Potential of natural language processing for metadata extraction from environmental scientific publications

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Abstract. ~~Climate change will most likely lead to an increase of extreme weather events, including heavy rainfall with soil surface runoff and erosion. Adapting agricultural management practices that lead to increased infiltration capacities of soil has potential to mitigate these risks. However, effects of agricultural management practices (tillage, cover crops, amendment, …) on soil variables (hydraulic conductivity, aggregate stability, …) often depend on the pedo-climatic context. Hence, the only possibility to gather information needed to advise stakeholders on suitable management practices is to quantify such dependencies using meta-analyses of studies investigating this topic. As a first step, structured information from scientific publications needs to be extracted to build a meta-database, which then can be analyzed and recommendations can be given in dependence to the pedo-climatic context.~~

Summarizing information from large bodies of scientific literature is an essential but work-intensive task. This is especially true in environmental studies where multiple factors (e.g. soil, climate, vegetation) can contribute to the effects observed. Meta-analyses, studies that quantitatively summarize findings of a large body of literature, rely on manually curated databases built upon primary publications. However, ~~he findingsulBy~~~~Manually building such a database by going through all publications is very time-consuming. G~~given the increasing amount of literature, this manual work~~task~~ is likely to require more and more effort in the future. Natural language processing (NLP) facilitates this task, but it is not clear yet to which extent the extraction process is reliable or complete. In this work, we explore three NLP techniques that can help support this task: topic modeling, tailored regular expressions and the shortest dependency path method. We apply these techniques in a practical and reproducible workflow on two corpora of documents: ~~were used, which we refer to as~~ the OTIM and the Meta corpus~~ in the following~~. The OTIM corpus contains the source publications of the entries of the OTIM database of near-saturated hydraulic conductivity from tension-disk infiltrometer measurements (https://github.com/climasoma/otim-db). The Meta corpus is constituted of all primary studies from 36 selected meta-analyses on the impact of agricultural practices on sustainable water management in Europe. ~~We focused on three NLP techniques: topic modeling, tailored regular expressions and dictionaries and the shortest dependency path. W~~As a first step of our practical workflow, we identified~~used topic modeling to identify~~

different topics from~~sort~~ the individual source-publications of the Meta corpus using topic modeling.~~ into diffferent6 topics (e.g. related to cover crops, biochar, …) with a coherence metric Cv ranging from 0.7 to 0.9~~.~~;~~ This enabled us to distinguish well--researched topics (e.g. conventional tillage, cover crops) where meta-analysis would be useful, from neglected topics (e.g. effect of irrigation on soil properties), showing potential knowledge gaps. Then, we used tailored regular expressions ~~and dictionaries~~ to extract coordinates, soil texture, soil type, rainfall, disk diameter and tensions on the OTIM corpus to build a quantitative database. We were able to retrieve~~ found that~~ the respective information ~~could be retrieved~~ with 56% up to 100% of all relevant information (recall) and with a precision between 83% and 100%. Finally, we extracted relationships between a set of drivers corresponding to ~~, here, practices keywords,~~ different soil management practices or amend~~s~~ments~~ managme~~ (e.g. ‘biochar’, ‘zero tillage’, …) and target variables~~soil properties~~~~variables~~ (e.g. ‘soil aggregate’, ‘hydraulic conductivity’, ‘crop yield’,…) from the source-publications’ abstracts of the Meta corpus using the shortest dependency path between them. These relationships were further classified according to positive, negative or absent correlations between the driver and the target~~soil~~ variable~~property~~. This quickly provided an overview of the different driver-variable relationships and their abundance for an entire body of literature. Overall, we found that all three tested NLP techniques were able to support evidence synthesis tasks~~ such as identifyingselecting relevant publications on a topics, extracting specific information to build databases for meta-analysis and providing an overview of relationships found in the corpus~~. While human supervision remains essential, NLP methods have the potential to support~~ fully~~ automated evidence synthesis which~~that~~ can be continuously updated as new publications become available.

1 Introduction

The effect of agricultural practices on agroecosystems is highly dependent upon other environmental factors such as climate and soil. In this context, summarizing information from scientific literature while extracting relevant environmental variables is important to establish pedo-climatic specific conclusions. This synthesis is essential to provide recommendations for soil management adaptations that are adequate for local conditions, both, today and in the future. Efforts to synthesize context-specific evidence through meta-analysis or reviews currently requires a lot of manual work to extract specific information from papers. This effort scales with the number of publications which makes it more difficult to collate exhaustive meta-databases from the literature. In the meantime, the use of automated methods to analyze unstructured information (like text in a scientific publication) has been developing during recent years and has demonstrated potential to support evidence synthesis (Haddaway et al. 2020). Natural language processing (NLP) is one of them.

In their 2019 review on the advances of the technique, Hirschberg and Manning explained that “natural language processing employs computational techniques for the purpose of learning, understanding, and producing human language content.” This definition is quite broad as NLP encompasses several considerably different techniques, like machine translation, information extraction or natural language understanding. Nadkarni et al. (2011) and Hirschberg and Manning (2019) provide a good overview on this field of research and how it originally developed. For applications to scientific publications, Nasar et al.

(2018) reviewed different NLP techniques (information extraction, recommender systems, classification and clustering and summarizations). However, an important limitation of supervised NLP techniques is that they require labels that need to be manually produced to train the model. Hence, humans are still needed for evidence synthesis, but can certainly receive great support from existing NLP techniques.

NLP methods are most widely used in medical research. The development of electronic health records significantly facilitated the application of automatic methods to extract information. For instance, information extraction techniques were used to identify adverse reactions to drugs, identify patients with certain illnesses which were not discovered yet at the time or link genes with their respective expression (Wang et al. 2018). A specific example is given by Tao et al. (2017) who used word embedding and controlled random fields to extract prescriptions from discharge summaries. Wang et al. (2018) provide an extensive review of the use of NLP for the medical context.

The rise of open-source software tools such as NLTK (Loper and Bird 2002) and SpaCy (Honnibal and Montani 2017) together with the increase in digitally available information has fostered the way for NLP applications towards other scientific communities. For example, SpaCy is able to recognize the nature of words in a sentence and their dependence on other words using a combination of rules-based and statistical methods. Building on that, there are open-source software tools that aim at automatically extracting information. A very popular tool is the OpenIE framework of the Stanford group (Angeli et al. 2015) included in the Stanford coreNLP package (Manning et al. 2014). Niklaus et al. (2018) present a review of open-source information extraction codes. All these tools greatly support novel implementations of NLP applications as they reduce the knowledge required for new users to start using NLP techniques.

In the context of evidence synthesis, several NLP methods can be useful. Topic modeling can help to identify common themes in a corpus of publications or classify publications by subject. In addition to selecting publications to be reviewed in the evidence synthesis, topic modelling also gives an overview over the number of publications per topic and helps to identify knowledge gaps. Regular expressions search the text for a pattern of predefined numbers and words. They have a high precision but only find what they are designed to find. This means the user already needs a lot of knowledge on the exact words/terms that should be found. They can be augmented by including syntaxic information such as the nature (noun, adjective, adverb, …) and function (verb, subject, …) of a word. Complemented with dictionaries that contain lists of specific words (e.g. World Reference Base soil groups), it can be a powerful method. More advanced NLP techniques aim at transforming words into numerical representations that can be further processed by numerical machine learning algorithms. For instance, word embeddings are vectors which encode information about a word and its linguistic relationships in the context it is found. They are derived from the corpus of available documents. An advanced machine learning technique that converts text to a numerical representation are transformer networks such as BERT (Koroteev 2021). BERT transformers are trained on specific corpus. For instance bioBERT is tailored to the medical context (Lee et al. 2020).

In contrast to the medical context, fewer studies applied NLP methods to soil sciences. Padarian et al. (2020) used topic modeling in their review of the use of machine learning in soil sciences. Furey et al. (2019) presented NLP methods to extract pedological information from soil survey description. Padarian and Fuentes (2019) used word embedding. They were able to establish relationships between soil types and soil or site properties through principal component analysis. For instance, ‘Vertisols’ were associated with ‘cracks’ or ‘Andosols’ with ‘volcanoes’ as their embeddings were similar.

The aim of this study is not to demonstrate the latest and most advanced NLP techniques. Rather, it presents practical workflows to apply NLP techniques to scientific publication in soil science to support different evidence synthesis steps: topic classification, knowledge gaps identification and database building. Our study aims to demonstrate the potential and practical limitations of several NLP techniques through examples of evidence synthesis for soil science. In this regard, we put special emphasis on the methodology used and its ability to recover information, rather than analyzing and interpreting the extracted data itself. We redirect the reader to chapters 1-3 in Garré et al. (2022) for detailed interpretation of the evidence synthesis.

