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Water Science is Becoming More Interdisciplinary

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Key Points:

- Interdisciplinarity of water science articles is increasing.
- Certain journals have become more interdisciplinary over time while others have become less interdisciplinary over time.
- Certain topics in water science are isolated while other topic are becoming more common on cross-disciplinary research.

Keywords:

- Interdisciplinarity
- Water Science
- Machine Learning
- Unsupervised Learning
- Natural Language Processing
- Topic Modeling

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Abstract

We use Natural Language Processing (NLP) to assess topic diversity at the level of (i) individual articles, (ii) individual journals, and (iii) the whole corpus of research article-abstracts in eighteen water science journals.

Interdisciplinarity within individual articles in water science and hydrology journals is increasing. No such discernible trend exists at the corpus level - topic diversity in the overall hydrology and water science corpus is not increasing. We assess the interdisciplinarity of 74,479 water science and hydrology research articles at multiple levels (article and corpus) for eighteen water science journals. In doing so, we leverage Natural Language Processing (NLP) tools, and apply unsupervised learning to extract a diverse range of topics and carry our contextual analyses. We observe the strongest rise in interdisciplinarity of articles published in Water Resources Research WRR, Advances in Water Resources AWR, and Journal of Contaminant Hydrology JCH, while rest of the journals demonstrate slightly rising to slightly decreasing trends. At the corpus level, Journal of Hydrometeorology JHM, Hydrogeology Journal HGJ, Hydrology and Earth System Sciences $HESS$, and Journal of the American Water Resources Association $JAWRA$ show slightly rising trend. We analyze the topics in terms of their trends, and also identify eleven isolated topics (subdisciplines) in this field, some of which have become increasingly isolated over time. These findings contribute to the discourse on interdisciplinarity in water science and hydrology domain.

1 Introduction

Around the middle of the 20th century, Langbein (1958) argued that hydrology was not yet recognized as a distinct discipline within the geosciences. Early emphasis on interdisciplinarity within hydrology and water resource science focused on bringing together natural scientists, engineers, and social scientists (Harshbarger & Evans, 1967). Freeze (1990) identified a separation between physical and social sciences in water research and encouraged WRR to persist with then-limited partnerships to bolster interdisciplinarity. A report by the National Research Council (1991) 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.), in addition to the maturing older topics (National Research Council, 2012).

In the modern era, Montanari et al. (2013) 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. (2015) 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 (2015) mentioned interdisciplinarity as one of the grand challenges in hydrology education, and that it must expand beyond traditional scopes to address the evolving (unique) needs of society (e.g., data and modeling driven cybereducation, developing an international faculty learning community, hydro-economics, etc.). Vogel et al. (2015) 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 non-stationarity associated with climate change (e.g., Bayazit, 2015; Galloway, 2011; Milly et al., 2008), and leverage large samples of available data (Gupta et al., 2014). Nearing et al. (2021) 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 if and how water science and hydrology are changing. In this study, we identify and quantify trends and interactions in and between subtopics within water science with regards to their trends, diversity, isolation etc., and use this analysis 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 (2017) attempted to assess interdisciplinarity in hydrology 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 topics in water science and hydrology literature, and their trends and mixing over time.

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 (Cambria & White, 2014). 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 (Sebastiani, 2002).

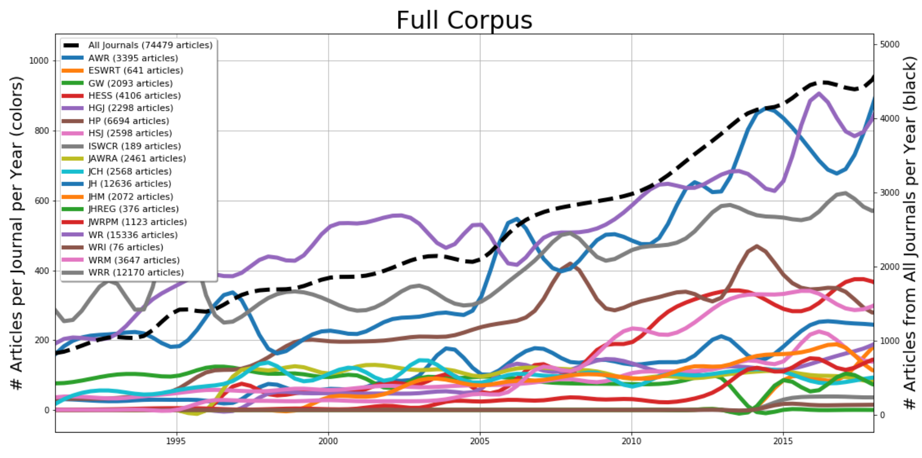

Figure 1. Number of articles published per year between 1991 and 2019 in 18 major water research journals (Source: Web of Science)

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 (Jiang, Qiang, & Lin, 2016). Topic models can be applied to massive collections of documents

