A Bibliometric Analysis of Input Parameter in Artificial Neural Network Approach for Groundwater Level Prediction

Putu Doddy Heka Ardana[1], I Wayan Redana[2], Mawiti Infantri Yekti[3] and I Nengah Simpen[4]

[1]Lecture of Civil Engineering Department, Ngurah Rai University, Denpasar, Indonesia
doddyhekaardana@unr.ac.id[1]
[2]Lecture of Doctoral Program Engineering Science, Udayana University, Denpasar, Indonesia
iwayanredana@yahoo.com[2]
[3]Lecture of Doctoral Program Engineering Science, Udayana University, Denpasar, Indonesia
wiwiet91@yahoo.com[3]
[4]Lecture of Doctoral Program Engineering Science, Udayana University, Denpasar, Indonesia
simpen.nengah@yahoo.com[4]

Abstract Rapid growth in the Artificial Neural Network (ANN) approach in groundwater level prediction literature calls for an assessment of the trajectory and impacts to identify key themes and future research directions. In this paper, reported a bibliometric analysis of this literature that focuses on examining input paramater uses, focus of research, and research forward. We used Elsevier's SCOPUS database, Dimensions, and Google Scholar to search for publications from January 2000 to May 2020 on the ANN approach in groundwater level prediction, and analyzed the final sample of 101 publications using RIS file from Mendeley and Vosviewer software tools. Thematic analysis of abstracts revealed a strong focus on groundwater level prediction with artificial neural network approach. The co-occurrence network map showed the hydro-climatology parameter like precipitation, temperature, and groundwater level connected with a large number of frequently used for input in ANN approach, while the evapotranspiration, evaporation, humidity, river stage, runoff parameter demonstrated much weaker links. Reflected on how these findings may useful for better understand and ultimately be able to use the other hydro-climatology input paramater on groundwater level prediction with artificial neural network approach.

Keywords: Artificial neural network, bibliometric, thematic analysis, hydro-climatology, prediction.

I. Introduction

GROUNDWATER plays an important role in water sources around the world and it is essential for a number of many purposes, such as for domestic, agriculture, tourism and industrial uses. Groundwater is the first choice in some areas because of its reliability and availability. One of the main factor in groundwater is groundwater level. The groundwater level, whether it be the water table of an unconfined aquifer or the piezometric surface of a confined aquifer, designates the height of atmospheric pressure of the aquifer [1]. Any occurrence that generates a variation in pressure on groundwater will cause the groundwater level to be different. Divergences between supply and withdrawal of groundwater cause levels to fluctuate. Some factors influence on groundwater level include hydro-climatology phenomena such as precipitation, evaporation, evapotranspiration, temperature, humidity; tidal phenomena; urbanization, earthquakes, external loads and streamflow variations are closely related too.

In groundwater management, the role of groundwater level fluctuations is very important. Groundwater storage and mobility are mostly influenced by relative water level or water table variations at neighboring locations. Water table fluctuation also influences optimal crop production. Therefore, rapid and precise water table prediction in areas under deliberation can help water resource users in developing better water resource planning [2].

Physical models [3]–[5], water balance models [6], and statistical regression models [7], [8] have been developed in the past to simulate water table variation in different areas. However, all of these models need extensive observations to perform the modeling. In addition to mathematical modeling, Artificial Neural Network (ANN) modeling provides another approach to predict water table fluctuation. The technique of ANN is to mathematically model neurons and their connections to simulate the work of the human brain to get a model to a level that is able to capture and represent complex input/output relationships [2]. It has the ability to learn both linear and non-linear relationships directly from the data being modeled. ANN has the advantage of simplicity, flexibility, and accuracy. It does not need a thorough understanding of the relationship between the input and output parameters and requires only a small amount of data [9]. ANN modeling began to be applied to solving hydrological problems in the early nineties [9] and has been successfully used in rainfall-runoff modeling [10]–[12], rainfall prediction [13], [14], water quality [15], [16], sediment transport [17], [18], drought forecasting [19] and and has also been applied in predicting groundwater level fluctuations [20]–[28]. The study showed that the simulation can be performed more rapidly with the application of ANN.

