Article: Bayesian Network Model for Flood Forecasting Based on Atmospheric Ensemble Forecasts

By: Leila Goodarzi et al.

Response to the comments of the editor and reviewers (text with marked changes attached):

Dear Reviewer and Associate Editor,

We would like to express our sincere gratitude for the insightful comments. Please see below our response to the comments. We have attached the new manuscript, where we have marked major changes in yellow color. Furthermore, we have made many formal corrections, mostly in the citations/list of references, which we have thoroughly checked for consistency.

Editor:

Many thanks for your response to the referees.

I think, that most of the referee comments have been addressed. But we need to check the new version of the manuscript.

Please in this new version include some comments about the sample size and the limitations of the method.

Thanks for your work."

Author response:

Thank you very much for appreciating our work. We have now incorporated the proposed changes of the text. In particular, we have extended the justification of using BN with a small sample size, and we discussed more extended about that aspect, limitations and future work. Our responses are the same as uploaded in the interactive discussion. Here, they are provided again together with the updated manuscript, where the major changes are marked.

Reviewer 1:

1) I have doubts about the reliability of those approaches compared to traditional methodologies, specifically the use of post-processing ensemble weather forecast as input of a distributed or lumped hydrological model. Usually, hydrological models are calibrated and validated for a long enough time-period, which ensure that they capture a wide range of hydrological conditions, including episodic floods. In this case, on the other hand, they were used 14 flood events to train and verified a BN and an ANN. Considering the large number of parameters those approaches include, a good performance and accuracy is expected. Under such circumstances, however, the risk of generating over parameterized models is significant. Although I recognize that flood events are statistically rare, it is important to demonstrate that the BN is able to capture a larger number of floods events.

Author response:

The data sample is relatively small due to the following reasons:

1) NCEP (GFS - FNL) data are not available for some historical storms.

2) During the above-mentioned period, a small number of actual flood events occurred in the study area, since the basin is located in a semi-arid region.

Considering the relatively small sample size, we proposed using the BN that is less sensitive to small data set size in comparison with ANN. We are aware that using a BN instead of a hydrological model does not remove the need for data, and we agree that data about flood events are scarce by nature. However, the number of parameters of a BN is not that high compared to distributed hydrological models. Our study is a proof of concept at the current stage that flood warnings can be done by evaluating hydrological pre-conditions and meteorological ensembles by a trained BN instead of a hydrological model. We do not yet promise that the method works in general, and further work must be done, thus we recommended future tests in the conclusions. We discussed our results accordingly. However, with the limitations described, the validation of the BN is given by the proof of better performance than the ANN.

A very useful advantage of BN is that there are no minimum sample data sizes needed to perform the analysis, and BN take into account the complete data set (Myllymaki et al., 2002). In addition, Kontkanen et al. (1997) demonstrate that BN can show good accuracy of prediction even with rather small data set and Zhang and Bivens (2007) showed that BN is less sensitive to small data set size in comparison with ANN.

The above paragraph will be added to paper.

2) Perhaps a suggestion to overcome such limitations is to analyze a longer period of time to incorporate a larger number of flood events, and using observed rainfall instead of ensemble weather forecast (which are difficult to implement) to test whether the BN performs adequately.

Author response: The purpose of this study is to develop a flood warning based on Atmospheric Ensemble Forecasts. BN model's input are Atmospheric Ensemble Forecasts and in case of using the observed rainfall, we have only a deterministic forecasting not the ensemble forecasting and that is why we didn't use the observed rainfall in our study. A BN trained against observation would not be comparable with the training against forecast ensembles. In the outlook of the article, we propose other steps to increase the confidence in the BN by increasing the lead time in large watersheds, using different cumulus schemes, etc.

3) It is well known that atmospheric models have acceptable skill scores for up to 4-5 days. Increasing the lead time will provide an opportunity for testing the use of BN for a larger number of cases.