(Blei, 2012) and have been used to recommend scientific articles based on content and user ratings (C. Wang & Blei, 2011). Topic modeling has also been used to cluster scientific documents (Yau, Porter, Newman, & Suominen, 2014), improve bibliographic search (Jardine & Teufel, 2014; M. Paul & Girju, 2009; Pham, Do, & Ta, 2018; Shu, Long, & Meng, 2009; Tang, Jin, & Zhang, 2008), and for a variety of application-specific objectives such as statistical modeling of the biomedical corpora (Blei, Franks, Jordan, & Mian, 2006), bibliometric exploration of hydropower research(Jiang et al., 2016), in the analysis of research trends in personal information privacy (Choi, Lee, & Sohn, 2017), development of meta-review in cloud computing literature (Upreti, Asatiani, & Malo, 2016), literature review of social science articles (Li & Liu, 2018), discovering themes and trends in transportation research (Sun, Luo, & Chen, 2017), identifying contribution of authors in knowledge management literature (Jussila et al., 2017), exploring the history of cognition (Priva & Austerweil, 2015), and exploring topic divergence and similarities in scientific conferences (Hall, Jurafsky, & Manning, 2008). As opposed to *scientometrics* techniques (Mingers & Leydesdorff, 2015), 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 a document level.
- The hydrology and water science corpus is becoming more topically-diverse.
- Articles published in certain journals are becoming more interdisciplinary.

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.

2.1 Data Acquisition and Preprocessing

2.1.1 Repository of Article-Abstracts

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 (Gatti, Brooks, & Nurre, 2015; Griffiths & Steyvers, 2004). Our corpus consists of the abstracts of all peer-reviewed articles from eighteen water science journals between 1991 and 2019 - that 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 that we used, along with corresponding IFs, years of available data, and total number of abstracts, are listed in Table 2. These Article-abstracts were acquired from Web of Science core collection in the form of bib files.

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
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
$\mathbf{z_d}$	Per-word topic vector for document d
$\mathbf{w_d}$	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

2.1.2 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 (Feldman, Sanger, et al., 2007). 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 (Řehřek & Sojka, 2011).

2.2 Topic modeling with Latent Dirichlet Allocation

LDA builds on another more traditional topic modeling approach (Latent Semantic Analysis) (Landauer, Foltz, & Laham, 1998), 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 (Blei, Ng, & Jordan, 2003):

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

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:

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

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, $\mathbf{z_d}$, - one topic assignment (out of K total topics) for each word in the document. This generating model is described in more detail by Blei et al. (2003) and others.

Training the LDA model involves estimating the per-document topic distributions, μ_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 (Griffiths & Steyvers, 2004), variational expectation-maximization

(VEM) (Blei et al., 2003), 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.

2.3 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 (Lu, Mei, & Zhai, 2011). We therefore adopted a hybrid quantitative/qualitative approach for deciding the optimal number of topics, K_{opt}.

2.3.1 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.

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 2. 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).

2.3.2 Qualitative Approach to Choosing Optimal Number of Topics

Qualitative perception of topics is a common step in essentially all topic modeling research (e.g., Jiang et al., 2016; M. J. Paul & Dredze, 2014; Sun et al., 2017) 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 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 $K_{opt} = 45$.

2.4 Analysis Methods

To reiterate from the introduction, our primary hypotheses are about whether individual research papers are becoming more or less topically diverse and whether the water science corpus as a whole is becoming more topically diverse (in conjunction with an increasing volume of hydrology research articles). 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 with $K_{opt} =$ 45

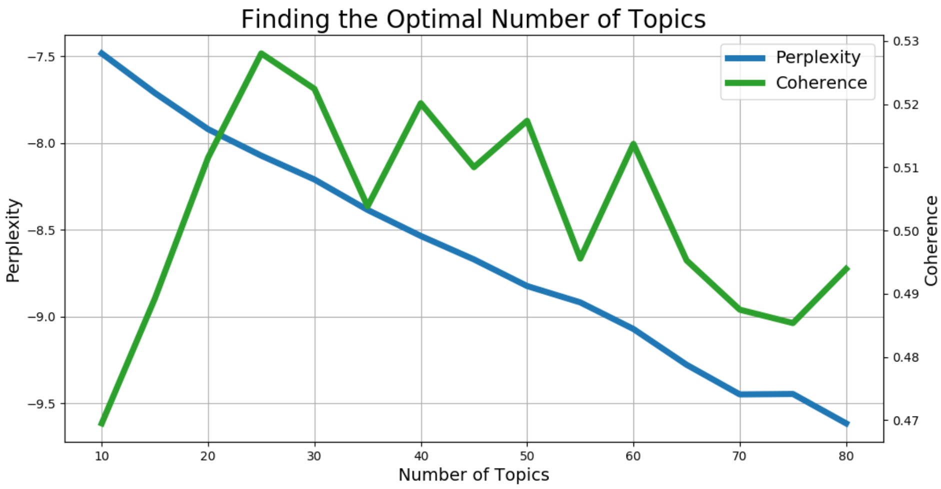

Figure 2. Variation of topic coherence c and perplexity p based on LDA models trained for a range of topic numbers ($K = 10$ to $K = 80$). Lower perplexity and higher coherence indicate a better model. These values guide our subjective analysis for choosing K_{opt}

2.4.1 Temporal Trends in Topic Distributions

There are multiple methods of analyzing temporal trends and distributions of topics. Griffiths and Steyvers (2004) applied a disjointed time-blind topic model and rearranged documents according to their publication dates. Blei and Lafferty (2006) developed a sequential topic modeling approach that learns time-dynamic parameters for the document-topic and topic-word distributions constrained by linear filtering theory. X. Wang and McCallum (2006) introduced a non-Markov joint modeling framework where topics are associated with a continuous distribution over document timestamps. We took Griffiths and Steyvers's (2004) approach of time-unaware topic modeling and post-hoc aggregation of results according to timestamps. 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:

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

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.