The objectives of this paper are (1) to demonstrate the potential of natural language processing as for the collection of structured information from scientific publications, (2) to illustrate the ability of topic classification to identify “popular” and less investigated~~researched~~ topics~~classify a new paper as relevant to a given topic~~ and (3) to assess the ability of natural language processing to extract relationships between a given driver (tillage, cover crops, amendment, …) and soil variables (hydraulic conductivity, aggregate stability, …) based on publication abstracts.

2 Materials and methods

2.1 Text corpora

This work used two corpora (sets of texts) which are referred to in the following as the OTIM and the Meta corpus. The OTIM corpus was related to OTIM-DB (https://doi.org/10.20387/bonares-q9b3-z989, EJP SOIL - CLIMASOMA 2022. Chapter 4) which is a meta-database extending the one analyzed in Jarvis et al. (2013) and Jorda et al., (2015). OTIM-DB contains information about the near-saturated hydraulic conductivity obtained from tension-disk infiltrometer between 0 and -10 cm tension . OTIM-DB also includes metadata on the soil (texture, bulk density, organic carbon content, WRB classification), 23 climatic variables that were assigned based on the coordinates of the measurement locations, among them annual mean temperature and precipitation, methodological setup (disk diameter, method with which infiltration data is converted to hydraulic conductivity, month of measurement) and land management practices (land use, tillage, cover crops, crop rotation, irrigation, compaction). All data in OTIM-DB were manually extracted by researchers from 172 source-publications. The collected data was then cross-checked by another researcher to catch typos and misinterpretations of the published information. The OTIM corpus consisted of the entire texts of the 172 source-publications used in OTIM-DB.

In contrast, the Meta corpus contained only abstracts, namely the one of the primary studies included in the meta-analyses by EJP SOIL - CLIMASOMA (2022) Chapter 1 which investigated how soil hydraulic properties are influenced by soil management practices. This Meta corpus contained 1469 publications. By number of publications, it was substantially larger than the OTIM corpus. The information given in the Meta corpus was not available in a meta-database. Therefore, the validation step had to be carried out by manually extracting information from a subset of the abstracts in this corpus. The references for both, the OTIM and the Meta corpus are available on the GitHub repository of this project (https://github.com/climasoma/nlp).

2.2 Extracting plain text from the PDF format

For both corpora, all publications were retrieved as PDF files. The software "pdftotext" (https://www.xpdfreader.com/pdftotext-man.html) was used to extract the text from these PDFs. The text extraction worked well apart from one exception where the extracted text contained alternating sentences from two different text columns, making it unsuited for NLP. Other two columns publications were correctly extracted. Other methods were tested, such as the use of the Python package PyPDF2 or the use of the framework pdf.js but did not provide better results than pdftotext. The difficulty of this conversion lies in the PDF format itself that locates words in reference to the page and does not preserve information on which words belong to individual sentences or paragraphs. Recovery methods (such in pdf.js or pdftotext) use the distance between words to infer if they belong to the same sentence and detect paragraphs. This makes extracting text from PDF harder for algorithms and is clearly a major drawback of this format. In addition, text boxes and figures can span multiple text columns and make the conversion difficult (e.g. the figure caption intercalated in the middle of the text). This led Ramakrishnan et al. (2012) to develop LA-PDFText, a Layout Aware PDF to text translator designed for scientific publication (which was not used in this study due to time restriction). The addition of a hidden machine-friendly text layer in the PDF itself or the use of the full-text HTML version can possibly alleviate this issue. Another limitation of the PDF format is that tables are encoded as a series of vertical/horizontal lines placed at a given position. When converting the PDF to text, only streams of numbers can be retrieved. Rebuilding the tables based on the regularity of the spacing between these numbers is possible in some cases (e.g. Rastan et al., 2019) but nevertheless understanding what these numbers represent based solely on the headers is for now out of reach of the NLP algorithm. For this issue too, HTML format has an advantage as tables are encoded in the HTML or provided as separate .xlsx, .csv files, hence enabling easier information extraction.

However, because online HTML full-texts were not available for all documents (mostly older publications) and PDF remains the most widespread format for exchanging scientific publication, we decided to pursue the analysis with the PDF format. From the extracted full-texts, abstract and references sections were removed and only the body of the text was used to form the documents for each corpus.

Several NLP techniques were applied. Table 1 summarizes which techniques were applied to which corpus.

Table 1: Overview of NLP techniques used and corpus considered.

Technique	Corpus
Topic classification	Meta corpus
Rules-based extraction (regular expression)	OTIM corpus

Co-occurrence of practices	Meta corpus
Knowledge gap identification	Meta corpus
Relationship extraction	Meta corpus

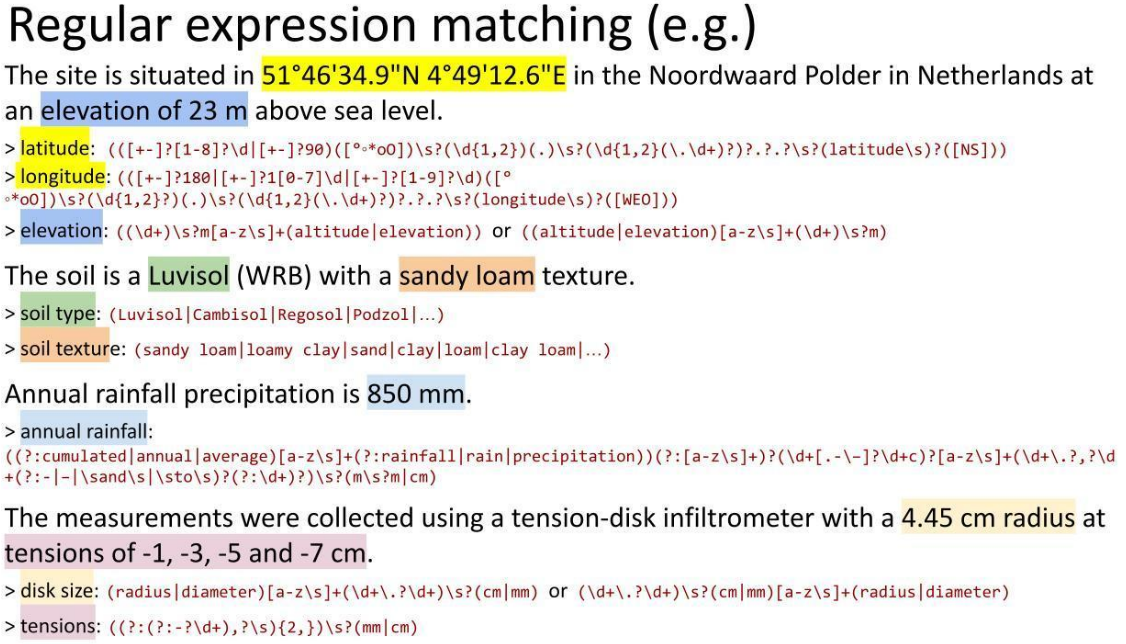
2.3 Topic modeling

Topic modeling creates topics from a corpus by comparing the similarity of the words between documents. We extracted all bigrams (two consecutive words) that occurred more than 20 times for each document in the Meta corpus. Each document was then represented by its bigrams. We found that using bigrams instead of single words help to obtain more coherent topics. This is intuitively explained by considering that the bigrams ‘cover crops’, ‘conventional tillage’ are more informative than ‘cover’, ‘crops’, ‘conventional’ and ‘tillage’ alone. Next, we removed all bigrams that appeared in less than 20 documents and more than 50% of all documents to avoid too specific or too common bigrams. Note that bigrams are usually added to monograms. However, in our case, we found that bigrams alone (e.g. ‘conventional tillage’, ‘cover crops’) led to more coherence topics than when combined with monograms (e.g. topics around ‘tillage’, ‘crops’, ‘water’). Topics were then created to be as coherent as possible using a latent dirichlet algorithm (LDA). A number of different coherence metrics exist (Röder et al. 2015). In this work, we used the LDA implementation of the *gensim* library (v4.1.2) with the C_V coherence metric. This C_V coherence metric is a combination of a normalized pointwise mutual information coherence measure, cosine vector similarity and a boolean sliding window of size 110 words as defined in Röder et al. (2015). The metric ranges from 0 (not coherent at all) to 1 (fully coherent). To define the optimal number of topics to be modeled, we iteratively increased the number of topics from 2 to 2~~4~~0 and looked at the ~~averaged topic~~ coherence. Based on this optimal number of topics, the composition of each topic was further analyzed using the figures generated by pyLDAvis package (v3.3.1) which is based upon the work of Sievert and Shirley (2014).