Author response: Increasing the lead time will provide new cases but in this case we have two different sources of error: one is the different lead time (the accuracy of the numerical weather prediction would not be comparable to a single day lead time) and another source is the BN model, so we cannot realize the source of the error. In other words, we cannot determine that the forecasting error is because of the high lead time or the proposed BN model. Also, our study is conducted in a small basin, where a lead time of one day is considered sufficient and adequate. Longer lead times are more important for large watersheds, but there is a different ratio between meteorological and hydrological effects. Thus, our method is designed for, and limited to, smaller headwater basins with short lead time. We will make this clearer in the final manuscript.

Reviewer 2

1) Beginning with the part of the Atmospheric modeling and the simulations performed for the analysis, it is not quite clear but the fine domain used in the model configuration might be too close to the eastern parts of the basin. The fine domain should be depicted at the same figure with the study area (Figure 1).

Response: Thank you so much for catching this confusing issue, which we will clarify in the next version. We should explain that the red region in Figure 1 is all of the Tehran province. Our case study is a small basin in the north western part of this province, so the model configuration is not close to eastern part and we will correct the Figure 1 in new manuscript.

2) A more important issue is the lack of important information regarding the simulations such as the spin up time, the length of each simulation etc. A table including these characteristics for the 14 cases would be useful.

Response: we will add a table like the following table in the next version.

Table2. Precipitation and streamflow data

event	Observed cumulative precipitation (mm)	Observed peak flow(m3/s)	Duration (hr)
27.03.2007	25.3	24.2	15
27.04.2007	33.5	57.1	2
07.12.2007	32.3	12.7	17
03.11.2008	37.3	20.9	17
30.04.2009	29	34.4	7
04.02.2010	68.1	11.6	11
08.04.2010	48.8	34.1	29
13.03.2011	32.6	20.9	14
05.04.2011	55.5	24.5	25
29.08.2011	56.4	26.4	11
28.10.2011	55.9	55.1	23
20.11.2011	48	44.7	31
14.04.2012	67.7	67.2	15
13.11.2012	78.9	25	41

3) The initial conditions are the FNL (page 9) data from NCEP, which are a post process product. The fact that the simulations are in a hindcast mode is something that should be mentioned clearly within the manuscript. Towards this direction it would be quite interesting to also employ a model running with the NCEP forecast analysis. Additionally, it would be interesting to run the model with different forecasting horizons in order to test its performance in periods with higher uncertainties. Finally the creation of an ensemble with the implementation of different cumulus schemes is something needed to be supported better, especially considering that some of them are already known to perform better than the rest.

Response: Thank you for this suggestion. We will mention the use of hindcast mode in the next version. Regarding the use of different forecasting horizons, please see our response to reviewer 1. It is an interesting aspect, but we focused on the short term as this is the recommended lead time for the size of catchment under consideration. Long lead time flood forecasting is very important for large watershed flood mitigation as it provides more time for flood warning and emergency responses (Li et al, 2017). Further work may deal with the transferability of BN to longer lead times and other catchments, and investigate the need for re-training of the BN based on the different characteristics of the meteorological uncertainty for the different lead times, and based on the different catchment characteristics and this can be recommended for future studied in the conclusion. We have used five various cumulus parameterization schemes. Running the model with more cumulus schemes would have been interesting to explore this aspect. However, in the case of our study, it seems out of scope because the purpose of our study is to propose the Bayesian Network (BN) model to estimate flood peak in case of small data size like flood forecasting. In other words, we focused on the hydrological forecasting aspects in our paper. However, we agree that using more cumulus schemes might improve the prediction so, following the reviewer suggestion, we will propose using different cumulus schemes for future work to explore the uncertainties of the meteorological forecast better

4) In the proposed manuscript only 14 flood cases were implemented resulting in good results. However there is the danger of bias by taking into consideration such a small number of test cases. In any case, the meteorological characteristics for these cases should be analyzed and the cases should be divided into categories. Finally, despite the fact that such events are rare, maybe the authors should also consider taking into account smaller-impact events or maybe employing as initial conditions a dataset covering larger periods.

