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Abstract

Soil erosion can present a major threat for agriculture due to loss of soil, nutrients and organic carbon. Therefore, soil erosion modelling is one of the steps used to plan suitable protection measures and detect erosion hotspots. A bibliometric analysis of this topic can reveal research patterns and bibliometric characteristics, which can help to identify steps needed in order to enhance the research conducted in the soil erosion modelling field. Therefore, detailed bibliometric analysis including investigations of collaboration networks and citation patterns should be conducted. The Global Applications of Soil Erosion Modelling Tracker (GaSEM) database is enhanced with information about citation characteristics and publication type, among others. Impact of number of authors, publication type, selected journal on the number of citations is investigated. Generalized Boosted Regression Trees

(BRT) model is used to evaluate different attributes that are related to the soil erosion modelling. Additionally, bibliometric networks are visualized. This study reveals that soil erosion model selection has the largest impact on the number of publication citation followed by modelling scale and publication CiteScore. Some of the attributes such as model calibration and validation have negligible effect on the number of citations. Moreover, bibliographic coupling and citation network show a clear continental pattern, although that co-authorship is more diverse. Thus, enhanced international collaboration is needed in order to enhance the field. Moreover, when evaluating soil erosion models, additional focus should be given on field measurements, model calibration and performance assessment because the results indicate that these attributes do not have an important impact on the number of citations, which could indicate that these issuesare not given enough attention by the soil erosion modellers.

Keywords

Bibliometric analysis; Collaboration network; Literature analysis; Citations; Soil erosion

1 INTRODUCTION

The use of systematic bibliometric analysis can be a useful analytical tool to gain a better understanding of research patterns (e.g., journal, author, country) and bibliometric characteristics of research topic in any research field (Wu et al., 2015). Recent applications showed that it can be used to recognize emerging topics (Small et al., 2014), study cooperation networking in research (Wagner et al., 2015) or to gain in-depth insight into a research topic (Tang et al., 2020). A search for “bibliometric analysis” or “citation analysis” as a topic in the Web of Science Core Collection yielded in February 2020 well over 4,000 published documents each (jointly over 8,500 documents), mainly articles in journals, and with a clear upward trend in the last few years. Moreover, in SCOPUS database, a joint search in article titles, abstracts and keywords for “literature analysis” or “citation analysis” in February 2020 yielded over 11,800 documents.

Literature analysis as a tool is gaining popularity among interdisciplinary academic fields such as earth sciences. For instance, Liu et al. (2012) performed a bibliometric study of earthquake research covering the period 1900-2010, Wu et al. (2015) performed a bibliometric analysis in order to study global research trends in landslides during 1991-2014, and Emmer (2018) studied research on natural hazards worldwide during 1900-2017. Gariano and Guzzetti (2016) reviewed published papers that have investigated the past, current, and future (expected, projected) impact of climate change on landslides. Moreover, Reichenbach et al. (2018) conducted a critical review of statistical methods for landslide susceptibility modelling and associated terrain zonation. For that they used as evidence a database of 565 articles published in peer reviewed international journals from January 1983 to June 2016 and identified by a systematic search of Web of Science database using a set of keywords and criteria.

Soil erosion as a research topic in the field of earth sciences is of interest to a wide audience of researchers from different points of view. For example, from the climate change perspective (Lal, 2019), sustainable agriculture production (Tarolli et al., 2019), understanding of sediment, water fluxes and extreme storm events at catchment scales (Keesstra et al., 2018; Lizaga et al., 2019), impact of soil erosion on biogeochemical cycling (Quinton et al., 2010), or modelling of soil erosion (Batista et al., 2019; Ricci et al., 2018). A literature review on research trends and hotspots in soil erosion from 1932 to 2013 was performed by Zhuang et al. (2015), using the SCI database. According to this study, the soil research got a rapid increase since 1990 with the major contributors from the USA and Europe before 2001, and additionally from China and Australia since 2001. They also found out through co-citation analysis that soil erosion research mainly focuses on three aspects, among them on soil erosion simulation based on models. Niu et al. (2014) used a keyword analysis to find out that "evolution", "water", "soil(s)", and "model" were consistent hotspots in sediment-related research in earth science during 1992-2011. To investigate how soil erosion model evaluation is approached in soil erosion research, Batista et al. (2019) compiled a database of 550 papers published between 1958 and 2018 and taken from Web of Science using a query “soil erosion model”. However, Batista et al. (2019) did not conduct detailed bibliometric investigation and focused on much smaller number of papers. Therefore, the “soil erosion modelling” topic was selected as the research topic to be studied by a bibliometric analysis with a focus on the citation perspective. Such an analysis starts by performing an extensive search to construct a dataset related to the research topic under study, and then bibliometric analysis of the dataset compiled is conducted.

The main aim of our study is to conduct a systematic literature reviews and bibliometric analyses on soil erosion prediction modelling to disentangle how bibliometric information (e.g., journal, number of authors), modelling framework (e.g., mathematical model used, calibration, validation) and case study characteristics (e.g., location) impact on the number of citations of the different scientific literature on this topic (journal papers, conference proceedings and book series). In order to do this, the information archived in the database 'Global Applications of Soil Erosion Modelling Tracker (GaSEM)' (Borrelli et al. 2020) was used. Moreover, bibliometric networks (i.e. journals, countries) among the part of the constructed database were also analysed. Thus, the main idea of this paper is to investigate how the soil erosion study characteristics (i.e. study scale, mathematical model used, etc.) and bibliometric characteristics of a published article (number of co-authors, country of affiliation of the leading author, etc.) influence the bibliometric impact of a given publication measured by the number of citations.

The literature analysis in the topic of soil erosion modelling presented in this paper should reveal:

- How does the number of authors and journal where paper is published affect the number of citations;
- Which mathematical models are widely used and taken as a reference when citing literature and how do other modelling framework characteristics impact on the bibliometric performance;
- How can a study of citation patterns and clusters help to recognize interrelated researchers (organizations-countries) and who are leading countries and leading journals publishing research results in this topic.

