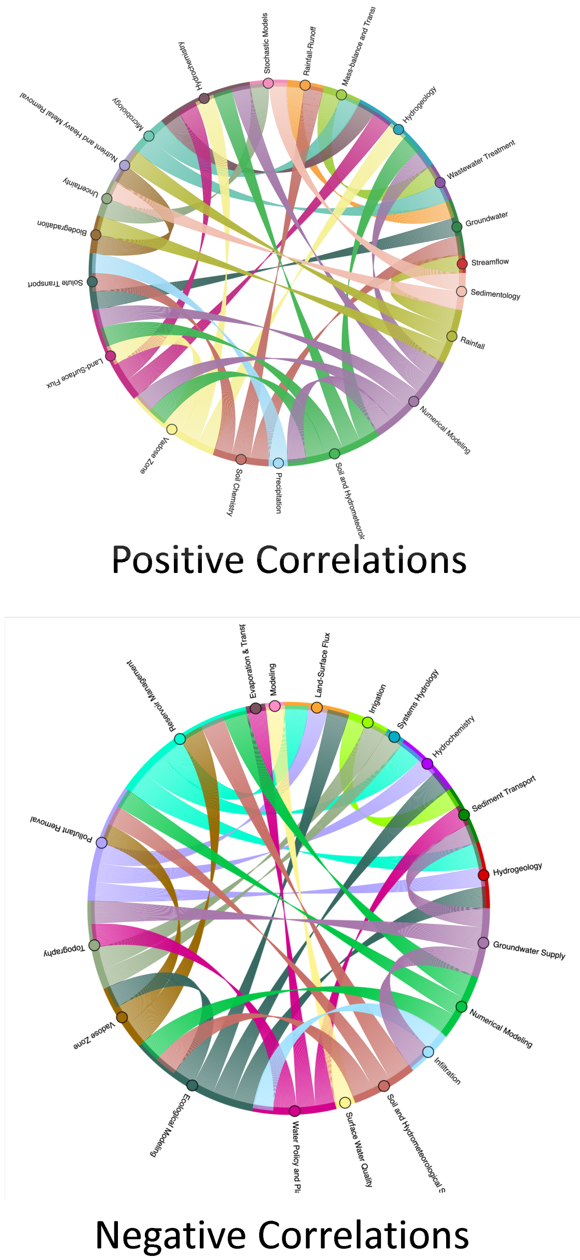

Figure 8: Inter-topic correlations: positive correlations in the upper subplot and negative correlations in the lower subplot. Only correlations $|r_{k,j}| > 0.20$ are shown.

"Spatial Variability", "Uncertainty" and "Stochastic Models", "Land Surface Flux" and "Hydrogeology", "Groundwater" and "Solute Transport", and "Microbiology" and "Wastewater Treatment". Anti-correlations indicate that there are set of vocabulary in the water science literature that are largely not shared between sub-communities. For example, "Pollutant Removal" and "Land Surface Flux", "Pollutant Removal" and "Vadose Zone", "Water Policy and Planning" and "Uncertainty", "Numerical Modeling" and "Reservoir Management", and "Irrigation" and "Sediment Transport" are less likely to co-appear within our corpus. These negative correlations between topics indicate potential for expanding avenues of collaborative research and also help us identify the most insular (isolated) topics in our corpus by complementing our findings, as we discuss in section 3.7.3.

3.7.3. 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 somewhat disconnected from other portions of the community. Therefore, the isolation we report should not be interpreted as being explicit, rather it should be used as guiding information.