Author response: We agree with the limitation of the small sample size. Using categories of events can be useful, but would even further reduce the sample size for the different categories. With the small number of events in total, we did not attempt to divide the dataset further and train the BN for the different categories. As it is a semi-arid catchment, we assume that rainfall characteristics is implicitly regarded by the incorporation of our input variables for the BN, which we have checked and documented. In particular, hydrological initial conditions showed to be relevant. A very useful advantage of BN is that there are no minimum sample data sizes needed to perform the analysis, and BN take into account the complete data set (Myllymaki et al., 2002). Also, Kontkanen et al. (1997) demonstrate that BN can show good accuracy of prediction even with rather small data set. Furthermore, Zhang and Bivens (2007) showed that BN is less sensitive to small data set size in comparison with ANN. It is a good idea to include smaller events in order to have more data, but these events would not have relevance for flood warning, and their characteristics is most probably much different, so there would maybe be a trade-off in training the BN for the large and the small events at the same time. We will extend our outlook regarding that aspect.

Once again, we wish to *express our* highest *appreciation* to the *reviewers* for *their comments*. We provided a first study of a new method in flood warning, which still has some limitations and much further work is required to get more insights and knowledge about general applicability. We hope the manuscript will suit the Journal Natural Hazards and Earth System Sciences and we are happy to provide a revised manuscript. We thank you for your continued interest in our research.

Yours sincerely,

the authors

(References cited in our response can be found in the updated manuscript)

Bayesian Network Model for Flood Forecasting Based on Atmospheric Ensemble Forecasts

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Abstract. The purpose of this study is to propose the Bayesian Network (BN) model to estimate flood peaks from Atmospheric Ensemble Forecasts (AEFs). The Weather Research and Forecasting model was used to simulate historic storms using five cumulus parameterization schemes. The BN model was trained to compute flood peak forecasts from AEFs and hydrological pre-conditions. The Mean Absolute Relative Error was calculated as 0.076 for validation data while it was calculated as 0.39 in artificial neural network (ANN) as a widely used model. It seems that BN is less sensitive to small data sets, thus it is more suited for flood peak forecasting than ANN.

Keywords: Artificial neural networks; Bayesian networks; ensemble flood forecasting; WRF model.

1 Introduction

Floods are the most threatening natural disaster across the world (Hénonin et al., 2010). Studies show that over 80% of the cities of Iran are at the risk of flooding (Chitsaz and Banihabib, 2015). Flood warning is an efficient way to reduce the flood damage. However, many flood forecasting systems in the world rely on observed rainfall and thus, the lead time of these systems is often short for small basins (Banihabib and Arabi, 2016). Numerical Weather Prediction (NWP) models can be used to increase the lead time of flood warning by using in advance forecasts of rainfalls. Although the combination of NWP and hydrological models can significantly increase the flood warning lead-time rather than using observed rainfalls, the deterministic weather prediction doesn't reflect the existing uncertainties. Thus, in the last decades, many operative and research on flood forecasting systems around the world are increasingly employing ensembles of NWPs instead of single deterministic forecasts, which have considerable uncertainties (Goodarzi et al., 2019). Ensemble methods are considered to be an effective way to estimate the probability of future states of the atmosphere by addressing uncertainties present in initial conditions and in model approximations (Tennant et al., 2007). Various approaches have been developed to produce atmospheric ensemble forecasts including perturbing the initial conditions, perturbing the input parameters of the model, using multi-model ensembles and using different parameterization schemes (Yang et al., 2011).

One of the most important parameterization schemes is the cumulus parameterization. NWP models often use Cumulus Parameterization Schemes (CPS) to consider the effects of cumulus clouds which are not represented in the modelling as they are much smaller than the model grid size (Pennelly et al., 2014). Common CPS are presented in table 1.

Table 1. Common Cumulus Parameterization Schemes.