2 METHODS

The global review and statistical analysis of research literature on soil erosion prediction modelling performed to create the Global Applications of Soil Erosion Modelling Tracker database (i.e. GaSEM database) is described in detail by Borrelli et al. (2020). Here, the analysis of the database offered by Borrelli et al. (2020) was enhanced by investigating the relationship between soil erosion modelling and bibliometric characteristics. In order to do this, for each of the 1,697 publication entry that is included in the GaSEM database the number of citations in the Scopus database was added. The number of citations shows the citation status in September 2019 when the number of citations database was downloaded. Additionally, Scopus CiteScore for the year 2018 of the publication (journal, conference proceedings or book series) was added to the database. Scopus CiteScore is based on the Scopus database and is for the year 2018 calculated as:

$$CiteScore_{2018} = \frac{Citations_{2017}+Citations_{2016}+Citations_{2015}}{Publications_{2017}+Publications_{2016}+Publications_{2015}}, \quad (1)$$

where "citations" and "publications" mean number of citations and citable items published in a specific year, respectively. Additionally, the number of authors of each publication was also added to the database. Moreover, for each publication (i.e. journal, conference proceedings or book series), the main (i.e. listed first) Scopus sub-subject area from the Scopus database was extracted.

Because the GaSEM database included studies published in the period between 1994 and 2018 it was decided to use the normalized number of citations, which was calculated as:

$$Normalized\ citations = \frac{Total\ number\ of\ citations}{Number\ of\ years\ from\ the\ publication}. \quad (2)$$

To investigate the impact of different soil erosion modelling characteristics on the gained number of citations, the generalized Boosted Regression Trees (BRT) model was used. This model is able to estimate the relative impact of different variables on the target variable. BRT is a machine learning tool and detailed description about the method is provided by Elith et al. (2008) and Ridgeway (2019). The BRT analysis was conducted using the program R "gbm" package (Greenwell et al., 2019). In our case, the target variable was the normalized number of citations. Next variables were used as an input to the BRT model: number of authors, publication CiteScore for year 2018, publication type, Scopus sub-subject category, erosion agent (e.g., water, wind), soil erosion model used, modelled period (e.g., present, past), continent, model time resolution, modelled area (e.g., forest, arable land), field soil sampling, scale of the study, model validation and model calibration. It should be noted that two different versions of the database were considered as an input. First one, when using all database entries (i.e. if a paper applied the same model to different catchments, this was considered multiple times) and second one where papers were considered only once (i.e. this means that different model applications were joined). Next BRT model parameters were used: minimum number of trees to 1,500, the minimum number of observations in the terminal nodes to 10, the learning rate to 0.005, number of cross-validation folds to 5 and used the Gaussian distribution was used as loss function (Greenwell et al., 2019).

As a result, the BRT model calculates the relative impact of input variables. The sum of a relative impact for all variables is 100%. The relative impact is determined considering the number of times that variable is used for splitting trees and weighted by squared improvement of the model as a result of splitting procedure where this is averaged over all trees (Elith et al., 2008; Friedman et al., 2000). The BRT model has been used successfully in different fields such as for calculating the relative impact of variables on the evapotranspiration (Maček et al., 2018) or investigating impact of different meteorological variables on the rainfall interception variables (Zabret et al., 2018).

To visualize bibliometric networks the VOSviewer software was used (Van Eck et al., 2010; van Eck and Waltman, 2010; VOSviewer, 2019; Waltman et al., 2010). VOSviewer is a freely available software that can be used for visualizing bibliometric networks, which can include journals, individual publications, authors affiliations, etc. (VOSviewer, 2019). Additional information about the software and its functionalities is provided by van Eck and Waltman (2010), VOSviewer (2019), Waltman et al. (2010). To visualize bibliometric networks, part of the GaSEM database that is included in the Clarivate Analytics Web of Science database (i.e. approx. 70%) was used. Moreover, also Schillaci et al. (2018) found approx. 60 % agreement between Scopus and Web of Science. Next type of analysis were conducted: co-authorship analysis between countries, co-occurrence analysis of keywords, citation analysis of documents, sources (e.g., journals) and countries, bibliographic coupling analysis of documents, sources and countries and co-citation analysis of cited sources (VOSviewer, 2019). In order not to stress out the personal data only investigated bibliometric networks from the country's perspective and not from the authors of organization point of view were used. Moreover, citation and bibliographic coupling analysis of most frequently used soil erosion models was also carried out. Co-authorship analysis investigates the relatedness of items based on the number of co-authored documents (VOSviewer, 2019). Co-occurrence analysis determines the relatedness of items based on the number of documents in which they occur together (VOSviewer, 2019). Moreover, citation analysis defines the relatedness of items based on the number of times that they cite each other (VOSviewer, 2019). Furthermore, bibliographic coupling investigated the relatedness of items based on the number of shared references (VOSviewer, 2019). Finally, co-citation analysis determines the relatedness of items based on the number of times that are cited together (VOSviewer, 2019). The difference between bibliographic coupling and co-citation is that in the first case link between two items that both cite the same document is considered and in the latter case a link between two items that are both cited by the same document is analyzed (VOSviewer, 2019). Full counting was used and documents with a large number of authors were not ignored. In order to achieve better readability of network visualization some thresholds were used and these are mentioned in section 3 where some of the results are presented. Due to the applied thresholds it can be argued that use of part of the initial GaSEM database (Borrelli et al., 2020) does not have significant impact on the results because this threshold would remove journal, authors, organizations, countries that do not appear frequently. For visualization, network visualization style was used where items are represented by a label and a circle. Moreover, the size of the circle and label indicates the weight of the item (i.e. the larger the circle, the higher is the weight and vice-versa). Moreover, the color of the item indicates the cluster to which the item is related. Detailed description of the clustering technique used is provided by Waltman et al. (2010). Additionally, lines represent links among items and maximum 1000 lines are displayed, which means that 1000 strongest connections are shown (VOSviewer, 2019). Furthermore, the distance between items also indicates the relatedness of the investigated items. Thus, the closer the items are together, the stronger is their relatedness (VOSviewer, 2019).