Specifically in the application of ANN in the prediction of groundwater level fluctuations using various input parameters produces a satisfactory output. The parameter include precipitation, evaporation, evapotranspiration, temperature, humidity, runoff, withdrawl of well, and previous water table data were used for ANN analysis. However, there are still deficiencies in the model so a systemic literature review exclusively focusing on the input parameters in the ANN model. The novel of this study is provides a comprehensive picture from the bibliometric analysis of the use of input parameters in the model of groundwater level fluctuations, and also predicts future trends in this field. We analyzed 101 publications on groundwater level fluctuation prediction with artificial neural network from the Elsevier's SCOPUS database, Dimensions, and Google Scholar to search for publications from January 2000 to May 2020, and analyzed the final sample using RIS file from Mendeley and VOSViewer software tools. By analyzing bibliometric indicators achieved on the Elsevier's SCOPUS database, Dimensions, PubMed, and Google Scholar, we illustrated the distribution of parameter input and focus of model research. This research has a contribution in the form of ANN model input parameters that are often used in predicting groundwater level fluctuations. While the purpose of this study is to look for the other input parameters that have never been used in predicting groundwater level fluctuations.

II. LITERATURE REVIEW

In literature review section, we will discuss about groundwater table or groundwater level fluctuations, Artificial Neural Networks (ANNs) approach in groundwater level prediction, and bibliometric analysis to publication research associated with Artificial Neural Networks (ANNs) approach in groundwater level prediction.

A. Groundwater Table Fluctuations

The role of groundwater level fluctuations or groundwater table fluctuations is very important in groundwater management. Groundwater levels change for many reasons. Some changes are due to natural phenomena, and others are caused by man's activities. Any phenomenon, which produces pressure change within an aquifer, results into the change of groundwater level. These changes in groundwater level can be a result of changes in storage, amount of discharge and recharge, variation of stream stages and evaporation. Some factors influence on groundwater level include hydro-climatology phenomena such as precipitation, evaporation, evapotranspiration, temperature, humidity; tidal phenomena; urbanization, earthquakes, external loads and streamflow variations are closely related too [1].

B. ANN in Water Table Fluctuation Prediction

Artificial Neural Networks (ANNs) are part of Artificial Intelligence. They are a mechanism that reproduces the cognitive function of the brain by simulating its architecture. By imitating the human brain's structure and function, ANNs are well-known to be powerful in solving complex, noisy and non-linear problems [9]. Functional mapping between predictor input and output predictor variables are obtained from the ANNs model through the processing of historical data interrelations. ANNs are ''learning'' based models and use an empirical-based approach that often eradicates the need to include difficult-to-estimate hydrogeologic parameters that usually using physical theories and calculations to model and simulate the system [29], [30]. The use of ANN approach in predicting groundwater level fluctuations has been applied widely [2], [20], [24], [31]–[38], [39]–[42]. These research use a conventional ANNs model with various input parameters. The development of the ANN model such as Wavelet-Neural Network, Adaptive Neuro-Fuzzy Inference System, Hybrid-Artificial Neural Network, Support Vector Machines (SVMs), Extreme-Neural Network, Wavelet-SVMs, and Non-linear Autoregressive with Exogenous (NARX) Neural Network model, has also been widely used to predict groundwater level fluctuations [23], [27], [28], [43]–[52]. Based on these studies, the prediction results of groundwater level fluctuations are quite accurate. Accurate prediction of groundwater levels will help the administrators to plan better the groundwater resources.

C. Bibliometric Analysis

Analysis or bibliometric methods are sometimes also referred to as terms scientometrics is part of the research evaluation methodology, and from various much produced literature, it is possible to carry out bibliometric analysis by using its own method [53]. The bibliometric method is a method of measuring the literature with using a statistical approach so that it includes the application of quantitative analysis [54]. Various studies in different fields of science have succeeded in empowering the bibliometric method [55]–[58]. Bibliometric mapping will benefit both the scientific community and public in general because it can help turn publication metadata into maps or visualizations, which are more easily managed to be processed in order to gain insight useful, for example visualizing keywords to identify research themes or clusters in certain scientific disciplines, mapping the author's affiliations from specific journals to identify the geographical scope of the journal, and map institutional and collaboration international collaboration as part of a framework for identifying technology emerging [59].

III. METHODS

In this study, we applied bibliometric methods to assess the trajectory of research in ANN approach in groundwater level prediction literature, using the Elsevier's SCOPUS, Dimensions, and Google Scholar database and collected to Mendeley. Bibliometric analysis of a field, subject or concept is a descriptive and statistical evaluation for tracking progress and identifying areas for future research [60]. Additionally, bibliometrics is useful for identifying the impact of specific journals, authors, author networks, and individual papers but in this study it is use for identifying the parameter input of ANN model in water table fluctuation predicton.