2.4 Rules-based extraction

Regular expressions are predefined patterns that can include text, number and symbols. For instance, disk-diameters of tension-disk infiltrometers are extracted from a text using the regular expression search term '(\d+\.\d)cm\sdiameter’, which will retrieve text passages like ‘5.4 cm diameter’. In this regular expression, \d denotes a digit, \s a space, \d+ one or more digits and parentheses are used to enclose the group we want to extract. Regular expressions are a widely used rule-based extraction tool in computer science. They have a high precision but their complexity can quickly increase for more complex patterns. Figure 1 provides examples of regular expressions used in our study. It can be observed that regular expressions for geographic coordinates are quite complex as they need to account for different notations such as decimal format (24.534 N) or degree-minute-second format (24°4’23.03" N) in the case of latitudes. In contrast, specific well-defined terms such as World Reference

Base (WRB) soil types are more easily retrieved as their wording is always unique in the text. Soil textures are likewise easy to extract but less well-defined as, for example, WRB soil types. Often, terms used to describe the soil texture of an investigated field site are also used to refer to general cases or unrelated field sites in the same text. This makes it more challenging to automatically extract information on the investigated site using regular expressions. To complicate matters, soil textures are not always given in the USDA (United States Department of Agriculture) classification system, which can be regarded as a standard. For the sake of simplicity, we did not attempt to identify the texture classification system but treated all textural information as if they were using the USDA system. When gathering information on tension-disk diameters, attention on the length units needed to be paid as well as whether the radius or the diameter was reported. In these more complex cases, we constructed the regular expression search terms iteratively to extract the greatest amount of information from the available papers. Regular expressions were used to extract latitude, longitude, elevation, soil type, soil texture, annual rainfall, disk size and tensions applied.



Regular expression matching (e.g.)

The site is situated in 51°46'34.9"N 4°49'12.6"E in the Noordwaard Polder in Netherlands at an elevation of 23 m above sea level.

> latitude: `(([+-]?[1-8]?\d|[+-]?90)([°◦*oO])\s?(\d{1,2})(.)\s?(\d{1,2}(\.\d+)?)?.?.?\s?(latitude\s)?([NS]))`

> longitude: `(([+-]?180|[+-]?1[0-7]\d|[+-]?[1-9]?\d)([° ◦*oO])\s?(\d{1,2}?)(.)\s?(\d{1,2}(\.\d+)?)?.?.?\s?(longitude\s)?([WEO]))`

> elevation: `((\d+)\s?m[a-z\s]+(altitude|elevation))` or `((altitude|elevation)[a-z\s]+(\d+)\s?m)`

The soil is a Luvisol (WRB) with a sandy loam texture.

> soil type: `(Luvisol|Cambisol|Regosol|Podzol|…)`

> soil texture: `(sandy loam|loamy clay|sand|clay|loam|clay loam|…)`

Annual rainfall precipitation is 850 mm.

> annual rainfall:
`((?:cumulated|annual|average)[a-z\s]+(?:rainfall|rain|precipitation))(?:[a-z\s]+)?(\d+[.-\-]?\d+c)?[a-z\s]+(\d+\.?,?\d+(?:-|–|\sand\s|\sto\s)?(?:\d+)?)\s?(m\s?m|cm)`

The measurements were collected using a tension-disk infiltrometer with a 4.45 cm radius at tensions of -1, -3, -5 and -7 cm.

> disk size: `(radius|diameter)[a-z\s]+(\d+\.?\d+)\s?(cm|mm)` or `(\d+\.?\d+)\s?(cm|mm)[a-z\s]+(radius|diameter)`

> tensions: `((?:(?:-?\d+),?\s){2,})\s?(mm|cm)`

Figure 1: Examples of different regular expressions used for information extraction. \d represents a digit, \s a space, . (a dot) an unspecified character, [a-z] all lower case letters and more generally squared brackets are used to denote the list of characters (for e.g. [°*o0] is used to catch the symbol of degree in latitude/longitude). A character can be "present once or absent" (\d\.?\d? will match both integers and decimal numbers), "present at least once" (\d+ will match 7, 73 and 735) or "present a given number of times" (\d{1,2} will match 7 and 73 but not 735). Parentheses are used to segment capturing groups and can also contains boolean operator such as OR denoted by | which is used to catch exact WRB soil name in (Luvisol | Cambisol | …). Non-capturing parentheses are denoted with (?:) like for the regular expression of tensions. The content inside non-capturing parentheses will not be outputted as results of the regular expression in contrast to other parenthesis groups.

To assess the quality of the extraction, different metrics were used. They are illustrated in Fig. 2. For rules-based extraction, two tasks are required by the algorithm: selection and matching. The selection task aims to assess the ability of the algorithm to extract relevant information from the text. The matching task assesses the ability of the algorithm to extract not only the relevant, but also the correct specific information as recorded in the database used for validation. For instance, if the NLP algorithm identified "Cambisol" as the soil group for a study conducted on a Cambisol, both, the selection was true positive (TP) and the matching was true. If the text did not contain any WRB soil type and the NLP did not return any, both selection and matching performed well with the selection being a true negative (TN) case. Eventually, when the NLP algorithm did not find a WRB soil type, but the database listed one, the selection was referred to as false negative (FN) and the matching as false. The opposite case, with a soil type found in the text but no entry in the database was called false positive (FP) and the matching was equally false. Eventually, there were cases where the NLP algorithm retrieved incorrect information but still provided a meaningful value, e.g. if the algorithm extracted 'Luvisol' as the soil type while the correct value was 'Cambisol'. Then the selection task was still successful since the found term represents a WRB soil type. However, the matching task failed. Such cases were still marked as true positives, but with a false matching.

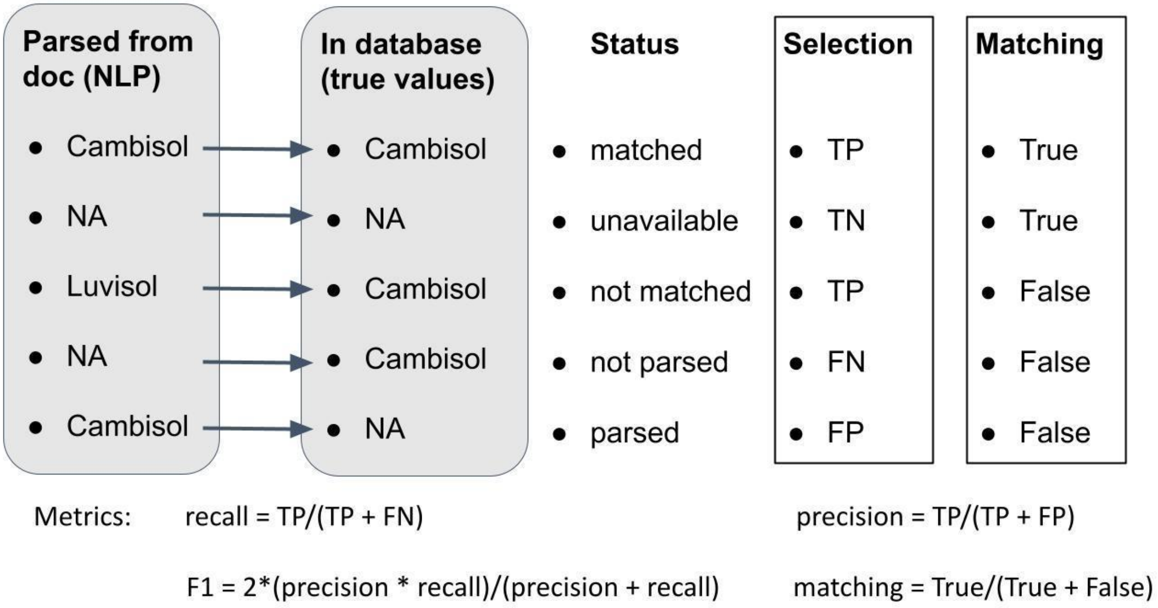
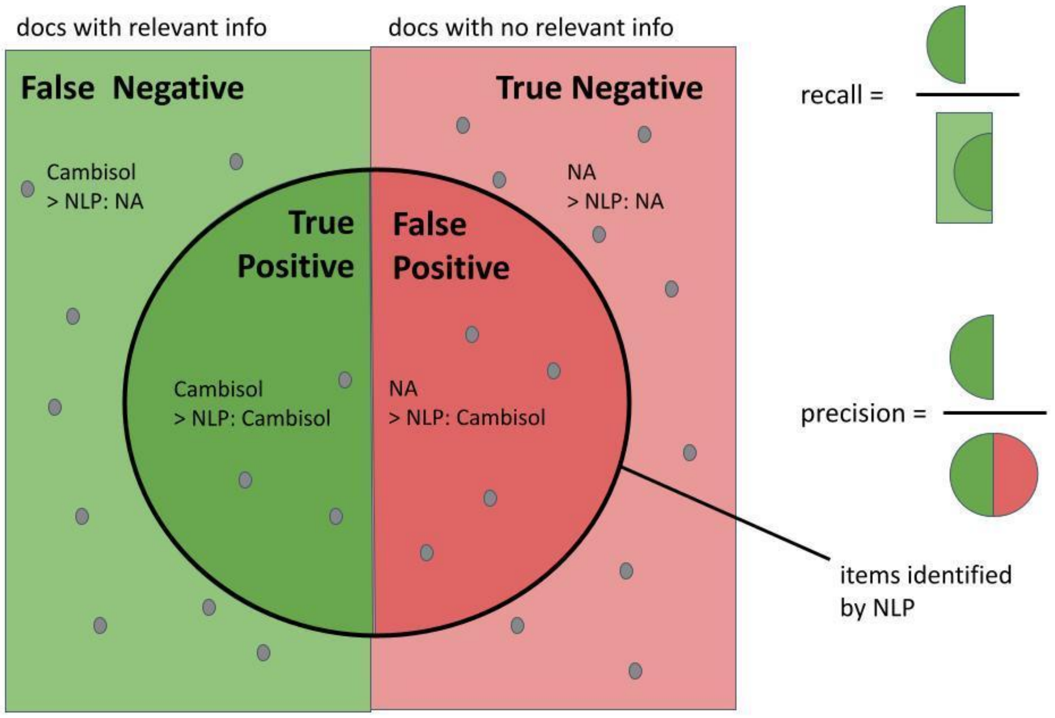