3 RESULTS AND DISCUSSION

Using the updated GaSEM database and the methodology described in section 2, the impact of different variables on the total and normalized number of citations was investigated. Firstly, the differences among different publication types, Scopus sub-subject categories and how does the number of authors and publication CiteScore impact on the publication citations was assessed (section 3.1). In the next step, the relative impact of different variables on the normalized number of citations was estimated using the BRT model (section 3.2). Then a detailed investigation of the most cited papers was carried out (section 3.3) and finally different characteristics of the bibliometric networks were visualized (section 3.4).

3.1 Publication type, journal selection and number of author's impact

Table 1 shows a comparison between papers published in journals, book series and conference proceedings included in the GaSEM database. One can notice that most (89%) of the soil erosion modelling papers are published in journals. Results in Table 1 indicate that journal papers also, on average, receive a considerably larger number of citations compared to book series and conference proceedings. The same conclusion also applies for the normalized number of citations where journal papers, on average, receive 2.78 citations per year (Table 1) against 0.42 and 0.22 of the book series and conference proceedings. Mikoš (2017) performed a comparison between the top 20 journals in 2016 from the SCI-Expanded category "Engineering, geological" and their ranking in CiteScore metrics in the category "Geotechnical Engineering and Engineering Geology". Using *Web of Knowledge* web tool *Essential Science Indicators*, the annualized expected citation rates for papers in three selected research fields for all years (average) were as follows: for Engineering 6.82 citations/paper, for Geosciences 11.34 citations/paper, and for Multidisciplinary 13.29 citations/paper. For SCI journal *Landslides* that is the top journal in the category "Engineering, geological", there are 613 documents in the database with 5,608 citations, yielding 9.15 citations/paper.

A difference between the citation rates of papers published in journals and in books or conference proceedings was also observed by Mikoš (2018) that studied 3,426 book chapters from 52 landslide-related books published by Springer Nature in the period from 2005 to 2018 in the earth sciences category, and confirmed that articles in conference proceedings are not cited as often as journal articles – the average number of citations per published chapter in these 52 books was 0.86 citations per year.

Figure 1 shows journals where more than 10 papers included in the database were published. One can notice that there are more than 20 journals that have more than 10 papers and most of them are published in CATENA followed by journals such as Land Degradation and Development, Journal of Hydrology, Geomorphology, and Hydrological Processes (Figure 1). Furthermore, Scopus also relates journals with primary Scopus sub-subject categories. Figure 2 shows Scopus sub-subject categories where more than 50 publications (per category) were included in the database. There are ten categories and most of the papers were published in the Water Science and Technology (journals such as Journal of Hydrology or Hydrological Processes) and Earth-Surface Processes categories (journals such as CATENA or Geomorphology). These two categories have around 200 publications whereas other seven categories shown in Figure 2 have from 50 to 90 papers and Geography, Planning and Development category has around 130 papers. Considering papers published in these categories, mean number of normalized citations was also calculated. Thus, Figure 2 shows the relationship between the mean number of normalized citations per publication and mean CiteScore for year 2018 of the category where mean was calculated, considering CiteScores for all journals in a specific category. There is a general tendency that in the field of soil erosion modelling on average, papers that are published in journals included in the Scopus sub-subject categories with lower mean CiteScore receive more citations. For example, the highest mean number of normalized citations is characteristic of the Earth-Surface Processes category in which also the highest number of papers is published. Thus, it seems that if a soil erosion modelling paper is published in a sub-subject category that is not a primary focus of the researchers that are publishing in this field, then this kind of paper receives, on average, less citations (e.g., General Environmental Science sub-subject category). Moreover, also papers that were published in journals such as SOIL journal that are included in the Soil Science category have, on average, less citations than Water Science and Technology and Earth-Surface Processes categories or even less than Forestry (e.g., Land Use Policy journal) and Development (e.g., Land Degradation and

Development journal) categories. This observation has something to do with the visibility of a published paper that is higher if published in a more focused journal than in a general one.

Table 1: Differences in the mean number and mean normalized number of citations for different publication types.

Publication type	Mean number of citations	Mean normalized number of citations [per year]	Percentage of entries in the database [%]
Journal	25.7	2.78	approx. 89
Book Series	4.8	0.42	approx. 1
Conference Proceedings	2.3	0.22	approx. 10

Figure 1: Word cloud of journals where more than 10 papers that are included in the database were published (i.e. larger font means more entries).

Figure 2: Scopus sub-subject categories where more than 50 publications that are included in the database were published. X-axis shows mean number of normalized citations per publication and y-axis shows mean Scopus sub-subject category CiteScore for year 2018. Bubble size indicates number of papers in this category.

Furthermore, the relationship between the number of citations and publication CiteScore was also analysed (Figure 3). As expected, papers that are published in journals with higher CiteScore metrics also have, on average, more citations (Figure 3). However, this dependence is not very significant and R^2 between normalized number of citations and publication CiteScore is 0.2 (p-value < $2.2*10^{-16}$) where a value of 1 would indicate a perfect linear dependence between these two variables. One can notice that papers with the very high number of the normalized citations such as Panagos et al. (2015) (i.e. the highest normalized number of citations) or Cerdan et al. (2010) were published in journals that have CiteScore lower than 6 (Figure 3). However, it is also true that Van Oost et al. (2007), (Borrelli et al., 2017) and Quinton et al. (2010), which have a high number of normalized citations were published in journals with high CiteScore (i.e., Science, Nature Communications and Nature Geoscience, respectively). Additionally, it is also true that papers published in low impact journals (i.e. CiteScore less than 1.5) do not receive more than five citations per year, while there is no paper with more than 60 citations in the analyzed database (Figure 3). Papers published in journals with CiteScore between 1.5 and 6 can have either a low number or a relatively high number of citations (Figure 3). As Seglen (1998) stated, it would nevertheless seem that scientific papers receive their due citations largely independently of the journals in which they appear, i.e., the journal impact is determined by the articles, not vice versa.