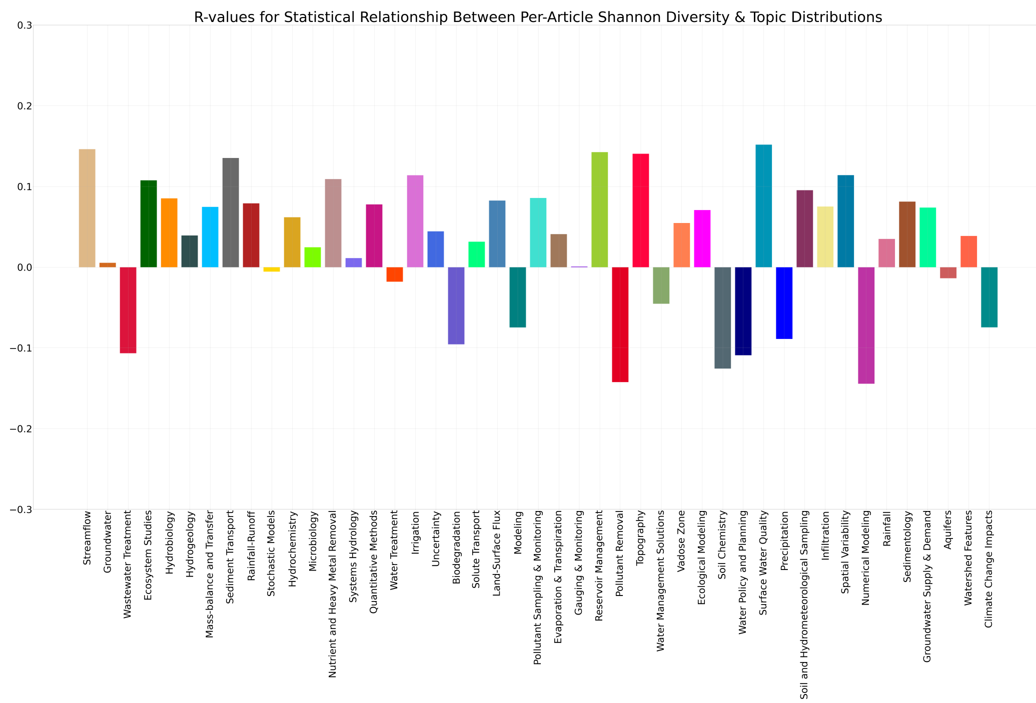

Figure 9: Pearson correlation coefficients for statistical relationships between per-article Shannon diversity metrics and per-topic distribution weights.

Statistical relationship between mean per-article Shannon Diversities H_d and their corresponding topic distribution weights μ are shown in Figure 9. Topics that demonstrate a negative relationship with per-article diversity ($r < -0.10$) are stamped as ‘isolated’. These five topics were (in decreasing order of isolation) “Numerical Modeling” ($r_{\mu,H_d} = -0.15$), “Pollutant Removal” ($r_{\mu,H_d} = -0.14$), , “Soil Chemistry” ($r_{\mu,H_d} = -0.13$), “Water Policy and Planning” ($r_{\mu,H_d} = -0.11$), and “Wastewater Treatment” ($r_{\mu,H_d} = -0.11$).

Figure 10 shows the temporal behavior of these isolated topics. Topics that have become less isolated with time include: “Numerical Modeling” (r

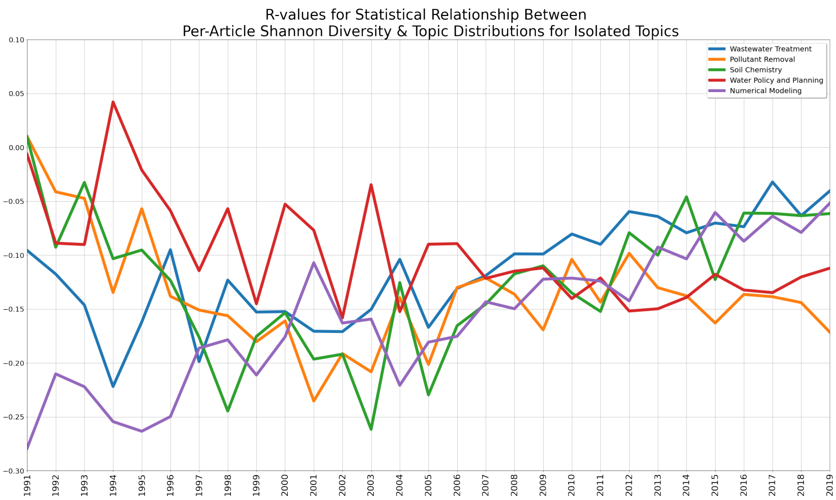

Figure 10: Trends of Pearson correlations between per-article Shannon diversity and topic distributions for isolated topics.