Figure 2: Cases of NLP extraction results in regards to the value entered in the database (considered the correct values) for the selection task and the matching task. TP, TN, FN, FP stand for true positive, true negative, false negative and false positive, respectively. The recall, precision, F1 score and matching values served as metrics for

each task.

Four different metrics were used to evaluate the results: the recall, the precision, the F1 score and the matching score. The recall assesses the ability of the algorithm to find all relevant words in the corpus (recall = 1). The precision assesses the ability of the algorithm to only select relevant words (precision = 1). If there were 100 soil types to be found in the corpus and the algorithm retrieved 80 words of which 40 were actually soil types, the recall was 40/100 = 0.4 and the precision was 40/80 = 0.5. The F1 score combines the recall and precision in one metric which is equal to 1 if both recall and precision were equal to 1.The recall, precision and F1 scores were used to assess the ability of the algorithm to extract relevant information from the text. Figure 2 also includes the equations for recall, precision, F1 score and matching score. Note the difference between precision and matching score: the precision expresses how many relevant words were extracted while the matching score quantifies the fraction of words corresponding to the correct information. Considering the example above, if out of the 40 correctly selected soil types, only 20 actually matched what was labeled in the document, then the matching score would be 20/100 = 0.2. Figure A1~~3~~ gives a graphical overview of the recall and precision metrics. In addition to these metrics, a matching score was used to illustrate how many NLP extracted values actually matched the one manually entered in the database. All rules-based extraction were applied on the OTIM corpus and the information stored in OTIM-DB was used for validation.



~~**Figure 3: Schematic representation of precision and recall. Recall aims to assess how much relevant information was selected out of all the ones available in the corpus while precision aims to assess how much relevant information was in the selection.**~~

In addition to the above extraction rules, we also identified agricultural practices mentioned in the publications and the co-occurrence of pairs of practices within the same publications. This enabled us to highlight which practices are often associated. To identify management practices in the OTIM corpus, we used the list of keywords from the Bonares Knowledge Library (https://klibrary.bonares.de/soildoc/soil-doc-search). Given that several keywords can relate to the same practice, the list was further expanded by using the synonyms available from the FAO thesaurus AGROVOC (Caracciolo et al. 2013).

2.5 Relationship extractions

Relationship extraction relates drivers (agricultural practices) defined by specific key terms to specific variables (soil and site properties). In this study, examples for drivers were 'tillage', 'cover crop', or ‘irrigation’. Among the investigated variables were ‘hydraulic conductivity’, ‘water retention’ or ‘yield’. A list of all considered drivers and variables is given in Table A2.

These keywords corresponded to the keywords used in early stages of assembling the Meta corpus (EJP SOIL - CLIMASOMA 2022, Chapter 1). To allow catching both plural and singular form, all drivers and keywords were converted to their meaningful root: their lemma (e.g. the lemma of ‘residues’ is ‘residue’).

~~Table A12: List of drivers and variables used in the relationships extraction.~~

~~Drivers~~	**~~Variables~~**
~~agroforestry~~	~~aggregate stability~~
~~biochar~~	~~aggregation~~
~~catch crop~~	~~available water~~
~~compaction~~	~~bulk density~~
~~cover crop~~	~~earthworm activity~~
~~fertilizer~~	~~earthworm biomass~~
~~intercropping~~	~~faunal activity~~
~~irrigation~~	~~faunal biomass~~
~~liming~~	~~hydraulic conductivity~~
~~compost~~	~~infiltration~~
~~manure~~	~~infiltration rate~~
~~residue~~	~~K~~
~~tillage~~	~~K(h)~~
~~traffic~~	~~K0~~
	~~Ks~~
	~~macroporosity~~
	~~microbial activity~~
	~~microbial biomass~~
	~~organic carbon~~
	~~organic matter~~
	~~penetration resistance~~
	~~rainwater penetration~~
	~~root biomass~~
	~~root depth~~
	~~root growth~~
	~~runoff~~
	~~soil strength~~

	~~water retention~~ ~~yield~~

The relationship extraction algorithm searched in the Meta corpus for sentences which contained lemmas of both, drivers and variables. Each sentence was then splitted in words (tokenized) and each word (token) was assigned a part-of-speech (POS) tag (e.g. noun, verb, adjective). Dependencies between the tokens were also computed. Using these dependencies as links, a graph with one node per token was built. The nodes corresponding to the driver and variables were identified and the shortest dependency path between them was computed (Fig. 34).

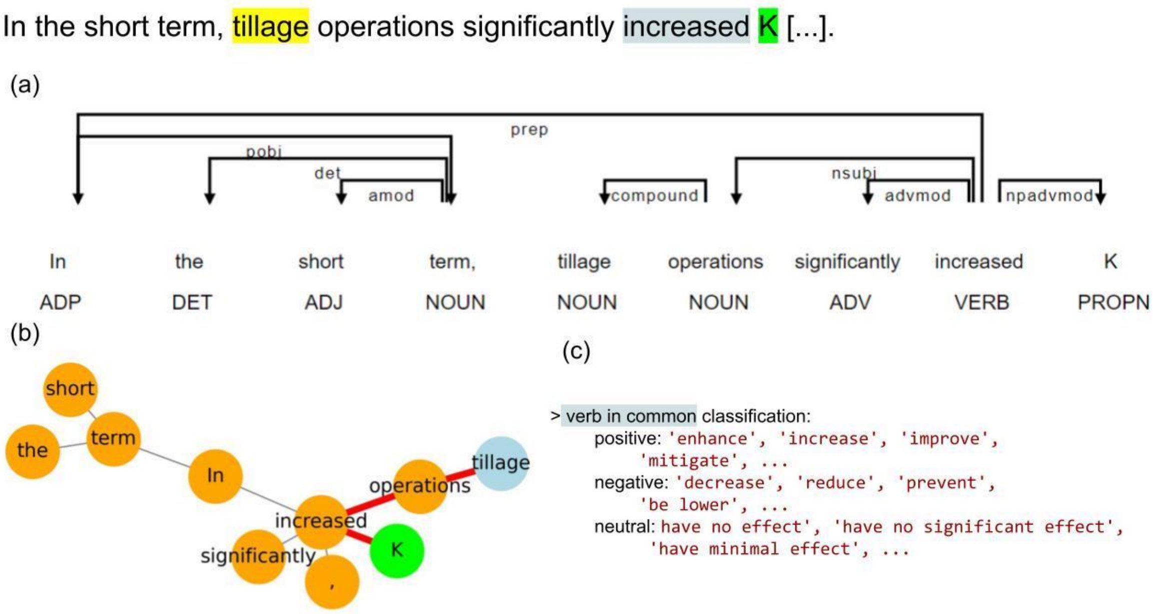

In the short term, tillage operations significantly increased K [...].
(a)
prep
pobj
det
amod
compound
nsubj
advmod
npadvmod
In ADP
the DET
short ADJ
term, NOUN
tillage NOUN
operations NOUN
significantly ADV
increased VERB
K PROPN
(b)
short
the
term
In
operations
tillage
increased
significantly
,
K
(c)
> verb in common classification:
positive: 'enhance', 'increase', 'improve', 'mitigate', ...
negative: 'decrease', 'reduce', 'prevent', 'be lower', ...
neutral: have no effect', 'have no significant effect', 'have minimal effect', ...