2.4.2 Measuring Interdisciplinarity

There are several common interdisciplinarity indicators of varying validity and consistency based on disciplines, multi-classification systems, similarity of research fields, and networks (Q. Wang & Schneider, 2020). Leydesdorff and Rafols (2011) explored some of these as citation-based indicators for interdisciplinarity of journals and found Shannon entropy (Shannon, 1948). 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., Harte & Newman, 2014; Sherwin & Prat i Fornells, 2019). 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 (2020) used Shannon entropy as one of the measures of interdisciplinarity in 1258 journals in the field of information and communication technology. Silva, Rodrigues, Oliveira Jr, and Costa (2013) 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 (Jin & Song, 2016) 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 (Sayama & Akaishi, 2012), research proposals (Seo, Jung, Kim, & Myaeng, 2017), and collaborations (Bergmann, Dale, Sattari, Heit, & Bhat, 2017).

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.

2.4.3 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:

$$H_d = -\sum_{k=1}^{K}(\mu log(\mu)), \tag{4}$$

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:

$$H_d^t = \frac{\sum_{d=1}^{M} H_d \; I(t_d - t)}{\sum_{d=1}^{M} I(t_d - t)}, \tag{5}$$

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

$$H_{dj}^t = \frac{\sum_{d=1}^{M} H_d \; I(|j_d - j| + |t_d - t|)}{\sum_{l=1}^{K}\sum_{d=1}^{M} H_d \; I(|j_d - j| + |t_d - t|)}, \tag{6}$$

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 2.4.2.

2.4.4 Measuring Interdisciplinarity at the Corpus Level

We calculated Shannon diversity at the corpus level and then computed these corpus indexes for each journal. To do this, we began by calculating the K-nomial distribution over topics μ_j in a particular journal j:

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

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:

$$H_j = -\sum_{k=1}^{K}(\mu_{kj} log(\mu_{kj})), \tag{8}$$

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:

$$\mu_{kj}^t = \frac{\sum_{d=1}^{M} \mu_d \; I(|j_d - j| + |t_d - t|)}{\sum_{l=1}^{K}\sum_{d=1}^{M} \mu_d \; I(|j_d - j| + |t_d - t|)}, \tag{9}$$

We used these per-year, per-journal topic distributions to construct timeseries 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.

2.5 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 the frequently co-appearing 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 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:

$$r_{k,j} = \frac{\sum_{d=1}^{M}(\mu_k - \hat{\mu_k})(\mu_j - \hat{\mu_j})}{\sqrt{\sum_{d=1}^{M}(\mu_k - \hat{\mu_k})^2}\sqrt{\sum_{d=1}^{M}(\mu_j - \hat{\mu_j})^2}}, \tag{10}$$

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 0.1.

We identified topics that frequently appear isolated using the correlation coefficient between document-topic distributions and their corresponding article diversity scores (entropy metrics), r_{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 LDA model outputs a certain number of words in each topic and assigns weights to each of those words based on their likelihood of appearance within a particular topic. 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 reputable hydrologists outside of our research group. Figure 3 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 in some ways similar to what was done by McCurley and Jawitz (2017), 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 3. Some topics demonstrated statistically significant rising trends in popularity, such as “Flood Risk & Assessment” (r = 0.66, p-value = 0.000073, BF10 = 409.14), “Wetland & Ecology” (r = 0.77, p-value = 5.39e-07, BF10 = 3.50e+04) , “Drought & Water Scarcity” (r = 0.90, p-value = 1.77e-07, BF10 = 4.67e+08), “Climate Change Impacts” (r = 0.84, p-value = 3.49e-10, BF10 = 3.65e+10), “Forecasting” (r = 0.86, p-value = 1.13e-09, BF10 = 1.00e+07), “Dynamic Processes” (r = 0.91, p-value = 1.22e-12, BF10 = 5.49e+09), “Spatial Variability of Precipitation” (r = 0.59, p-value = 0.00062, BF10 = 60.25), and “Watershed Hydrology” (r = 0.90, p-value = 6.66e-12, BF10 = 1.49e+09). 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: “Water Quality” (r = -0.86, p-value = 1.13e-09, BF10 = 1.00e+07), “Sediment Transport” (r = -0.57, p-value = 0.001, BF10 = 36.98), “Hydrogeology” (r = -0.88, p-value = 1.00e-10, BF10 = 9.41e+07), “Surface-GW Interactions” (r = -0.87, p-value = 2.44e-10, BF10 = 4.14e+07), “Solute Transport” (r = -0.95, p-value = 9.35e-16, BF10 = 4.23e+12), “Numerical Modeling” (r = -0.935, p-value = 9.80e-14, BF10 = 5.69e+10), “Hydrochemistry” (r = -0.85, p-value = 1.29e-09, BF10 = 8.94e+06), “Uncertainty” (r = -0.70, p-value = 0.000014, BF10 = 1780.46), “Microbiology” (r = -0.84, p-value = 6.19e-09, BF10 = 2.10e+06), “Hydraulics” (r = -0.97, p-value = 3.27e-19, BF10 = 6.77e+15), and “Aquifers & Abstraction” (r = -0.94, p-value = 3.85e-14, BF10 = 1.35e+11). The remainder of topics do not demonstrate any significant trend.