We used "groundwater level" and "artificial neural network" to search titles, abstracts, and keywords for the year 2000 to May 2020. This resulted in a sample of 101 publications for this bibliometric study. We downloaded publications including information about authors, title, publication year, journals, author keywords, abstract, digital object identifier (DOI), and references. Then we conducted a bibliometric analysis of the 101 publications using Mendeley and export to RIS file, to assess the characteristics of the publications such as abstract and keywords. To examine the linkages among terms used in artificial neural network in groundwater table prediction literature, VOSviewer software [61] was used to create a network map of the co-occurrence of terms extracted from abstracts and author keywords. VOSviewer extracts terms in the form of noun phrases from abstracts and author keywords. We compiled and analyzed terms that co-occurred more than 5 times based on their relevance score. We then created a term network map to show co-occurrence and linkages among the terms.

IV. RESULTs

It was identified and analyzed 101 bibliometric articles from the Elsevier's SCOPUS, Dimensions, and Google Scholar database. The articles are exported to Mendeley and then exported to RIS file, inputted and analyzed with VOSViewer, the following results are obtained.

Starting from the entire text of the title and abstracts, including 2614 total terms, only 62 terms met this threshold. Using the relevance scores in VOSviewer, we determined a calculation for the level to which a term is specific and informative or general and uninformative [61]. Only the terms within the highest 60% of the relevance scores were selected,reducing the number of terms to 37. The terms were then manually screened to remove words that discussed the research process (e.g., data, research, article, svm, model) and remove synonyms (e.g., water level and water table depth, ANN and artificial neural network). Excluding such general terms left us with 5 terms in the network. Figure 1 shows the relevant terms and their network of co-occurrence. This term co-occurrence network can help us understand the knowledge components and knowledge structure of this field.

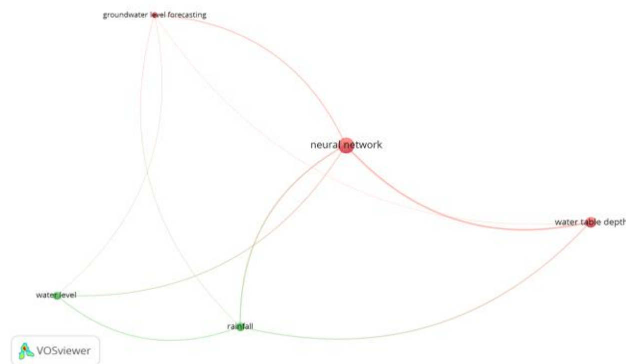

Fig 1. Network of terms from title and abstracts of the publication

According the entire text of the abstracts, including 2474 total terms, only 57 terms met this threshold. Only the terms within the highest 60% of the relevance scores were selected,reducing the number of terms to 34. Excluding such general terms left us with 5 terms in the network. The relevant terms and their network of co-occurrence showed in Figure 2.

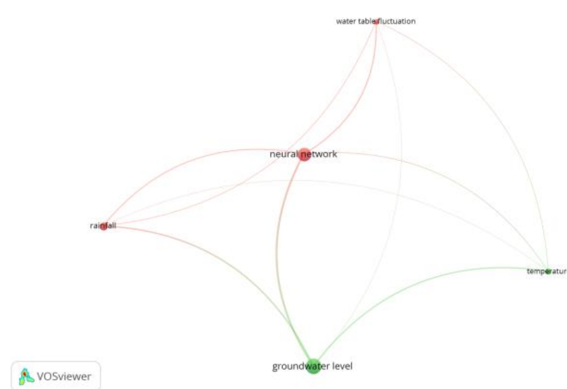

Fig 2. Network of terms from abstracts of the publication

The map from bibliographic data with co-occurrence analysis of the keywords, including 249 keywords, only 54 keywords met this threshold and the total strength of the co-occurrence links with other keywords will be calculated. The keywords with the greatest total link strength will be selected. For this analysis, the number of to be selected are

54. The keywords were then manually screened again to remove words that discussed the research process. Excluding such general terms left us with 5 terms in the network. Figure 4 shows the relevant terms and their network of co-occurrence.