For majority of scientific disciplines the citability of publications increases with the number of co-authors (e.g., Abramo and D'Angelo, 2015). Therefore, the relationship between the number of publication authors and the normalized number of citations was investigated (Figure 4). It seems that in the soil erosion modelling field large number of authors does not necessarily guarantee also large number of citations and no clear relationship between number of authors and citations per year can be found (Figure 4). More specifically, the 7 publications that have more than 30 citations per year have 2, 5, 6, 8, 13, 14 and 19 authors, respectively (i.e. Borrelli et al., 2017; Cerdan et al., 2010; Fu et al., 2011; Panagos et al., 2015; Quinton et al., 2010; Syvitski and Milliman, 2007; Van Oost et al., 2007). These are publications that have based on the secondary y-axis more than 30 normalized citations. All other publications included in the database receive less than 20 citations per year (Figure 4). On the other hand, it is also true that all single-authored publications have less than 10 citations per year (Figure 4). One can also see that soil erosion modelling studies are most often conducted in groups between two and six co-authors (Figure 4). Moreover, relatively low number of papers were co-authored by more than 10 researchers (Figure 4). In addition, 8.5 % of the papers included in the database have not yet received any citation. This value is close to the value report by Van Noorden (2017) that showed that about 10% of papers is uncited. Moreover, Ioannidis et al. (2019) and Van Noorden and Singh Chawla (2019) pointed out that the median self-citation rate in the constructed database was around 12.7%. According to the soil erosion modelling database used and Web of Science (WoS) database 12% of citations are attributed to the self-citations.

Figure 3: Relationship between publication CiteScore for year 2018 and total and normalized number of citations for database entries. Best-fit linear functions are also shown.

Figure 4: Relationship between number of authors and total and normalized number of citations for soil erosion modelling database entries (upper plot) and another graphical representation of the total number of citations and number of authors using 10 bins (below plot).

3.2 What does affect the number of citations in soil erosion modelling

Overview of the citation characteristics from the publication type, Scopus sub-subject category, journal and number of publication authors indicated that some differences exist among soil erosion modelling publications (section 3.1). Moreover, the impact of these variables on the normalized number of citations was also studied. For this purpose, the Boosted Regression Trees (BRT) model was applied. Additional variables were included in the BRT model (description is available in section 2). Table 2 shows relative impact of different variables using two versions of the database. One can notice that there are not many differences in the results if papers that apply the same model or multiple models to different catchments are considered only once (Table 2). Quite surprisingly, the soil erosion model selection has the larger relative impact on the normalized number of citations. Model selection is followed by soil erosion modelling scale, publication CiteScore, Scopus sub-subject category, continent and number of authors (Table 2). Other considered variables have according to the results of the BRT model no significant impact on the normalized number of citations (Table 2). Next sub-section provide discussion about the impact of these variables. Impact of the publication CiteScore, Scopus sub-subject category and number of authors was already discussed in section 3.1..

Table 2: Relative impact of different variables on the normalized number of citations. Relative impact was calculated using generalized boosted regression tree (BRT) model.

Variable	Relative impact using all database entries [%]	Relative impact using only unique entries [%]
Soil erosion model used	48.9	50.9
Modelling scale	20.6	23.0
Publication CiteScore	17.4	22.3
Scopus sub-subject category	9.7	2.5
Continent	3.2	0.2
Number of authors	0.2	1.1
Publication type, erosion agent, modelled area, modelled period, model time resolution, field activity, soil sampling, model calibration, validation of results	0	0

3.2.1 Soil erosion model

Table 3 shows the mean normalized number of citations for different soil erosion models. One can notice that, on average, the largest number of citations receive studies that use WaTEM/SEDEM model. There are several studies with more than 12 citations per year using this model (Bakker et al., 2008; Feng et al., 2010; Quinton et al., 2010; Van Oost et al., 2000; Van Rompaey et al., 2005). WaTEM/SEDEM is followed by the STREAM (e.g., Simonneaux et al., 2015), RHEM (e.g., Nearing et al., 2011), RUSLE2 (Sahoo et al., 2016), EROSION 3D (e.g., Routschek et al., 2014), EPIC (e.g., Gao et al., 2017), PESERA (e.g., Kirkby et al., 2008) models. STREAM, RHEM, RUSLE2, EROSION 3D, EPIC, PESERA are used by less than 1.5% of studies/catchments included in the database. If one compares USLE and RUSLE models it can be seen that the revised USLE model version on average receives 0.8 citations per year more than the original version. It should be also noted that SWAT model is relatively widely used (i.e. in around 6% of papers in the database) and on average papers using this model receive more citations than RUSLE and USLE models (Table 3). Papers with the highest number of citations per year that use SWAT model are Betrie et al. (2011), Gessesse et al. (2015) and Yesuf et al. (2015). Similar relationship among most frequent cited soil erosion models is obtained also in case that only unique entries are considered where most of the models have a bit lower mean normalized number of citations; but also in this case the highest number of normalized citations is characteristics of the WaTEM/SEDEM model. Moreover, it can be also seen that RUSLE model has the largest number of total citations (i.e. multiplying normalized citations and percent of database entries), followed by the WaTEM/SEDEM, USLE, SWAT and WEPP models. Moreover, it was checked if the higher average number of citations is perhaps due to the self-citations of authors that are using specific models. The comparison was done for the WaTEM/SEDEM, SWAT, RUSLE, USLE and WEPP models. However, the self-citation in the case of specific models was similar where the maximum value was characteristic of the RUSLE model with around 8%. Other models had self-citation rate equal to around 5%. Moreover, there are also some differences among the Scopus sub-subject categories and most frequently used models. For example, most frequently used models in the Water Science and Technology category are RUSLE and USLE whereas WaTEM/SEDEM model is only used in a small number of studies included in this category. Similar pattern can be seen for the Forestry, Geography, Planning and Development and General Earth and Planetary Sciences. On the other hand, in the Earth-Surface Processes category RUSLE and USLE models are less frequently used and WaTEM/SEDEM model is more frequently used than in case of the Water Science and Technology category. Additionally, some differences also exist in different publication types. For example, WaTEM/SEDEM model is only included in journal publications. Moreover, it seems that USLE model is used in almost half of the publications that are published as book series and in about 40% of publications in case of conference proceedings. While in case of journals, USLE is used by 27% of publications. Similar pattern can also be seen for the RUSLE model.