Figure 4 shows the relative popularity of topics over time plotted on the same scale (Figure 3 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 5. 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 decreasing trend (R = -0.71, p-value = 0.000017, B10 = 1554), meaning the average highest topic distribution weight per article is decreasing.

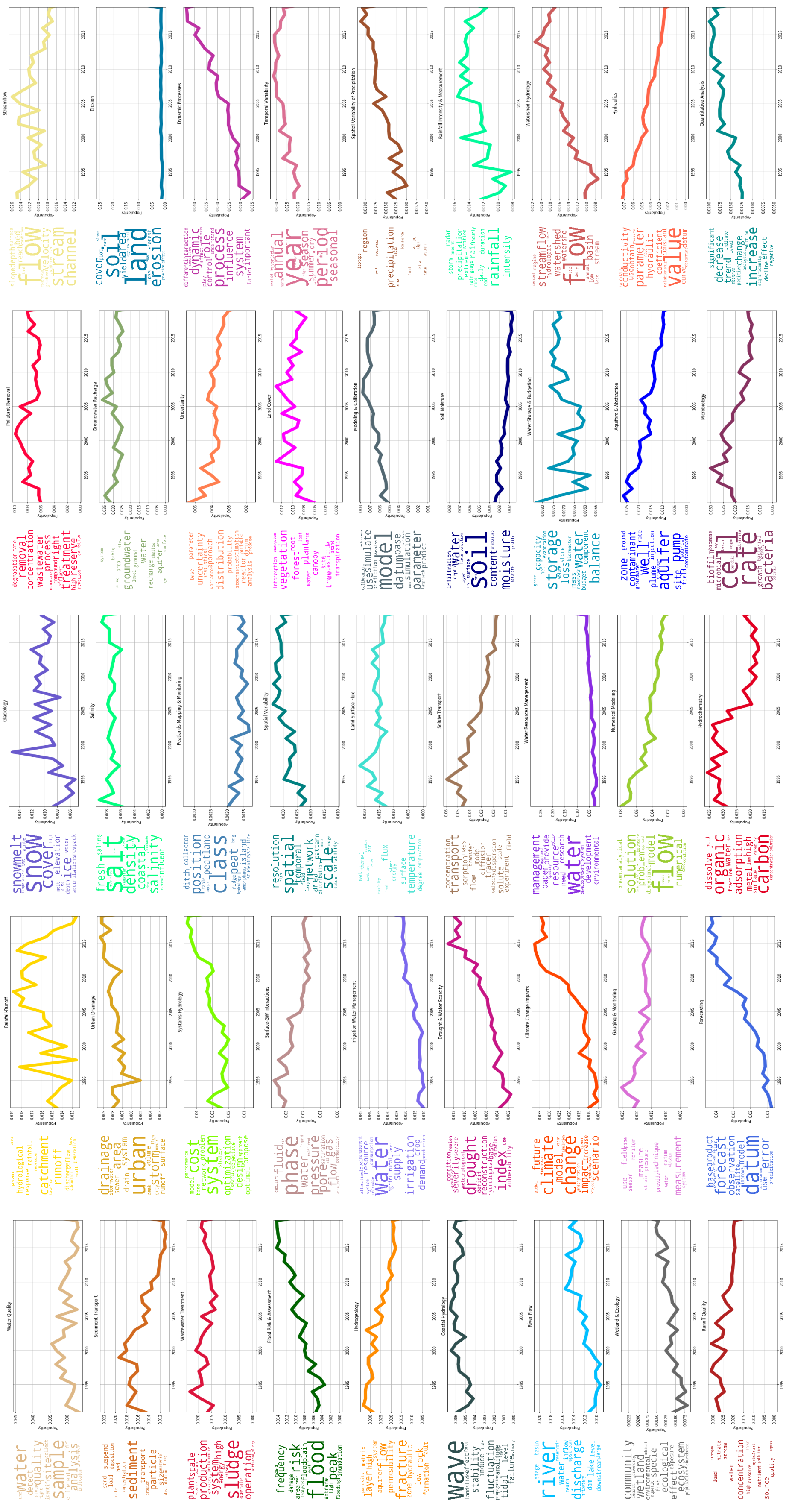

Figure 3. Wordclouds show the words most strongly associated with each topic, and the sizes of words within the wordclouds are proportional to their likelihood of appearance within individual topics. Topic trends are independent and not depicted relative to each other (see Figure 4).