= 0.91, p-value = 1.23e-11, BF10 = 6.32e+08) and "Wastewater Treatment" (r = 0.94, p-value = 3.13e-14, BF10 = 1.57e+11), indicating an increasing co-appearance with a wider variety of other topics in individual articles. Opposite trend (increasing isolation) was observed for "Water Policy and Planning" (r = -0.63, p-value = 2.28e-4, BF10 = 147.57). Topics with increasing isolation are more likely to be dominant topics when they appear in articles. "Pollutant Removal" (r = -0.32, p-value = 0.06, BF10 = 1.21) and "Soil Chemistry" (r = 0.17, p-value = 0.37, BF10 = 0.34) do not demonstrate any significant trend.

4. Conclusions & Discussion

We use semantic-based topic diversity to quantify two types of topic diversities 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 diversity 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 = 0.95, p-value =1.36e-14, B10 = 3.39e+11). There was a 4.44% rise in mean per-article topic diversity, translating to a 12.26% rise in the number of equally-common topics per article between 1991 and 2019.
2. At a corpus level, the average (Shannon) diversity of topics in the whole corpus is neither increasing nor decreasing (r = -0.43, p-value = 0.02, BF10 = 0.69).

3. At a journal level, the most topically-diverse water science journals are Water Resources Research WRR (3.45 nats), Journal of Hydrology JH (3.40 nats), Hydrological Processes HP (3.35 nats), and Journal of the American Water Resources Association $JAWRA$ (3.25 nats). Certain journals are increasing in their average per-article topic diversity (Water Resources Research WRR, Advances in Water Resources AWR, Water Research WR, Journal of Contaminant Hydrology JCH, and Journal of Hydrology JH), and three journals are decreasing in their average per-article topic diversity (Hydrological Sciences Journal HSJ, Hydrology and Earth System Sciences $HESS$, and Journal of Hydrometeorology JHM).
4. At a topic level, certain topics are more semantically isolated than others. The most semantically isolated topics are: "Numerical Modeling" and "Soil Chemistry".

Our interpretation of these findings is that water science research articles are becoming more topically diverse. The increasing mixture of research topics in articles is most likely 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]. However, diversity of the overall corpus is not increasing. If it were the case that both per-paper diversity and the overall corpus diversity were increasing, it would have been difficult to disentangle these effects. The hydrology community could benefit from top-down policies and actions which encourage more topically diverse and cross-disciplinary research, which we think will raise overall diversity.

The ability to automatically detect distinct sets of vocabularies (as topics) is a strength of unsupervised dynamic topic modeling, however it is important to remember that any results from an analysis of topic model outputs is related to the words that define the topics. As more topics emerge within our discipline through new knowledge, increasing collaborations, and conducive policies, we expect topic modeling to continue being helpful towards tracking the evolution of hydrological sciences.

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 topic diversity 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., 51, 52, 53, 54, 14], however NLP has the potential to allow for faster, and more contextual analyses of larger corpora. LDASeq also allows us to look at the evolution of topics in terms of their probabilistic distance and also their varying word-topic distributions. This paper serves as a preface to a currently undergoing hydrology topic evolution study.

Interdisciplinary research has been identified as one of the ways to solve the world's biggest problems [55]. However, the academia continues to be strangled by traditional stereotypes: interdisciplinary proposals are less likely to receive funding [56] and institutions continue to enable this discrimination [55]. While we cannot definitively say that interdisciplinarity is increasing in hydrological sciences, the increasing per-article diversity is an indicator that it may be. This article lays the groundwork for further, and much needed, focus on interdisciplinarity in hydrological sciences.

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Appendix A. Preprocessing the Corpus

Performance of dynamic topic modeling is influenced by the quality of input training data. Article-abstracts were preprocessed into a canonical format for efficacious feature extraction [57]. 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 LDASeq model implemented in *Gensim* - a Python library for NLP [35].