A comparison of models used for soil erosion assessment in Chinese Loess Plateau (Li et al., 2017) that found eleven empirical and process-based models, showed that even for regional studies many different models are applied. Batista et al. (2019) investigated soil erosion models from the performance perspective and found out that different models do not systematically outperform each other. Validation or uncertainty evaluation is in many cases as important as the choice of a soil erosion model. Thus, differences in the mean number of citations shown in Table 3 cannot be explained with better model performance.

Table 3: Mean normalized number of citations where different soil erosion models were used. Only models that were used in more than 15 publications are shown and all the database entries were considered. Models are sorted based on the mean normalized number of citations.

Soil erosion model	Mean normalized number of citations [per year]	Percentage of entries in the database [%]
WaTEM/SEDEM	8.9	4.6
STREAM	6.2	< 1
RHEM	5.1	1.5
RUSLE2	4.0	<1
EROSION 3D	3.9	<1
EPIC	3.8	<1
PESERA	3.7	<1
MMF	3.7	1.6
USPED	3.2	<1
SWAT	3.1	6.1
RUSLE	3.1	16.8
ALISEM	2.9	1.9
WEPP	2.8	6.3
Customized approach	2.6	1.8
USLE	2.3	13.6
AnnAGNPS	2.2	1.5
GeoWEPP	1.9	<1
RUSLE-SDR	1.9	3.8
MUSLE	1.9	1.7
USLE-SDR	1.7	2.1
Unknown	1.3	1.2
EPM	1.2	<1
RUSLE/SEDD	0.8	<1

3.2.2 Scale and continent impact

According to the BRT model, besides soil erosion model used and variables that were also investigated in section 3.1 also the scale of the study and the investigated continent have impact on the normalized number of citations. Table 4 and Table 5 show mean normalized number of citations for these two cases. As one could expect, global studies, on average, receive much more citations than studies that are dealing with some specific local catchment or even performing soil erosion modelling at regional scale (Table 4 and Table 5). Examples of highly cited global scale studies are Borrelli et al. (2017), Quinton et al. (2010), Syvitski and Milliman (2007), Van Oost et al. (2007), Yang et al. (2003). Moreover, examples of highly cited soil erosion modelling studies that focused on the continental scale are Borrelli et al. (2016), Bosco et al. (2015), Cerdan et al. (2010), and Panagos et al. (2015). Furthermore, it is also true that performing modelling at global or continental scale does not guarantee a high number of citations since there are also studies with relatively low normalized number of citations (e.g., Batjes, 1996; Borrelli et al., 2015; Naipal et al., 2015). When comparing the mean normalized number of citations for different continents one can notice that studies that focused on Europe, on average, receive more citations than studies dealing with catchments/areas located in other continents despite the fact that the most studies are conducted in Asia (Table 4). The co-citation investigation results are presented in section 3.4 and based on these one could also assume if the higher average values shown in Table 4 are result of the co-citations. Moreover, Borrelli et al. (2020) also showed that higher erosion rates are generally characteristic of papers dealing with Africa, Asia or even South America where some areas with very high soil erosion rates can be found. Thus, obviously calculated erosion rate does not have a direct impact on the normalized number of citations. It should also be noted that database collected by Borrelli et al. (2020) only included publications that were written in English language. Quite interestingly, studies that focused on regional and national scale do not, on average, receive more citations than studies dealing with specific watershed or even with plot scale (Table 5).

Table 4: Mean number of normalized citations per publication based on the continent of the study.

Investigated continent/area	Mean normalized number of citations [per year]	Percentage of entries in the database [%]
Global	17.5	0.8
Europe	3.8	30.7
Africa	2.5	8.2
North America	2.5	20.5
Oceania	2.3	3.5
South America	2.1	4.2
Asia	2.0	32.1

Table 5: Mean number of normalized citations per publication based on the scale of the study.

Scale of the soil erosion modelling	Mean normalized number of citations [per year]	Percentage of entries in the database [%]
Global	18.8	0.6
Continental	10.6	0.4
Farm/landscape	4.5	0.7
Regional	2.8	13.7

Watershed	2.8	58.0
Plot	2.7	13.4
National	2.4	2.2
Hillslope	2.3	10.2
Unknown	0.9	0.6

3.2.3 Other variables with negligible impact according to the BRT model

Several other variables were also used as an input to the BRT model but according to the results presented in Table 2 these variables do not have an impact on the normalized number of citations (Tables 6-12). Table 6 shows comparison between different erosion agents. One can notice that papers dealing with tillage and harvest erosion, on average, have slightly more citations than studies dealing with water or wind erosion (Table 6). Multiple examples of highly cited papers dealing with these two erosion agents can be found (De Alba et al., 2004; Quinton et al., 2010; Verstraeten et al., 2002). However, it is also true that tillage and harvest erosion is only investigated in less than 2% of publications included in the database.

Table 7 shows how does the investigated time period impacts on the mean number of citations per year. One can notice that, on average, more citations receive papers that are dealing with both future and present or with present and past compared to papers dealing only with present or only with future. Thus, this can be seen as relatively surprising result because term “climate change” and “future projections” are hot scientific topics. For example, Web of Science topic “climate change” search shows that number of papers where this topic is mentioned is significantly increasing (i.e. 241 in 1990, 2,655 in 2000, 11,630 in 2010 and 33,814 in 2018). Similar trend can also be found for the “future projections” Web of Science search. However, in the field of soil erosion modelling obviously focusing on future projections is something that does not yield, on average, more citations than dealing with past or present situation (Table 7).