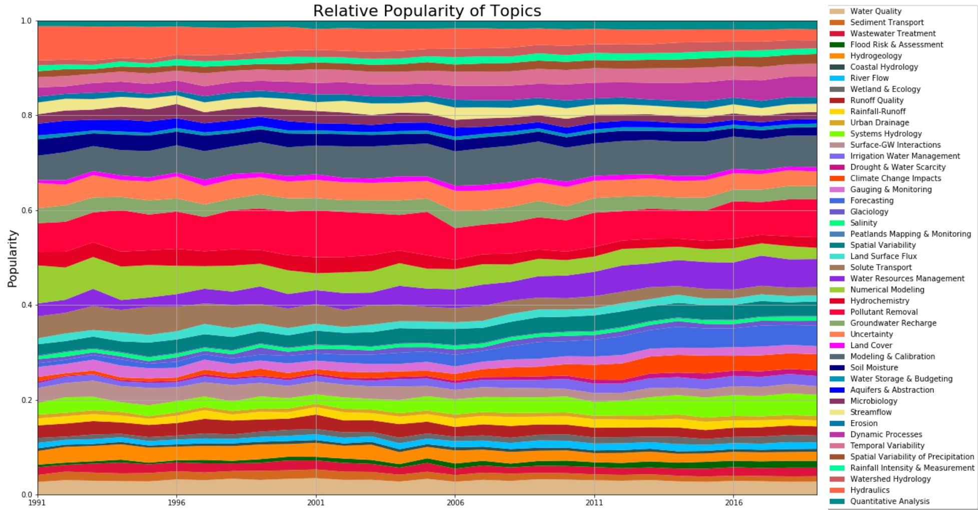

Figure 4. Temporal variation of topic popularity relative to each other.

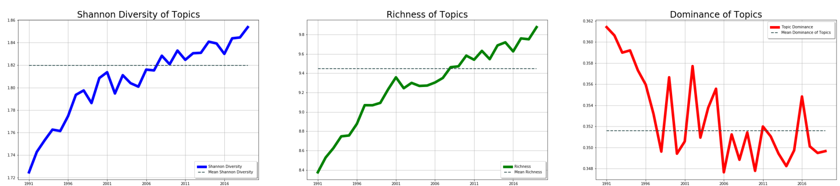

Figure 5. Mean per-article diversity, species richness and topic dominance per year

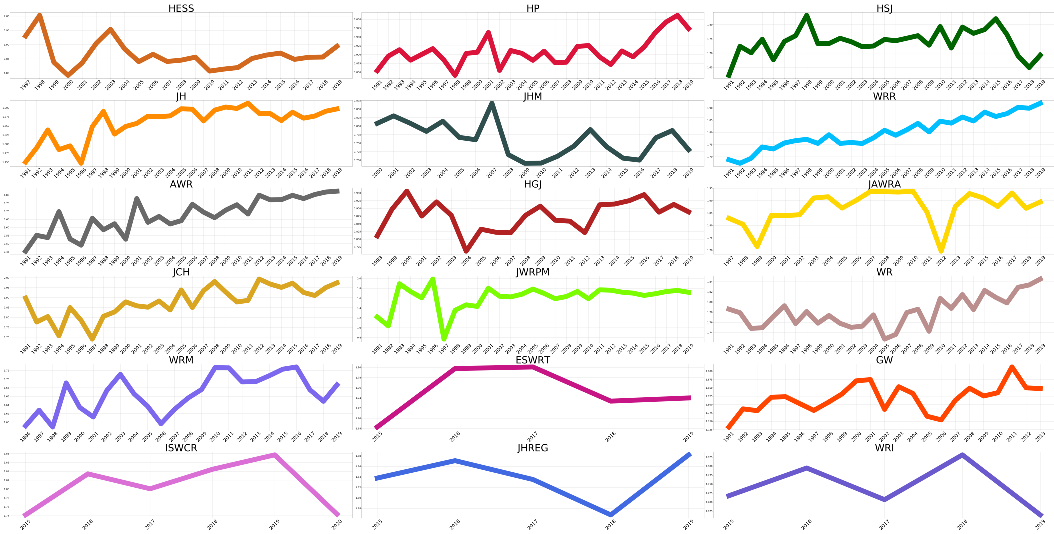

Figure 6. Mean per-article diversity (Shannon entropy) per-journal over time

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 6. As before, we used linear regression to assess the significance of temporal trends in these per-journal time series.

As a journal, WRR demonstrates the strongest rise 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 = 0.000004, BF10 = 5063), and JH (R = 0.74, p-value = 0.000008, BF10 = 3005). Journals which demonstrate moderate rises in per-article diversities are HP (R = 0.51, p-value = 0.0058, BF10 = 8.755), WR (R = 0.57, p-value = 0.0014, BF10 = 29.29), and WRM (R = 0.61, p-value = 0.00201, BF10 = 22.3). GW(R = 0.48, p-value = 0.023, BF10 = 2.911), $JWRPM$ (R = 0.41, p-value = 0.031, BF10 = 2.125), $JAWRA$ (R = 0.36, p-value = 0.096, BF10 = 0.97), HSJ (R = 0.25, p-value = 0.193, BF10 = 0.53), and HGJ (R = 0.29, p-value = 0.199, BF10 = 0.585) 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 = 0.077, BF10 = 1.15) decreased. The rest of the journals do not have publication records long enough for trend analysis.

3.5 Is the Whole Corpus becoming More Interdisciplinary?

Figure 7 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.