Figure 34: Example of NLP extraction on a sentence. (a) shows the part-of-speech (POS) tag below each token and the dependencies (arrows) to other tokens. (b) Based on these dependencies a network graph was created and the shortest dependency path between the driver (blue circle) and the variable (green circle) is shown in red. (c) The verb contained in the shortest dependency path was classified into positive, negative or neutral according to pre-established lists.

All tokens that were part of this shortest dependency path between the driver token and the variable token were kept in a list. From this list, the tokens containing the driver/variables were replaced by the noun chunk (=groups of nouns and adjectives around the token) as important information can be contained in this chunk. For instance the driver token “tillage” was replaced by its noun chunk “conventional tillage”. The list of tokens that constituted the shortest dependency path always included the main verb linking the driver and the variable token. This verb depicted a positive, negative or neutral correlation between the driver and the variable. Other modifiers such as negation marks or other modifiers that can be part of the noun chunk (e.g. ‘conservation’ or ‘conventional’ with the noun ‘tillage’) were also searched for in each sentence. In cases where a positive correlation was negated (e.g. “did not increase”, “did not have significant effect on”), the relationship was classified as neutral. Sometimes, the relationship did not relate directly to the correlation between the driver and the variable but rather mention that this relationship was studied in the manuscript. Then, the status of the relationships was set to “study”. To assess the recall and precision of the technique, a subset of 129 extracted relationships was manually labeled. Table 2~~3~~ offers examples of relationships classified by the algorithm.

Table 2~~3~~: Examples of relationships identified and their corresponding classified labels. Note that the modifiers present in the noun chunk (e.g. “conservation tillage” or “zero tillage”) and the negation in the sentence were taken into account in the status of the relationship. Some sentences contain multiple driver/variable pairs and, hence, multiple relationships. In such cases, only one of the two was indicated in the table below (but all were considered in the code).

Relationship (driver/variable in bold)	Status
In the short term, **tillage** operations significantly increased **K** (P < 0.05) for the entire range of pressure head applied [...].	positive
In humid areas, soil **compaction** might increase the risk of surface **runoff** and erosion due to decreased rainwater infiltration.	positive
Both tillage treatments were designed to prevent runoff and both increased rainwater penetration of the soil.	negative
After 3 years of continuous **tillage** treatments, the soil **bulk density** did not increase.	neutral
No-tillage increased water conducting macropores but did not increase **hydraulic conductivity** irrespective of slope position.	neutral
A field study was conducted to determine the effect of **tillage**-residue management on earthworm development of macropore structure and the **infiltration** properties of a silt loam soil cropped in continuous corn.	study
Dry **bulk density** , saturated hydraulic conductivity (Ks) and infiltration rate [K(h)] were analysed in untrafficked and **traffick**ed areas in each plot.	study

When identifying driver and variable pairs among abstracts, the case can be encountered where one of the driver/variable is expressed using a pronoun. This prevents keyword-based detection. The *neuralcoref* Python package was used to replace the pronouns by their initial form using co-references. This package uses neural networks to establish a link between the pronoun and the entity it refers to. The pronoun is then replaced by the full text corresponding to the entity. For the Meta corpus, the co-reference substitution did not enable to increase the amount of relevant sentences extracted. It turned out that the use of pronouns in the investigated abstracts was very limited. In addition, the accuracy of the co-reference substitution was not always relevant and substitution errors were more frequent than desired. For these reasons, we left this step out of the final processing pipeline. Nevertheless, we want to stress that replacing pronouns may be very useful for other corpora. Automatic relationships extraction using OpenIE was also tried but given the specificity of the vocabulary in the corpus of abstracts, it yielded relatively poor results.

To ensure reproducibility, all codes used in this project were written down in Jupyter notebooks. This enabled the results to be replicated and the code to be reused for other applications. Jupyter notebooks also enable figures and comments to be placed directly inside the document, hence helping the reader to better understand the code snippets. All notebooks used in this work are freely available on GitHub https://github.com/climasoma/nlp/.

3 Results and discussion

3.1 Topic modeling

Figure 4~~5~~ shows the evolution of the coherence metric with respect to the number of topics. The overall model~~averaged topic~~ coherence increases up to 6 topics then slowly starts to decrease. Note that the coherence scores can slightly change between runs as the algorithm starts from a different random seed to build the topics. Nevertheless, we observed a stagnation of the overall coherence after 6 topics, meaning that increasing the number of topics above 6 did not increase the overall coherence of the model.

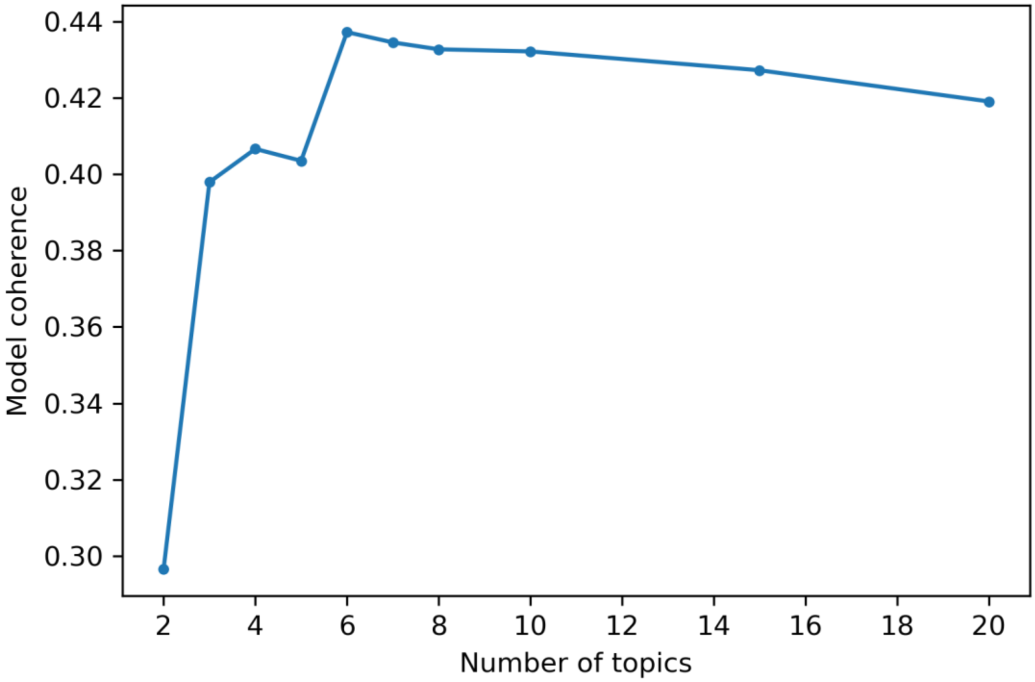


Figure 4~~5~~: Evolution of overall model coherence according to the number of topics chosen to train the LDA model. The coherence metrics is the CV described in Röder et al. (2015) which is a combination of a normalized pointwise mutual information coherence measure, cosine vector similarity and a boolean sliding window of size 110.~~ The error bars represent the standard error of the mean across the different topics~~.