Model	Reference	Software used
Kain-Fritsch (KF)	Kain and Fritsch (1990)	WRF version 3.8
Betts-Miller-Janjić (BMJ)	Janjić (1994)	WRF version 3.8
Grell 3D ensemble (GR3D)	Grell (1993)	WRF version 3.8
Multi-scale Kain-Fritsch (MSKF)	Zheng et al. (2016)	WRF version 3.8
Grell-Dévényi ensemble (GDE)	Grell and Dévényi (2002)	WRF version 3.8

Kerkhoven et al. (2006) compared various CPS for a summer monsoon in east China and found that the Kain–Fritsch scheme is the best scheme at simulating moderate rainfall depths. Pennelly et al. (2014) applied the WRF model with diverse cumulus parameterization schemes for three flood events in Alberta, Canada, and they showed that the Kain–Fritsch and explicit cumulus parameterization schemes were the most accurate for simulating the rainfalls. Other studies indicated that ensemble forecasting is promising for predicting heavy rainfall (Deb et al., 2008; El Afandi, 2013; Li et al., 2014).

Ensemble meteorological forecasting is widely coupled with a hydrological model to predict stream flow ensembles. Li et al. (2017) coupled the WRF model with a distributed hydrological model for flood forecasting in a large watershed in southern China. The results suggest that the simulated floods are rational and could benefit the flood management communities due to its longer lead time. Rogelis and Werner (2018) assessed the potential of NWP models for flood early warning in tropical mountainous watersheds. The results showed that the streamflow forecasts resulted from a hydrological model forced by post-processed rainfall using the WRF added value to the flood early warning systems.

Only few case studies report how flood hydrographs derived from Atmospheric Ensemble Forecasts (AEFs) can be converted into warning decisions during a flood event. Li et al. (2017) and Abebe and Price (2005) used the exceeding ensemble members. Dietrich et al. (2009a) used the quantile of the predicted flow ensemble. Yang et al. (2016) integrated ensemble rainfall forecasts, rainfall thresholds and a real time data assimilation method. Leandro et al. (2019) reduced the ensemble to the upper and lower range of the uncertainty band. Other concepts of deriving a single (deterministic type) warning indicator from ensembles are weighting of ensemble members, e.g., averaging by Bayesian model average (Raftery et al., 2005) or by machine learning (Doycheva et al., 2016) or by reduction of members to create a multi-model sub-ensemble (Dietrich et al., 2009b).

According to previous studies, converting the ensemble forecasts into warnings and also deriving a single warning indicator from ensembles are not yet adequately considered and remains a challenging question in ensemble based flood warning. The main objective of this study is to propose the BN model to estimate the flood peak from a meteorological ensemble forecast without employing a hydrological model. BN has been widely used by researchers in many water resources fields. Applications of BN in water resources can be found in Mediero et al. (2007), Sharma and Goyal (2016) and Shin et al. (2016). Phan et al. (2016) reviewed 111 BN applications in water resources management but only 4 were in the domain of river flow, 5 were in operational decision making context and none in operational flood warning. BN application in ensemble flood forecasting has not been reported yet to our best knowledge.

In previous studies, meteorological ensemble forecasts are coupled with a hydrological model to predict a set of flood hydrographs with different peak discharge. Ensemble decision making according to a range of possible flood peaks is a challenging issue especially in case of equal likelihood of each ensemble member. In the present study, the hydrological model is replaced by a Bayesian network for deriving a single warning indicator from atmospheric ensemble forecasts.

The purpose of the present study is therefore to predict the flood peak addressing the uncertainties and the probability of occurrence of each ensemble member. Floods are rare extreme events that occur with low frequency in the studied area. Thus, one of the problems in flood modelling is small data size. In the present study, we try to deal with small data size by using Bayesian Network, which is less sensitive to a small data size (Zhang and Bivens, 2007). As a case study, flood peaks were forecasted in a relatively small mountainous basin, Kan Basin, Tehran, Iran. The Weather Research and Forecasting (WRF) model was used to simulate 14 historic precipitation events using five different cumulus parameterization schemes. Then atmospheric ensemble forecasts were coupled to the BN to estimate the flood magnitude for an ensemble forecasting, from which flood warnings could be derived. Forecasting performance of the BN was compared with the results obtained from an artificial neural network (ANN) as a widely used data based model.