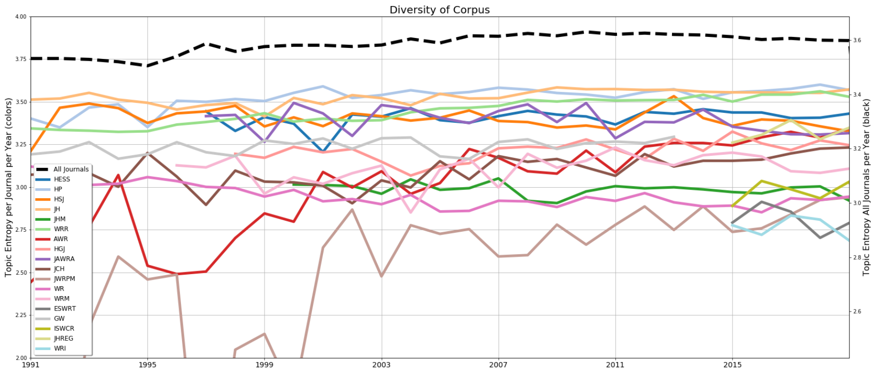

Figure 7. Temporal variation of the diversity of each journal, as measured by the entropy of that journal's topic distribution in a particular year.

The diversity for our 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 = 0.365, BF10 = 0.336). This shows the increasing article-level interdisciplinarity does not translate to overall corpus interdisciplinarity. Hydrology research projects are becoming more comprehensive but the evidence does not suggest that the discipline as a whole is necessarily increasing in topic diversity.

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 Appendix B. Although most trends in per-journal topic diversity were visually weak (Figure 7, there were statistically significant (upward trends) in *JHM* (R = 0.65, p-value = 0.0001, BF10 = 300.90), *HGJ* (R = 0.59, p-value = 0.0007, BF10 = 56.13), *HESS* (R = 0.53, p-value = 0.0025, BF10 = 17.55), and *JAWRA* (R = 0.51, p-value = 0.0037, BF10 = 12.49). Other journals did not demonstrate any significant trend in entropy over time.

3.6 Identifying Isolated Topics

To reiterate from Section 2.5, 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.

3.6.1 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 cor-

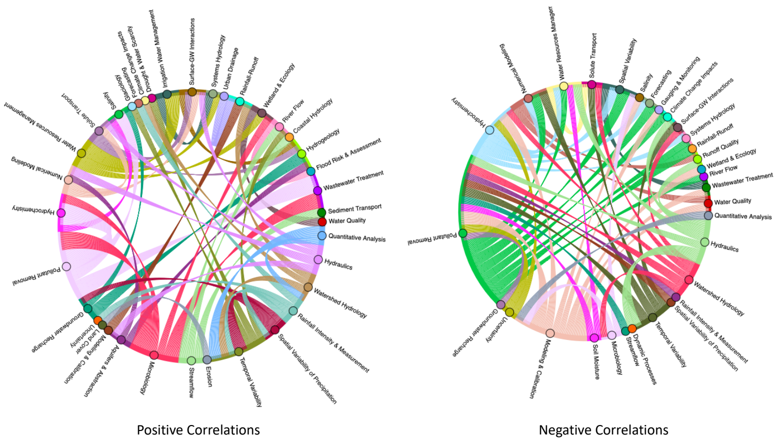

Figure 8. Inter-topic correlations: positive correlations in the left subplot and negative correlations in the right subplot. Only correlations $|r_{k,j}| > 0.10$ are shown.

pus lends us a snapshot of co-appearing and disjointed topics, they also assist in segregating isolated topics.

3.6.2 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 (Peel & McMahon, 2020). The "Rainfall-Runoff" topic also correlates with "Urban Drainage" ($r_{k,j} = 0.14$), and "Watershed Hydrology" ($r_{k,j} = 0.15$). Several studies exclusively focus on the relationship between urban drainage and runoff (e.g., Ahn, Cho, Kim, Shin, & Heo, 2014; Burian & Edwards, 2002; Previdi, Lovera, & Mambretti, 1999). Runoff (including rainfall-runoff modeling) and watershed hydrology are intrinsically connected in hydrological sciences (e.g., Betson, 1964; V. P. Singh & Woolhiser, 2002; Smith & Eli, 1995).

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 (V. Singh, 1997), and scale dependencies in rainfall studies and forecasting (e.g., Chiew et al., 2010; Faurès, Goodrich, Woolhiser, & Sorooshian, 1995; Koren et al., 1999). 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 (Ologunorisa & Abawua, 2005). Similarly, many studies have focused on the impacts of global climate change on watersheds, and subsequently, natural hydrosystems (e.g., Gornitz, Rosenzweig, & Hillel, 1997; Haddeland et al., 2014; Mittal, Bhave, Mishra, & Singh, 2016), which is reflected by a notable co-appearance of "Climate Change Impacts" and "Watershed Hydrology" ($r_{k,j} = 0.11$) in our 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., Bork & Lang, 2003; Cebecauer & Hofierka, 2008; Z. Wang et al., 2017). "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., Gallego-Ayala, 2013; McKinney, 1999; Rahaman & Varis, 2005).

"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 inter-topic 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 plausible due to the fact that open channel hydraulics often use numerical modeling techniques (Szymkiewicz, 2010). "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 (Holzbecher & Sorek, 2006). Intuitively, 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.

3.6.3 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" ($r_{k,j} = -0.11$). Intuitively, these negative correlations indicate potential for expanding avenues of collaborative research. A combination of intrinsic and extrinsic reasons likely dictate such negative relationships.

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 3.6.4.

3.6.4 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 3), 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.