Figure 5~~6~~ (left) shows the frequency of the topic in the corpus (as percentage of documents in the corpus that belong to this topic). The circles are placed according to the first two principal components based on their inter-topic distance computed using the Jensen–Shannon divergence (Lin, 1991). Topics closer to each other are more similar than topics further apart. Figure 5~~6~~ (right) shows the frequency of each bigram in the topic and in the corpus. Different themes are visible from the topics: microbial biomass and aggregate (topic 1), conventional/conservation tillage (topic 2), crop residue and crop rotation (topic 3), water retention and porosity (topic 4), infiltration rate and grazing (topic 5) and cover crops (topic 6).~~conventional/conservation tillage and crop residue (topic ~~2~~1), microbial biomass and aggregate (topic ~~1~~2), water content and ~~retention~~biochar (topic ~~4~~3), cropping system and green manure (topic 4), cover crops (topic 5), rainfall intensity and vegetation cover (topic 6)~~. The left part of Figure 5~~6~~ shows how topics 1 to~~and~~ 4 are close in contrast to topic 6 that~~2~~ mainly focus on cover crops~~microbial biomass and aggregate stability~~. These subtopics nicely correspond to some of the main drivers initially set in the search query string used to build the Meta corpus (EJP SOIL - CLIMASOMA 2022, Chapter 1).The topic modeling shows that bigrams such as “cover crops” have a large term frequency (blue bars), which means they are relatively frequent inside the set of documents. Bigrams such as “conservation tillage”, “aggregate stability” or “microbial biomass” are less frequent (smaller blue bars). The topic modeling also shows that terms such as “grain yield~~crop residue~~” appear in several topics (topic 2~~1~~ and 3~~2~~). But it is more frequent in topic 2~~1~~ than topic 3~~2~~ (size of the orange bars). On the opposite, bigrams such as “hairy vetch~~biochar applicationaddition~~” or “winter cover~~biochar amendment~~” are entirely specific to topic 6 on cover crops~~3~~. It should be also noted that bigrams such as “deficit irrigation”, while present in the corpus, do not appear in the top 6 more relevant terms. This shows that this theme is less represented in the corpus and possibly indicates a knowledge gap around it. Another possible explanation is that, while few papers mentioned “deficit irrigation”, the inclusion of monograms such as “irrigation” might have led to the construction of a topic around irrigation techniques (where papers around ‘deficit irrigation’ might have been found)~~.n~~ ~~In this regard, topic modeling can help identify knowledge gaps and quantify the extent of information available on a specific topic~~. While different runs of the LDA algorithm led to slightly different topic distributions due the randomness internally used by the algorithm, we observed the appearance of the same coherent topics around tillage, cover crops or biochar. This highlights the fact that the LDA algorithm is not a deterministic method, but a probabilistic one as the probability of a topic per document and the probability of a term per topic are iteratively optimized to maximize the coherence by the LDA algorithm. Overall, we consider that topic modeling can serve as a first tool for an exploratory analysis of the corpus content.

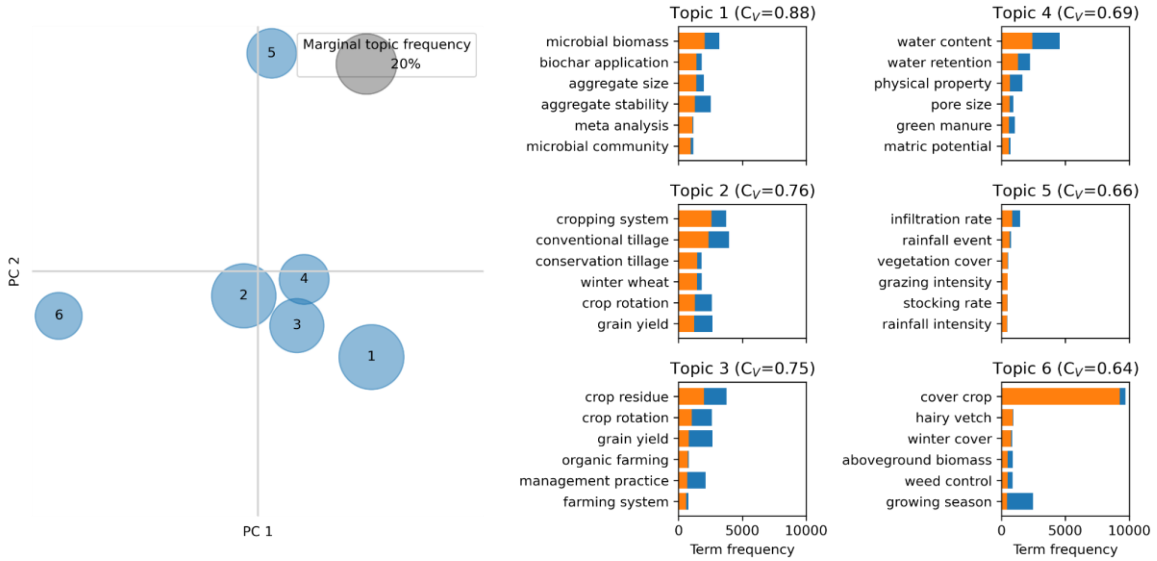


Figure 5~~6~~: (left) Map of topics according to the first two principal components after dimension reduction. (right) For each topic, the 6 more relevant bigrams inside the topic. The orange bars represent the term frequency inside the topic while the length of the full bars (orange + blue) represent the term frequency in the entire corpus. The gray circle represents the size of a topic that contains 20% of the documents of the corpus.

3.2 Rules-based extraction

Table 34 shows the metrics relative to the different rules-based extraction techniques. Note that "n" does not always represent the number of documents in the corpus as a document can contain multiple locations for instance. Regular expressions associated with a dictionary for soil texture and soil type provide the best precision overall due to their high specificity. This clearly highlights the usefulness of the international scientific community agreeing on a common vocabulary or classification system. Soil type had the highest recall, which means that all instances of soil types mentioned in the document had been successfully extracted. Regular expression matching quantities such as 'rainfall', 'disk diameter', 'tensions' or 'coordinates' had lower recall than rules making use of a dictionary. Coordinates had a high precision but a lower recall as some coordinate format could not be extracted from the text. This could be partly explained by the conversion of the symbols for degree, minute, seconds from PDF to text. As the encoding of these characters varies a lot between journals, the conversion sometimes led to "°" converted to "O", "*" or "0". Identifying all these different cases while retaining a high accuracy on more frequent cases was challenging with regular expressions.

Table 34: Scores of the rules-based extraction methods. n is the number of items to be extracted. It varies as several coordinates can be provided in the same paper. The method can use only a regular expression (regex) or a combination of regular expression and dictionary (regex + dict.).

Extracted	Method	n	Precision	Recall	F1-score	Matching
Soil type (WRB/USDA)	Regex + dict.	174	0.92	1.00	0.96	0.95
Soil texture (USDA)	Regex + dict.	174	0.95	0.88	0.91	0.83
Rainfall	Regex	174	1.00	0.81	0.90	0.89
Disk diameter	Regex	174	0.83	0.66	0.73	0.41
Tensions	Regex	154	1.00	0.56	0.72	0.31
Coordinates	Regex	209	0.92	0.77	0.84	0.73

Regular expressions have to be flexible enough to accommodate the various formats found in the publications (e.g. for coordinates) but also discriminant enough to not match irrelevant items. For instance, the regular expression about soil texture catches a lot of terms related to soil texture but not all were related to the soil texture of the actual field site. Applying regular expression on specific parts of the manuscript (for instance, just on the material and methods section), could help improve the precision of the technique. Note that the regular expression algorithm itself is infallible by nature (it will always return exactly what is matched). Rather, here, we assess our ability to generate regular expression patterns that are general enough to extract information for most cases. Adjusting the regular expression to fit all edge cases encountered is, in theory, possible but will be work intensive and will not scale well with an increasing number of papers.

In addition to extracting specific data, general information about which management practices are investigated in the studies is also important. Figure 6~~7~~ shows the co-occurrence of the detected practices inside the same document as the percentage of documents in the OTIM corpus that contains both practices. For instance, the practice of 'crop residue' and 'conversion tillage' is often found with documents that contain 'conventional tillage'. This can be put in parallel with the topic modeling where these two bigrams were often associated. 'herbicide' is also often mentioned with documents containing 'crop residue'. Given the small size of the chosen corpus, the co-occurrences need to be interpreted in connection to experimental sites chosen for tension-infiltrometer measurements and hence provide an overview of which practices have been most studied with tension-disk infiltrometers.