Table 6: Mean number of normalized citations per publication based on the erosion agent.

Erosion agent in the erosion model	Mean normalized number of citations [per year]	Percentage of entries in the database [%]
Tillage erosion	3.3	1.8
Harvest erosion	3.1	0.4
Water	2.9	94.5
Wind	2.3	2.3
Water and wind	1.6	0.9

Table 7: Mean number of normalized citations per publication based on the investigated time period.

Investigated time period	Mean normalized number of citations [per year]	Percentage of entries in the database [%]
Present and future	3.9	5.9

Present and past	3.7	8.5
Present	2.9	52.4
Future	2.7	3.8
Past	2.4	26.6
Unknown	1.9	2.8

Figure 5 shows impact of the field activity and soil sampling activity on the mean normalized number of citations. The opposite of what one would expect, additional field activity or soil sampling does not have a significant impact on the mean number of citations of publications included in the database. It could be argued that soil erosion modelers assume that model parameters and input variables can be determined quality enough without additional field activities or that available input data are of good quality in order to conduct soil erosion modelling. Moreover, Figure 5 shows model calibration and validation impact on the mean normalized number of citations. One can notice that publications where soil erosion model was calibrated, on average, receive 0.8 citation per year more than publications where model was not calibrated. This can be connected with the conclusions made by Batista et al. (2020) who argued that model calibration seems to be the main method for model improvement in the soil erosion modelling field. Moreover, Borrelli et al. (2020) emphasized that models for which calibration is most frequently performed are LISEM, SWAT, WaTEM/SEDEM and MMF. SWAT, WaTEM/SEDEM and MMF are also models that, on average, receive more citations than more frequently used USLE or RUSLE models (Table 3). Additionally, Batista et al. (2019) also pointed out that focus on model validation should be replaced with the uncertainty assessment or model evaluation since no model can be completely valid since all models are only simplified representation of the environmental processes. This of course also applies for all other environmental models (e.g. Beven and Young, 2013). However, since model validation is presenting terminology that is still used in the field this was included in the global review and statistical analysis performed by Borrelli et al. (2020). Based on the results shown in Figure 5 one could argue that model validation or evaluation, on average, leads to slightly larger number of citations as if this step is not performed.

Figure 5: Mean number of normalized citations per publication based on the field activity, soil sampling activity, calibration attempt and validation attempt. Numbers written at the top of bars indicate the percentage of entries in the database.

Two additional variables were used as an input to the BRT model, these were temporal model resolution and modelled area. Table 8 shows comparison between mean normalized number of citations for the different model temporal resolutions. However, results for the modelled area (e.g., agriculture, forest, bare soil, all land types) are not shown since no significant differences among different types were detected. Regarding the model temporal scale one can notice that if daily time step is used then such papers, on average, receive more citations than publications where model is applied on annual or monthly time scale (Table 8). These differences can be related to the results shown in Table 3 because for example SWAT model can only be used at daily time step and RUSLE and USLE should be used at annual resolution. As pointed out by Govers (2011) care should be taken when performing soil erosion modelling as for example USLE model was developed for the long-term annual soil loss assessments and not for short time period calculations. Gessesse et al. (2015) is an example of a study that used daily time step model and has a large number of citations.

Table 8: Mean number of normalized citations per publication based on the temporal model resolution.

Temporal model resolution	Mean normalized number of citations [per year]	Percentage of entries in the database [%]
Sub-hourly	3.6	6.4
Daily	3.3	17.9
Annual	3.0	25.0
Monthly	2.8	9.0
Unknown	2.6	31.0
Event	2.2	6.5
Hourly	2.1	3.0
Seasonal	1.8	1.2

3.3 Most cited papers

In the next step of this bibliometric investigation, the 20 most cited papers included in the database where the most cited papers were selected based on the normalized number of citations were analysed in detail (Bakker et al., 2008; Benavides-Solorio and MacDonald, 2001; Betrie et al., 2011; Borrelli et al., 2017; Cerdan et al., 2010; Fu et al., 2011; Ganasri and Ramesh, 2016; Gessesse et al., 2015; Haregeweyn et al., 2017; Leh et al., 2013; Panagos et al., 2015; Parras-Alcántara et al., 2016; Prasannakumar et al., 2012; Quinton et al., 2010; Syvitski and Milliman, 2007; Van Oost et al., 2007, 2000; Van Rompaey et al., 2005; Viglizzo et al., 2011; Yang et al., 2003). It can be seen that these papers were published in almost 20-year time window. Number of authors ranges from 2 to 19 with an average of 6.4. Moreover, these papers were published in 17 different journals, which indicates that none of the journals has dominant impact in the publishing of the most cited papers. Figure 5 shows affiliations of authors (counties) of these 20 most cited papers. One can notice that authors of the most cited papers are mostly coming either from Europe or from the United States. This presence of EU countries could partly explain higher normalized citations of publications that investigated EU areas (Table 4), if it is assumed that EU authors mostly investigated EU catchments/areas. Additional networking analysis are shown in section 3.4. Moreover, Figure 6 also shows word cloud of the most frequently used words in the titles of the 20 most cited papers about soil erosion modelling. It can be seen that word “Europe” appears, which confirms previously mentioned hypothesis. Additionally, words as “land”, “soil”, “erosion”, “model” could be expected in such a word cloud since the focus in on soil erosion modelling but words such as “change”, “impact”, “risk” and “assessment” indicate that most cited papers are either dealing with change/variability assessment or with risk or impact evaluation. Thus, the main aim of applying the soil erosion models is to estimate the potential food and water security threats (e.g., Batista et al., 2019).