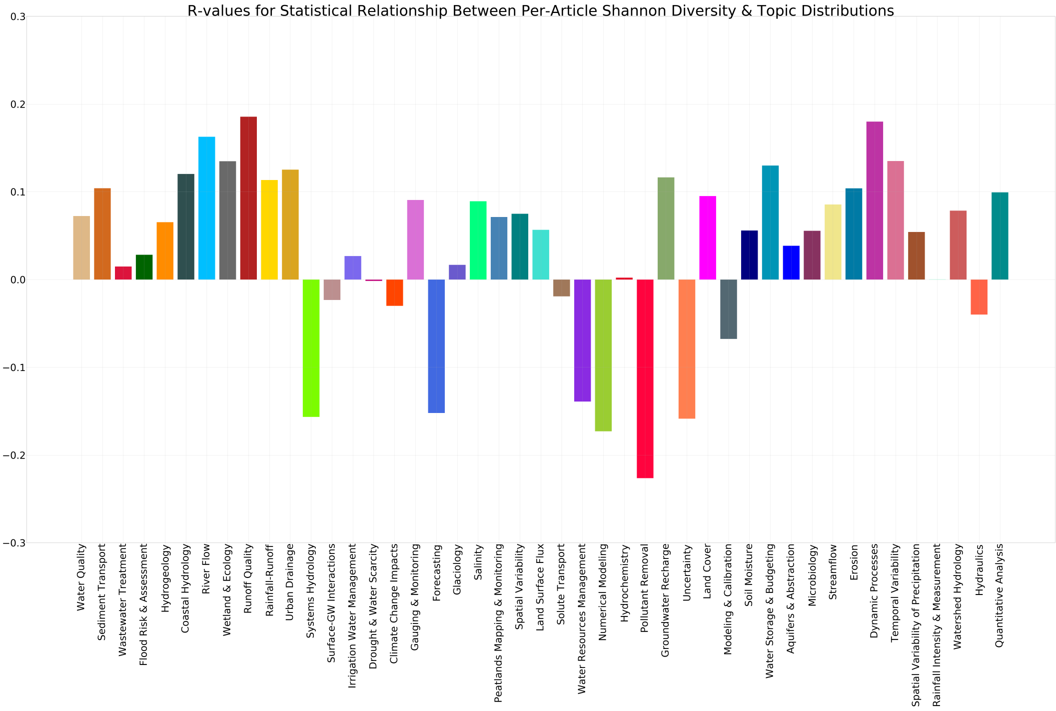

Figure 9. Pearson correlation coefficients for statistical relationships between per-article Shannon diversity metrics and per-topic distribution weights.

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 ($r < 0$) 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 = 0.000002, 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 = 0.000005, BF10 = 4250.94), "Climate Change Impacts" (r = -0.70, p-value = 0.00002, BF10 = 1329.65), "Water Resources Management" (r = -0.58, p-value = 0.00097, 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 = 0.087, BF10 = 0.41), "Modeling & Calibration" (r = -0.29, p-value = 0.119, BF10 = 0.734), and "Surface-GW Interactions" (r = 0.28, p-value = 0.144, BF10 = 0.638) do not demonstrate any significant trend.

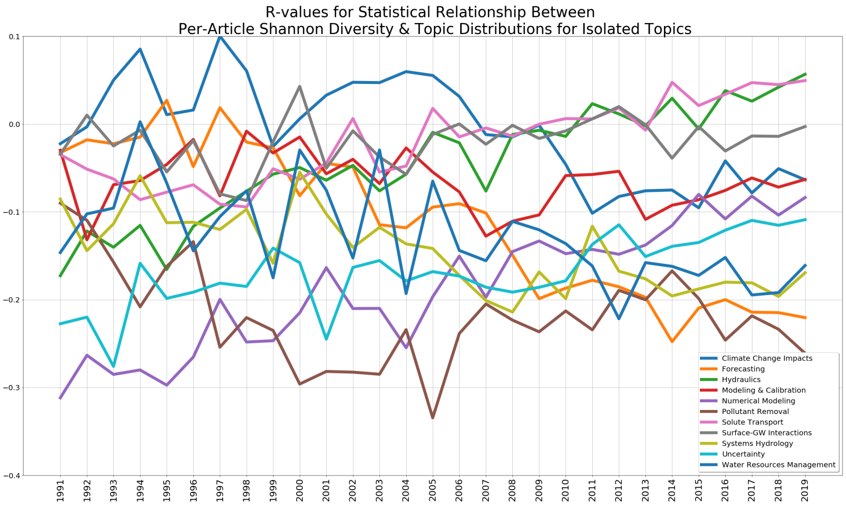

Figure 10. Trends of Pearson correlations between per-article Shannon diversity and topic distributions for isolated topics.

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 5), and while individual topics are changing in popularity over time (Figure 4), the water science and hydrology corpus as a whole is not becoming overall more or less topically-diverse (Figure 7).

The primary findings of this study are:

1. The average diversity of topics in individual papers is increasing over the entire corpus (r = 0.94, p-value =4016.79e-14, B10 = 7.68e+10).
2. The average diversity of topics in the whole corpus is neither increasing nor decreasing (r = -0.17, p-value = 0.365, BF10 = 0.336).
3. The most topically-diverse water science journals are *HP* (3.7 nats), *JH* (3.65 nats), *WRR* (3.5 nats), and *HESS* (3.45 nats).
4. 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*).
5. Certain journals are increasing in their overall (not per-article) topic diversity (*JHM*, *HGJ*, *HESS*, *JAWRA*).
6. Certain topics are more semantically isolated than others (“Pollutant Removal”, “Numerical Modeling”, “Uncertainty”, “Systems Hydrology”, “Forecasting”, “Water Resources Management”, “Modeling & Calibration”, “Hydraulics”, “Climate Change Impacts”, “Solute Transport”, and “Surface-GW Interactions”).