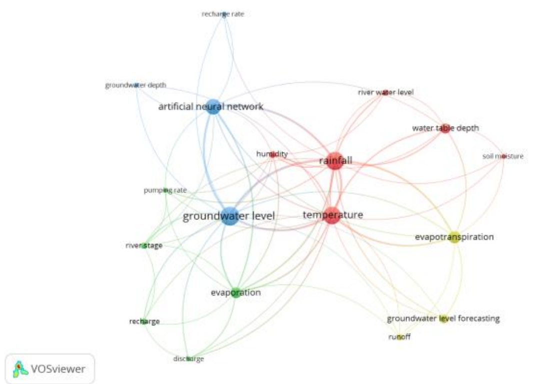

Fig 3. Network of terms from keywords of the publication

The researchers assisted by graphic analysis to classify research focuses to advance a scientific area by emphasizing terms that are not extremely associated to one another as areas for forthcoming research, by classifying terms that are lost from the network map or are inadequately signified as potential research gaps, and by categorizing the parameter input in groundwater table prediction with artificial neural networks approach. In the visualization, the size of the node designates the number of title, abstracts or keywords where the term was present. The thickness of the lines between the nodes designates the level of a straight relationship between two or more terms, the number of title, abstracts or keywords in which the two or more terms co-occurred. VOSviewer also provides distance-based visualizations of bibliometric networks, where the range between two nodes roughly shows the connection of the nodes [61].

VOSviewer also delegates the nodes in a network to clusters. A cluster is a set of closely interrelated nodes and each node in the network is assigned to exactly one cluster. The number of clusters is controlled by a resolution parameter. The higher value of the parameter, the larger the number of clusters. In the visualization of a bibliometric network, VOSviewer usages colors to show the cluster to which a node has been assigned. The terms were clustered in to four groups, as shown by the four colors in Figure 3, to reflect how the terms were linked together in the literature. The blue cluster centers on “groundwater level” and includes other terms such as “groundwater depth” and “recharge rate” which is an input paramater in groundwater table prediction with ANN model. The theme of the green cluster is other parameter input, with terms such as “evaporations”, “discharge”, “river stage” and “pumping rate”. The theme of the red cluster is parameter input too, including terms such as “rainfall”, “temperature”, “humidity”, “water table depth” and “soil moisture”. Finally, the yellow cluster includes only the two terms “runoff” and “evapotranspiration” focusing on the theme of the parameter input in groundwater level forecasting. Looking at the network map, we find “rainfall”, “temperature”, and “groundwater level” as the central nodes, with most connections to nodes in the other clusters. The description of network include number of items, number of clusters, number of links, total link strength, and minimum or maximum score of overlay showed in Table 1.

TABLE 1. THE VOSVIEWER ANALYSIS

Description	Items	Clusters				Link	Total Link Strength	Min Score Overlay	Max Score Overlay
		1	2	3	4				
Abstract and Titles	5					9	240	0.999	1.001
		Groundwater level forecasting	Rainfall	-	-				
		Neural network	Water level	-	-				
		Water table depth (link strength = 77)		-	-				
Abstract	5					10	399	0.998	1.001
		Neural Network	Groundwater level (link strength = 141)	-	-				
		Rainfall	Temperature	-	-				
		Water table fluctuation	-	-	-				
Keywords	18					67	158	0.998	1.002
		Humidity	Discharge	Artificial neural network	Evapotranspiration				
		Rainfall (link strength = 12)	Evaporation	Groundwater depth	Groundwater level forecasting	12			
		River water level	Pumping rate	Groundwater level	Runoff				
		Soil moisture	Recharge	Recharge rate	-				
		Temperature	River stage	-	-				
		Water table depth		-	-				

According to Table 1, the researchers used rainfall and water level (groundwater table) as the main input parameter of artificial neural network approach. In term “Abstract and Titles”, the strongest link is water table depth (water level or groundwater level) of 77. Based on “Abstract”, groundwater level give a value of 141 and make it the strongest link. Finally, rainfall as the strongest link from the term “Keywords” of 12. In addition, there are other input parameters such as evaporation, evapotranspiration, humidity, temperature, soil moisture, recharge rate, pumping rate, and river water level data.

V. CONCLUSION

From the VOSviewer analysis, the artificial neural network approach input parameters in groundwater level prediction that are often used can be determined. The hydro-climatology parameter such as rainfall, evaporation, evapotranspiration, humidity, temperature, soil moisture, groundwater level especially previous groundwater table data, recharge rate, pumping rate, and river water level or river stage are often used for analysis. Even though, there are still other factors that influence the groundwater level fluctuation such as infiltration, transpiration, tidal phenomena, urbanization, earthquakes, and external loads. For further research can combine parameters that have never been applied with parameters that are often used in prediction models.

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