Moreover, it was also checked if any of the above-mentioned papers is defined as either highly cited paper or hot paper according to the Essential Science Indicators by the Clarivate Analytics. Hot papers by definition are papers published in the past two years that received enough citations in May/June 2019 in order to put them in the top 0.1% of papers in the specific academic field. On the other hand, highly cited papers received enough citations as of May/June 2019 to be in the top 1% of the specific academic field based on the field threshold and publication year. Moreover, it should also be noted that there are some differences in these thresholds regarding different fields (Mikoš, 2017). Borrelli et al. (2017) is by the above definition defined as hot paper. Moreover, there are six highly cited papers included in the 20 most cited in the soil erosion GaSEM database. These are Borrelli et al. (2017), Panagos et al. (2015), Cerdan et al. (2010), Fu et al. (2011) and Quinton et al. (2010) in the Environment/Ecology, Environment/Ecology, Geosciences, Environment/Ecology and Geosciences fields, respectively. Moreover, Wang et al. (2012) is a highly cited paper in the field of Agricultural Sciences and according to the soil erosion modelling database is in the top 30 most cited papers. This indicates that papers dealing with soil erosion modelling are among the highly cited and top papers in these fields, which shows the relevance of this topic for a wider scientific community. For example, Borrelli et al. (2017) was also cited by at least 3 papers in journals such as Remote Sensing, Scientific Reports, Progress in Physical Geography and Sustainability, which are not on the list of the most frequently used journals where soil erosion modelling studies are published (Figure 1).

Figure 6: Affiliations countries (left figure) and most frequent title words (right figure) of the 20 most cited papers.

3.4 Investigation of the relationship among papers about soil erosion modelling (VOS Viewer)

Additionally, bibliometric networks using the methodology described in section 2 were also analysed. Next two sub-sections present bibliometric networks from the journals and countries perspective. As mentioned in section 2 only part of the database that is included in the Web of Science database was used to the VOS Viewer software.

3.4.1 Journals

Figure 7 shows citation analysis of the soil erosion modelling database. Citation analysis indicates the relatedness of journals based on the number of times that these cite each other (VOSviewer, 2019). One can notice that six different clusters are identified (i.e. indicates with different colors in Figure 7). Quite surprisingly, CATENA journal, where most of the papers included in the database are published, (Figure 1) is clustered together with Climatic Change and Agricultural and Forest Meteorology journals, which somehow confirms assumptions made in the section 3.3 that soil erosion modelling papers are also cited in other fields since these two journals are not shown in Figure 1. Moreover, this at the same time also means that papers published in CATENA often cite papers published by these two journals. However, it is true that CATENA journal connection is the strongest (i.e. line width) with the Journal of Hydrology, Hydrological Processes and Geomorphology journals. Furthermore, one can also see that journals are not clustered in the same way as they are categorized based on the Scopus sub-subject categories. For example, Hydrological Processes journal is clustered together with Land Degradation and Development, Landscape Ecology and Soil Science Society of America journals and not for example with Journal of Hydrology or Hydrological Sciences Journal. Similar conclusion can be made for some other cluster/journals. Additionally, it can be seen that journals, which title starts with word "environment" are clustered together (i.e. dark blue cluster group in Figure 7). Figure 8 shows the co-citation investigation, which shows the relatedness of journals based on the number of times that journals are cited together (VOSviewer, 2019). In this case, three different clusters are identified. In this case one can notice stronger connections of the CATENA journal with Journal of Hydrology, Hydrological Processes, Earth Surface Processes and Landforms, Geomorphology and surprisingly also with Journal of Soil and Water Conservation (Figure 8). The latter journal has relatively strong connections with Journal of Hydrology and Transactions of the ASABE journal.

Figure 7: Citation investigation of the journals with more than 250 citations.

Figure 8: Co-citation investigation of the journals with more than 250 citations.

Figure 9: Bibliographic coupling of journals with more than 250 citations.

Figure 9 shows bibliographic coupling of journals with more than 250 citations where this kind of investigation shows the relatedness of journals based on the number of shared references (VOSviewer, 2019). In this case, four different clusters are identified. For example, CATENA journal has strong connections with Geomorphology, Hydrological Processes, Journal of Hydrology and Environmental Earth Sciences journals (Figure 9). Otherwise, some of the identified connections are similar to the ones shown in Figure 8.

3.4.2 Countries

In the next step, bibliometric networks from the country's perspective were investigated. Figure 10 shows bibliographic coupling of countries with more than 12 documents in the database. As mentioned, bibliographic coupling indicates relatedness of shared references. One can notice that three clusters are identified whereas one of the clusters only include two members (i.e. Japan and Ethiopia). Quite interestingly, all European countries except Turkey, which is partly in Europe and partly in Asia, are clustered together. This means that authors from Europe usually cite similar references and these are at least to some extent different to the ones that other countries are using. Moreover, some regional European patterns can also be seen (i.e. position of the countries in the plot) whereas for example Italy and Greece or Belgium and Netherlands are located close together. Moreover, connection of the USA with China is stronger than connection with European countries. Bibliographic coupling of organizations was also tested and found out that three major clusters appear, first one with European organizations (mostly from Belgium and Netherlands), second one with mainly Chinese organizations and third one mainly with USA organizations. Thus, it seems that reference lists in the field of soil erosion modelling are very regionally focused.

Figure 10: Bibliographic coupling of countries with more than 12 documents in the database

Additionally, Figure 11 shows citation analysis from the country perspective, which shows the relatedness of papers based on the number of times that these cite each other. One can notice that two clusters are identified where one includes all European countries (except Turkey) and the other cluster includes all other countries with more than 12 documents. Thus, the pattern is very similar to the one shown in Figure 10, which indicates that not only that European authors use similar references but also these papers are cited by each other. Thus, this kind of pattern could partly explain the results shown in Table 4, which shows that papers dealing with European areas/catchments, on average, receive more citations. It seems that papers dealing with other continents often cite also papers from different continent whereas for Europe this is more regionally based.