Appendix A.1. Dynamic Topic modeling

To understand dynamic topic modeling, we must start with Latent Dirichlet Allocation (LDA). LDA builds on another more traditional topic modeling approach (Latent Semantic Analysis) [58], 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 α), and that the per-topic word distributions also share a (different) common Dirichlet prior (parameterized by parameters β). The distribution over a particular word w in a document d with topic distribution μ_d can be understood as [59]:

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

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 μ_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, 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 [59] and others.

In a static topic model (LDA), it is implicitly assumed that the documents are drawn from a fixed set of topics in an exchangeable sense. However, for many collections of documents, the order of the documents reflect an evolving set of topics. In the Dynamic Topic Model (DTM) or LDASeq (Figure A.11), we divide the data by timestamps and then model each slice of documents with a number of topics where topics in time slice t_d evolve from the topics associated with slice t_d-1. Unlike the static LDA model, the uncertainty about the distributions over words cannot be modeled by a Dirichlet prior β. We instead chain the natural parameters of each topic in a state space model which evolves with statistical noise. In the same way, the uncertainty over the per-document topic distribution in each time slice is modeled using a logistic normal distribution with a mean α. In this way topics and topic proportion distributions are chained together, sequentially tying a collection of topic models.

Here, we use an LDASeq implementation in the Python *Gensim* package. We trained our models with the number of passes set to 5000 and chunksize (number of documents in a batch) set to 100. For finding the optimal number of topics, 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. Given that the LDASeq models take in the order of weeks to run, we used the parallelized static LDA for this analysis, because our objective was to estimate a range of topics which might be optimal for both these classes of models.

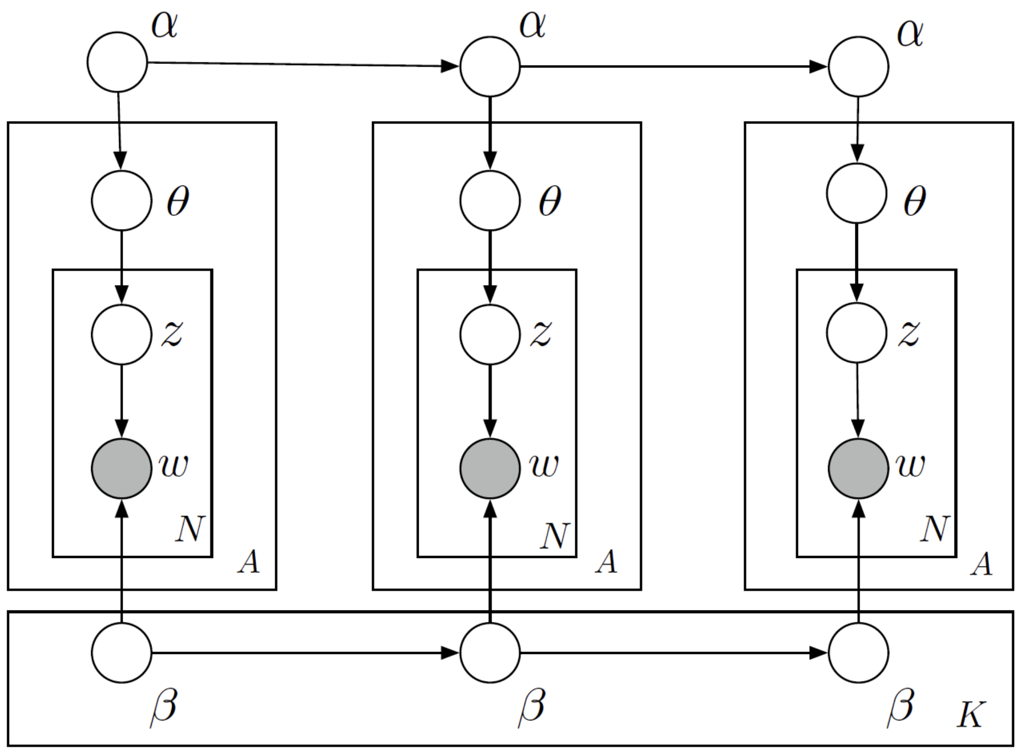

Figure A.11: Graphical model of a DTM with three time slices. Natural parameters $\beta_{t,k}$ and the mean parameters α_t of the logistic normal distribution for topic proportions of each topic evolve together. A represents the slices of documents.