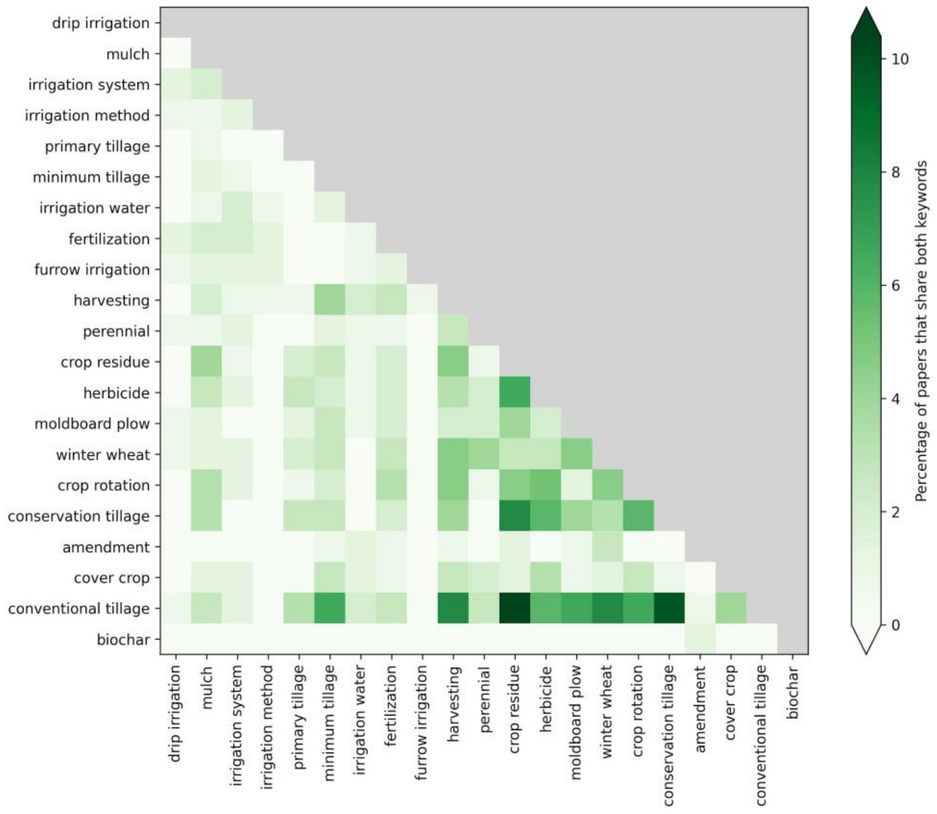


Figure 6~~7~~: Co-occurrence matrix of identified management practices from the OTIM corpus.

3.3 Relationship extraction

Figure 7~~8~~ shows the number of relationships from abstracts extracted according to the pair driver/variable identified within them. Relationships including “biochar” or “tillage” as drivers were the most frequent while “yield” was the variable most commonly found. Note as well that for some combination of drivers/variables, no statements were available. This helped to identify knowledge gaps within our corpus. For instance, the effect of liming on aggregates and infiltration properties was not studied in our corpus. Similarly the effect of irrigation on soil organic carbon was also not present in the corpus.

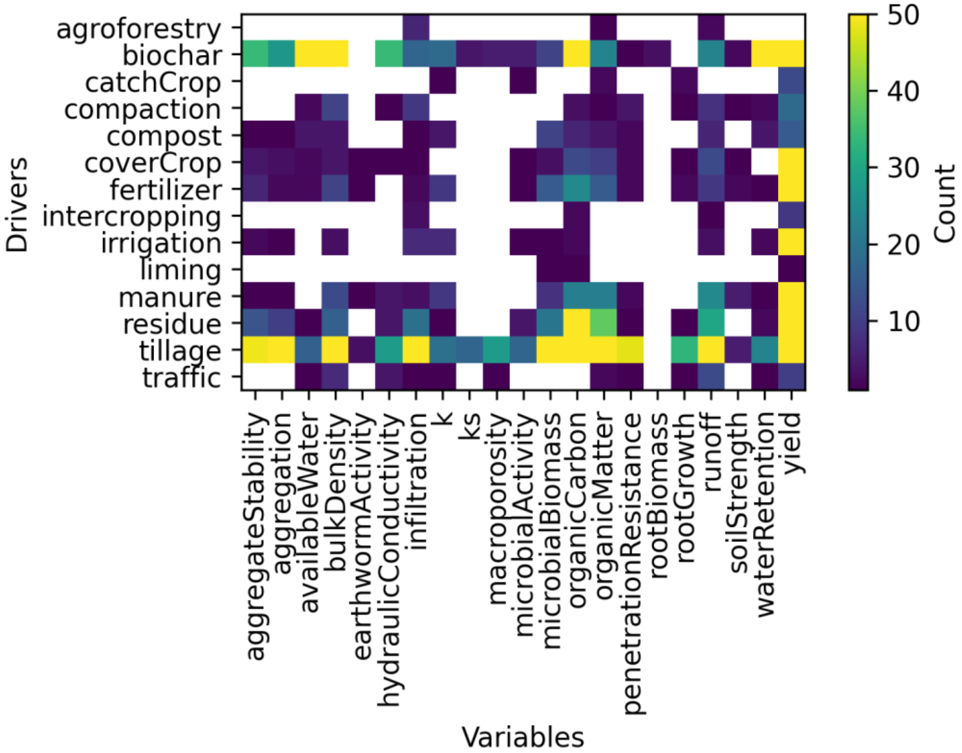


Figure 7~~8~~: Number of relationships identified from abstract according to the pair driver/variable they contain. White cells mean that no relationships were found for the pair inside. Results obtained from the analysis on the Meta corpus.

However, one important limitation of the approach is that the algorithm can only find the keywords it was told to look for. For instance, no social drivers were found in the statements as there were no keywords associated with it. Social drivers are important to estimate the acceptability of management practices (EJP SOIL - CLIMASOMA 2022, Chapter 3) and they would gain to be included in the workflow. Another limitation is the fact that the algorithm is limited to what is written in the text. For instance, in Fig. 7~~8~~, the token ‘k’, ‘Ks’ and ‘hydraulic conductivity’, all associated with hydraulic conductivity are all extracted by the NLP algorithm as they appear in this form in the abstracts. The use of synonyms can help associate tokens with similar meaning.

Figure 8~~9~~ shows the recall and the precision of the extracted relationships according to their labeled status. For each category (negative, neutral, positive or study), the dark color represents the proportion of relationships correctly identified by the NLP algorithm. The faded color represents the relationships wrongly classified by the NLP or not found at all. Overall, most identified relationships belong to the "study" class. Note as well the larger amount of "positive" relationships compared to "negative" which may be a manifestation of some bias in reporting positive results or at least writing them as positive relationships. The precision of the NLP algorithm was high for "negative" (precision = 0.88) or "study" (precision = 1.00) classes. In terms of recall, the highest score is achieved for both "positive" and "study" categories.

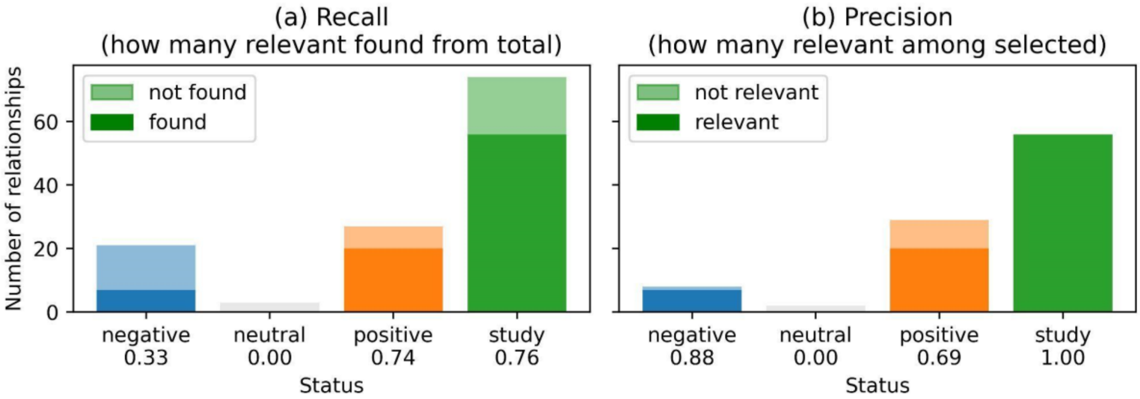


Figure 8~~9~~: Recall (a) and precision (b) of classified relationships extracted from abstracts. Dark color represents the proportion of relationships correctly classified while the faded color represents relationships not found or not correctly classified. The recall and precision metric for each category is given on the X axis. Results obtained on the Meta corpus.

Based on manually labeled relationships and the ones recovered from NLP, Figure 9~~10~~a offers a detailed comparison according to the number of statements recovered (size of the bubble) and their correlations (colors). Such a figure has the potential to be used to get a first overview of the relationships present in a large corpus of studies (e.g. for evidence synthesis). It is also comparable to figures presented in the report EJP SOIL - CLIMASOMA 2022 Chapter 1. which presents a similar layout with the results from the selected meta-analysis. Note that not all statements have the same relationships for specific driver/variable pairs (not all studies have the same conclusions), which causes the bubbles in Fig. 9~~10~~ to contain multiple colors (e.g. biochar/yield, tillage/runoff). According to the relationship extraction, compost addition was positively correlated to yield, residues were positively associated with lower bulk density and lower run-off, and biochar was negatively correlated to bulk density and positively correlated to microbial biomass. Most of these relationships correspond well to what is reported in meta-analysis (EJP SOIL - CLIMASOMA 2022, Chapter 1). As demonstrated already in Fig. 8~~9~~, the NLP did not recover all relationships perfectly (low recall for negative relationships) and can sometimes be completely wrong (e.g. residue/bulk density). But in two thirds of all cases (66%), the relationships were classified correctly.