Figure 12 shows co-authorship of papers from the country's perspective. Similarly, as in Figure 10 and Figure 11 one can notice relatively strong connection between USA and China. Moreover, four clusters are identified whereas one of these is composed only from the European countries. However, France, Germany and Netherlands are located in different cluster than most of the European countries. Thus, co-authorship of documents is a bit more international but still, as one could expect, some strong regional connections can be detected. Similar investigation was also performed from the organizations point of view and in this case different organizations were more regionally clustered (e.g., Belgium and Netherlands organizations together, Chinese organizations together, etc.).

Figure 11: Citation of countries with more than 12 documents in the database.

Figure 12: Co-authorship of papers from the country's perspective for countries with more than 12 documents in the database.

3.4.3 Models

The citation and bibliographic coupling networks of 12 most frequently used soil erosion models was also investigated. Figures 13 and 14 show the results obtained using the VOSviewer (2019). One can notice that USLE, RUSLE, USLE-SDR and RUSLE-SDR are clustered into one group. This means that publications that discuss or apply these models often cite similar literature and they also often cite each other. This can be regarded as an expected result since these interrelated models have the same theoretical background and were all developed based on USLE model. WaTEM/SEDEM model is in both cases (i.e. citation and bibliographic coupling analysis, respectively) clustered into a different group despite the fact that soil loss calculations in this model are based on RUSLE equation (Van Rompaey et al., 2001). In the case of the bibliographic coupling analysis (Figure 13), MUSLE model is also clustered in a one-group member while in case of the citation analysis this model is part of a cluster with more models (Figure 14). Other larger cluster of models mostly contains physically based models such as WEPP, LISEM or RHEM. Therefore, it seems that in terms of citations and bibliographic coupling there exist some differences between more empirical based and more physically based soil erosion models.

Figure 13: Citation network of 12 most frequently used soil erosion models.

Figure 14: Bibliographic coupling network of 12 most frequently used soil erosion models.

4 CONCLUSIONS

Based on the presented extensive bibliometric investigation, next conclusion can be made that are relevant for the soil erosion modelling community:

-Journal publications, on average in the field of soil erosion modelling, receive much more citations than conference proceedings and book series.

-Papers published in the Scopus Earth-Surface Processes category have, on average, the highest number of normalized citations. This category also has the largest percent of papers. If soil erosion modelling paper is published in a category that is not “primary” focus such as General Environmental Science then it obviously receives less citations despite the fact that the mean CiteScore of this category is higher. Moreover, soil erosion modelling studies are mostly published in journals such as CATENA, Land Degradation and Development, Journal of Hydrology, Hydrological Processes or Geomorphology. These journals are mostly categorized in the group of journals with CiteScore larger than 25% quantile (Q1) but are not in the top 1 or 2% of the category journals.

-Journal CiteScore obviously has some impact on the number of citations that papers receive but this dependence is not very significant. Papers published in very low impact journals do not obtain many citations. Moreover, highly cited paper can also be published in the journal with moderate or high CiteScore (i.e. journals with CiteScore above Q1). The paper quality or interest of the topic also plays a role in leading to the total number of citations. In addition, soil erosion modelling publications are usually co-authored by 2-6 people. Furthermore, single authored publications, on average, receive less citations.

-According to the BRT model, the model selection has the largest impact on the number of citations. This variable is followed by the modelling scale and publication CiteScore. On average, WaTEM/SEDEM model receives the highest number of citations. Moreover, there are some other differences among the most frequently used models (Table 3) whereas as pointed out by Batista et al. (2019) these are not due to outperformance of specific models. Furthermore, the reason for higher average citations of some models (e.g., WaTEM/SEDEM) is also not the self-citation, since the self-citation rate of this model is similar to the SWAT, USLE and WEPP models while research works that used RUSLE model have the self-citation rate equal to around 8%. Additionally, citation and bibliometric coupling analysis revealed that more empirically-based (e.g., USLE) and more physically-based models (e.g., WEPP) are not clustered together. Furthermore, WaTEM/SEDEM model is clustered into different group than others most frequently used soil erosion models.

-More or less as expected, papers dealing with global scale, on average, receive much more citations than papers dealing with continental, national, or smaller scale. However, it seems that papers dealing with European study sites have, on average, more citations than publications dealing with other continents. The bibliometric network investigation revealed that European countries have high level of co-citations and shared bibliographic content, which could partly explain these higher values.

-Some of the tested variables such as temporal model resolution, model calibration, model validation had according to the BRT criteria negligible impact on the normalized number of citations. Unexpectedly, papers dealing with future do not have, on average, more citations than papers dealing with past or present despite the significant growth of papers that are investigation “climate change” or “future projections” topics. Moreover, additional field activity does not lead to improvement of the citation performance. However, better citation characteristics can be seen for papers where the model was calibrated. This can be related to the fact that in the field of the soil erosion modelling model calibration seems to be the main method for model improvement Batista et al. (2019). As pointed out by Batista et al. (2019), detailed model evaluation (or validation) should be more frequently carried out in the soil erosion modelling field.

-The 20 most cited papers were analysed whereas most of the papers where authored by the organizations located in Europe and United States and published in 17 different journals. Moreover, the title of these papers often includes words such as “climate”, “impact”, “risk” and “assessment”. Some of the 20 most cited papers are also identified as highly cited or hot papers according to the Essential Science Indicators, which means that soil erosion modelling topic is of interest for a wider community. This is additionally confirmed using the bibliometric network analysis that reveals that soil erosion modelling papers are also published by journals that are not shown in Figure 1 that shows most frequently used journals where soil erosion modelling studies are published.

-Publications co-authorships are not so continentally divided as such for example co-citations but some continental patterns still exist. Connections among some countries could be expected (e.g., Belgium and Netherlands) while connections among other are more surprising (e.g., China and USA).

To sum up, this review reveals that soil erosion modelling is an important scientific topic that also attracts citations/readership from different fields. Besides the useful suggestions made by Batista et al. (2019) so as to enhance the body of knowledge on soil erosion modelling, this review identifies the following insights: (i) better international cooperation at a global scale would be needed, (ii) additional field activity/measurements, model calibration and evaluation should be carried out more frequently in order to improve model performance.

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