Appendix A.2. Choosing an Optimal Number of Topics

Ideally it is desirable to maximize the number of topics identified by LDASeq 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 [60]. 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.12. 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, 61, 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

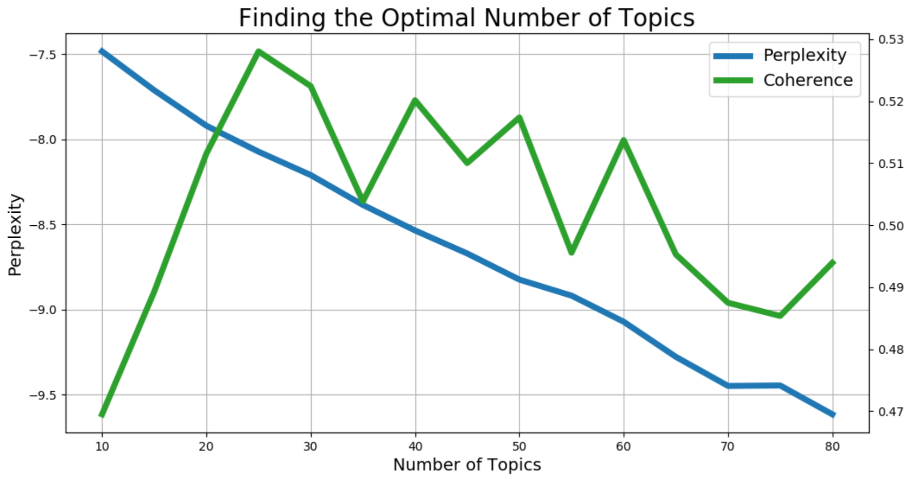

Figure A.12: Variation of topic coherence c and perplexity p based on LDA models trained for a range of topic numbers ($K = 10$ to $K = 80$). Lower perplexity and higher coherence indicate a better model. These values guide our subjective analysis for choosing K_{opt}

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 [62]. Perplexity is an information theory metric that measures something like how surprised the model might be on the introduction of new data [63]. Formally defined by [59], 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 [64]. Calculating topic coherence is a four-stage process involving segmentation of word subsets, probability calculation, confirmation measure, and aggregation.

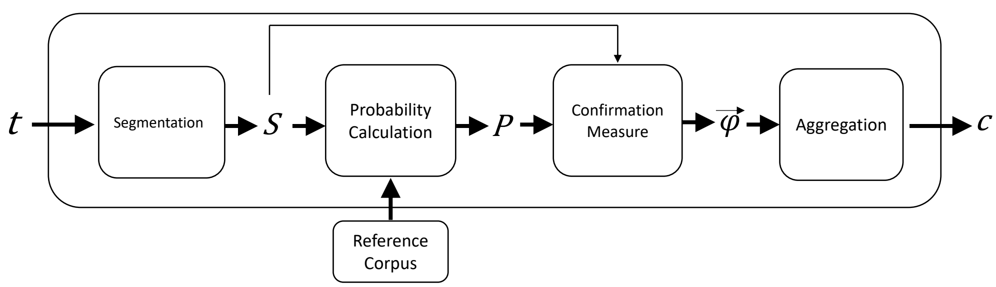

Figure A.13: Illustration of the four stages of the unified topic coherence framework. In stage 1, input words t are segmented into smaller sets S. Probabilities of occurrence P of words are calculated based on the reference corpus in the second stage. In the third stage, P and S are ingested to measure φ between pairs of words S. Coherence c is calculated in the final step.

Figure A.13 [adapted from 64] 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 φ of pairs of S. In the final step, the aforementioned scores are aggregated to compute coherence c.