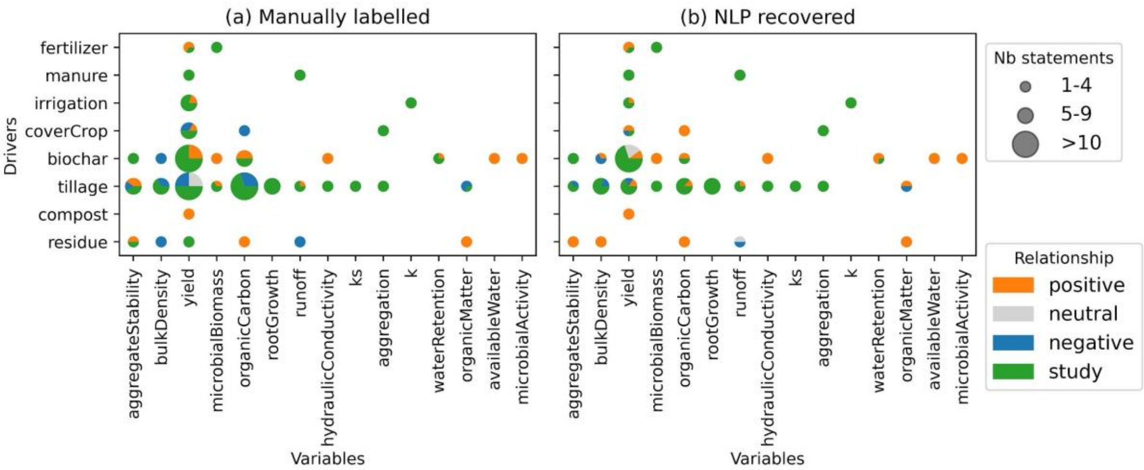


Figure 9~~10~~: Relationships between drivers and variables as (a) manually labeled and (b) recovered by NLP for the Meta corpus.

Relationship extraction based on abstract provides a quick overview of the conclusions from a given set of documents (Fig. 9~~10~~). However, the classification of the extracted relationships remains a challenging task and a lot of statements just mention that the pair of drivers/variables has been studied but not the outcome of it. That is one of the limitations of the approach as not all information is contained in the abstract. Applying this technique on the conclusion part of a manuscript could help complement the relationships found.

In addition, to confirm that the relationships extracted are well classified, one has to manually label a given proportion of the statements found and then compare the labels with the NLP finding and iteratively improve the NLP algorithm. This procedure is tedious, but needed, as general relationships algorithms (often trained on newspaper articles or wikipedia) failed to extract meaningful relationships from field-specific scientific publications. This is in agreement with the conclusions of Furey et al. (2019). However, despite our efforts, the complexity of certain sentences (long sentences with comparison and relative clauses) was too high for our algorithm to reliably detect the relationships between a driver and a variable.

4 Conclusion

With the growing body of environmental scientific literature, NLP techniques can help support the needed evidence synthesis. We explored practical applications of NLP to classify documents into topics, identify knowledge gaps, build databases using regular expression and extract the main conclusion of the abstract through relationships extraction. While NLP techniques cannot replace human intervention, their automatic nature enables to quickly process a large corpus of scientific publications. When compiling an evidence synthesis, one can start by querying online search engines with specific query strings. Sets of documents can then be analyzed using topic modeling and newer publications can be classified into the found topics. This approach enables to identify possible knowledge gaps or topics less studied. A second step would be to extract a set of specific contextual information. In this work, we demonstrated the usefulness of simple regular expressions for these tasks. Instead of manually entering data into a database form, the algorithm could prefill the form for the user to verify. The database produced can later be used for more quantitative analysis such as meta-analysis or machine learning techniques. Finally, a third step would be to extract the main conclusion of the publications. While natural language understanding is a fastly growing field, the relationship extraction algorithm developed in this work already was able to extract and classify pairs of practices (drivers) and variables (soil and site properties). While their classification remains challenging and field-specific given the complexity of human language, this approach already provides a good overview of the main conclusions drawn from a corpus of documents.

Overall the NLP techniques presented in this work have practical potential to support high-throughput semi-automated evidence synthesis that can be continuously updated as new publications become available. Given sufficient training data, the use of more advanced methods that convert sentences to numerical vectors by the use of transformer networks (e.g. BERT, Koroteev 2021), coupled with deep learning algorithms present new exciting possibilities for language understanding.

Data availability

All processing and figures presented in this manuscript are available in the form of Jupyter notebooks on the following GitHub repository: https://github.com/climasoma/nlp. Due to copyrights restriction, the papers are not provided but a list of references used is available on the GitHub repository.

Acknowledgements

This work was developed inside the CLIMASOMA project from the EJP SOIL consortium. EJP SOIL has received funding from the European Union’s Horizon 2020 research and innovation programme: Grant agreement No 862695 and was co-funded by the involved partners: ILVO, Agroscope, SLU, WUR and CREA.

Appendices

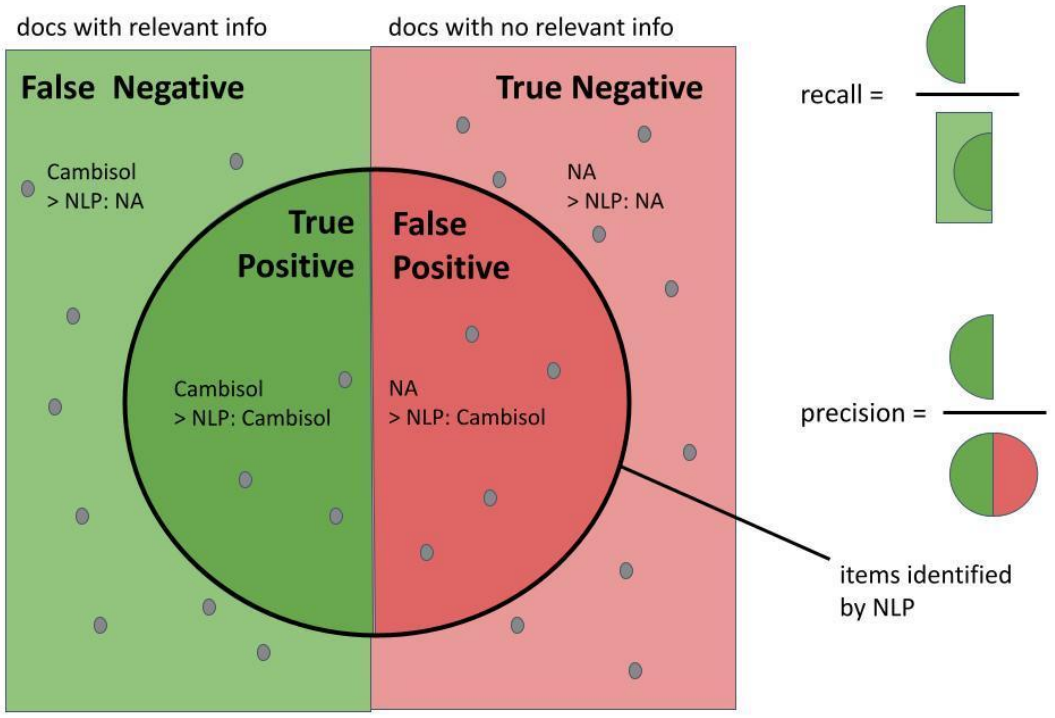


Figure A1: Schematic representation of precision and recall. Recall aims to assess how much relevant information was selected out of all the ones available in the corpus while precision aims to assess how much relevant information was in the selection.

Table A2: List of drivers and variables used in the relationships extraction.

Drivers	Variables
agroforestry	aggregate stability
biochar	aggregation
catch crop	available water
compaction	bulk density
cover crop	earthworm activity
fertilizer	earthworm biomass
intercropping	faunal activity

irrigation	faunal biomass
liming	hydraulic conductivity
compost	infiltration
manure	infiltration rate
residue	K
tillage	K(h)
traffic	K0
	Ks
	macroporosity
	microbial activity
	microbial biomass
	organic carbon
	organic matter
	penetration resistance
	rainwater penetration
	root biomass
	root depth
	root growth
	runoff
	soil strength
	water retention
	yield

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