Our interpretation of these findings is a clear indication that water science research is becoming more interdisciplinary. If it were the case that both per-paper and the overall corpus diversity were increasing, it would be difficult to disentangle these effects, however because the topic distribution in disciplines overall has been relatively stable over the past $\tilde{3}0$ years, the increasing trend in per-paper topic diversity indicates that per-article diversity is an organic effect driven by changing efforts, attitudes, and vision by individual researchers and - perhaps - of increasingly interdisciplinary education, as called for by National Research Council (1991).

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 strong sign of organic, expanding interaction within the community.

4.1 Future Outlook

The volume of scientific research in general is exploding. 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., Clark & Hanson, 2017; Koutsoyiannis & Kundzewicz, 2007; McCurley & Jawitz, 2017; Rajaram et al., 2015; Zare, Elsawah, Iwanaga, Jakeman, & Pierce, 2017), however NLP has the potential to allow for faster, and more contextual analyses of larger corpora.

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The code and data to reproduce all results and figures are available at `https://doi.org/10.5281/zenodo.4852439`.

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A Appendix: Perplexity and Coherence

Perplexity is a popular metric for evaluating language models (Chen, Beeferman, & Rosenfeld, 1998). Perplexity is an information theory metric that measures something like how surprised the model might be on the introduction of new data (Zhao et al., 2015). Formally defined by Blei et al. (2003), perplexity for a collection of M documents is:

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

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 (Röder, Both, & Hinneburg, 2015). Calculating topic coherence is a four-stage process involving segmentation of word subsets, probability calculation, confirmation measure, and aggregation.

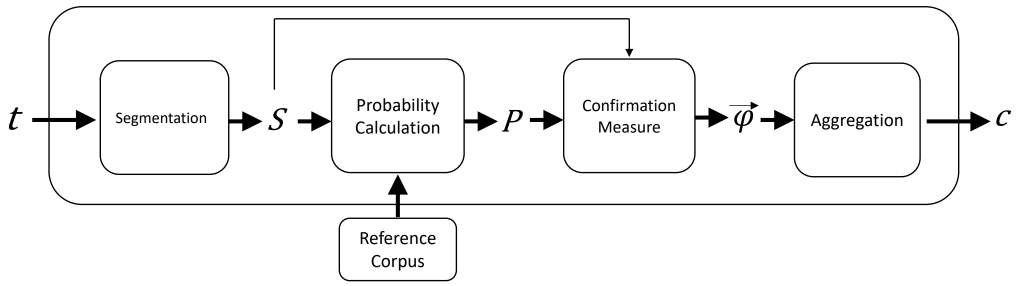

Figure A.1. Illustration of the four stages of the unified topic coherence framework. In stage 1, input words t are segmented into smaller sets S. Probabilities of occurrence P of words are calculated based on the reference corpus in the second stage. In the third stage, P and S are ingested to measure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

Figure A.1 (adapted from Röder et al., 2015) 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.

B Appendix: Overall Journal Diversity

The stacked bar plots in Figure B.1 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, $JWRPM$.

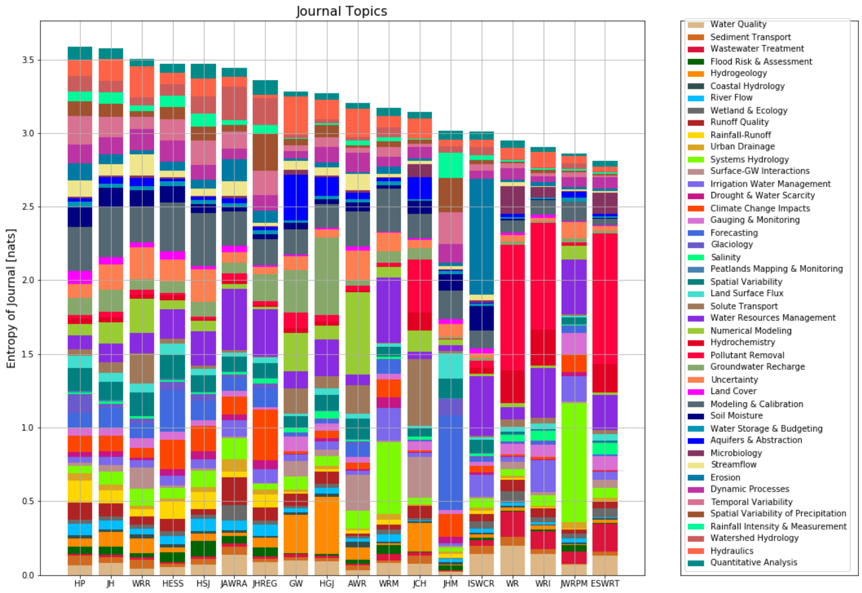

Figure B.1. Total bar height represents the overall diversity of topic distributions of each journal for the whole study period. The stacked color bars represent the fraction of papers representing each individual topic in that journal.

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.