2 Data and methodology

2.1. Study Area

The case study of this research is Kan Basin, Tehran, Iran with an area of 197 km². The geographical limits lie between 35°46′ N to 35°58′ N latitudes and 51°10′ E to 51°23′ E longitudes. Figure 1 shows the location of the study area. Average elevation is 2428.7 m above sea level and the annual rainfall is about 600 mm. The rainfall data was from Emamzadeh-Davood rainfall station and the flow data was collected from Sooleghan hydrometric station that is located downstream of the basin as shown in Figure 1. The time of concentration (Tc) of the basin is about 3 hours, so the NWP models can significantly increase the lead time of flood warning compared to using observed precipitation. Since the increasing of lead time decreases the accuracy of NWP forecasts (Sikder and Hossain, 2016), thus the forecasting was conducted one day before the observed event. Long lead time for flood forecasting is very important in large watershed flood mitigation as it provides more time for flood warning and emergency responses (Li et al, 2017). A flow chart of the proposed flood forecast approach is presented in Figure 2 and the precipitation and streamflow data are presented in table 2.

Table2. Precipitation and streamflow data.

event	Observed cumulative precipitation (mm)	Observed peak flow(m3/s)
27.03.2007	25.3	24.2
27.04.2007	33.5	57.1
07.12.2007	32.3	12.7
03.11.2008	37.3	20.9
30.04.2009	29	34.4
04.02.2010	68.1	11.6
08.04.2010	48.8	34.1
13.03.2011	32.6	20.9
05.04.2011	55.5	24.5
29.08.2011	56.4	26.4
28.10.2011	55.9	55.1
20.11.2011	48	44.7
14.04.2012	67.7	67.2
13.11.2012	78.9	25

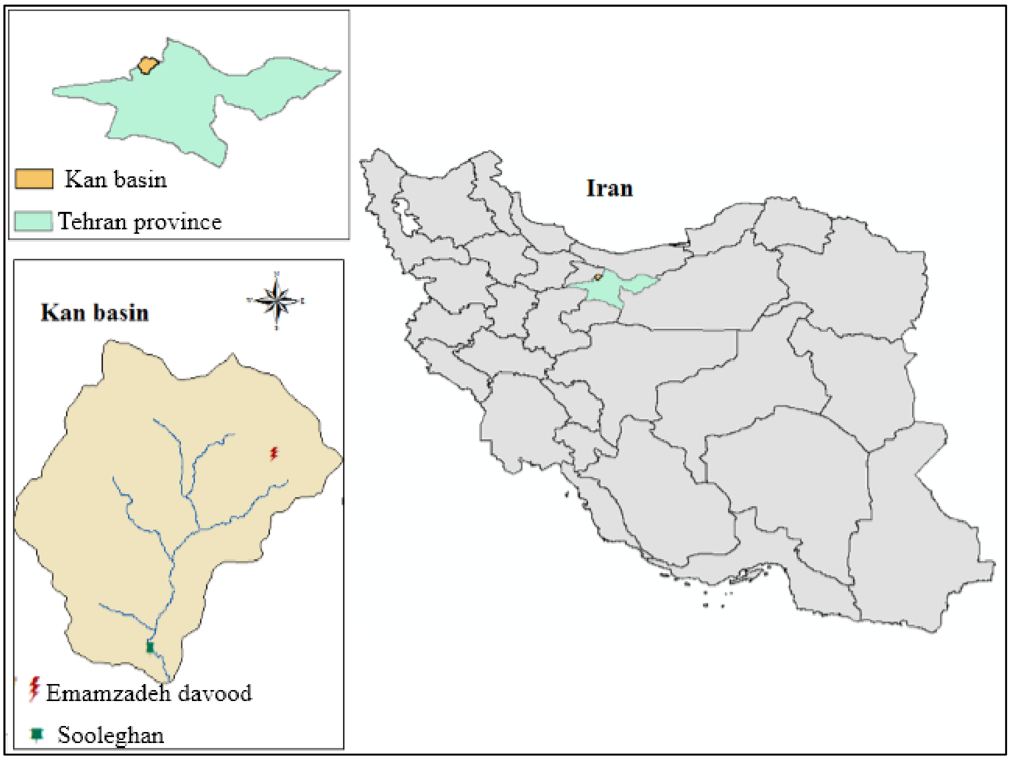

Figure 1. Location of study area, rainfall and flow stations.

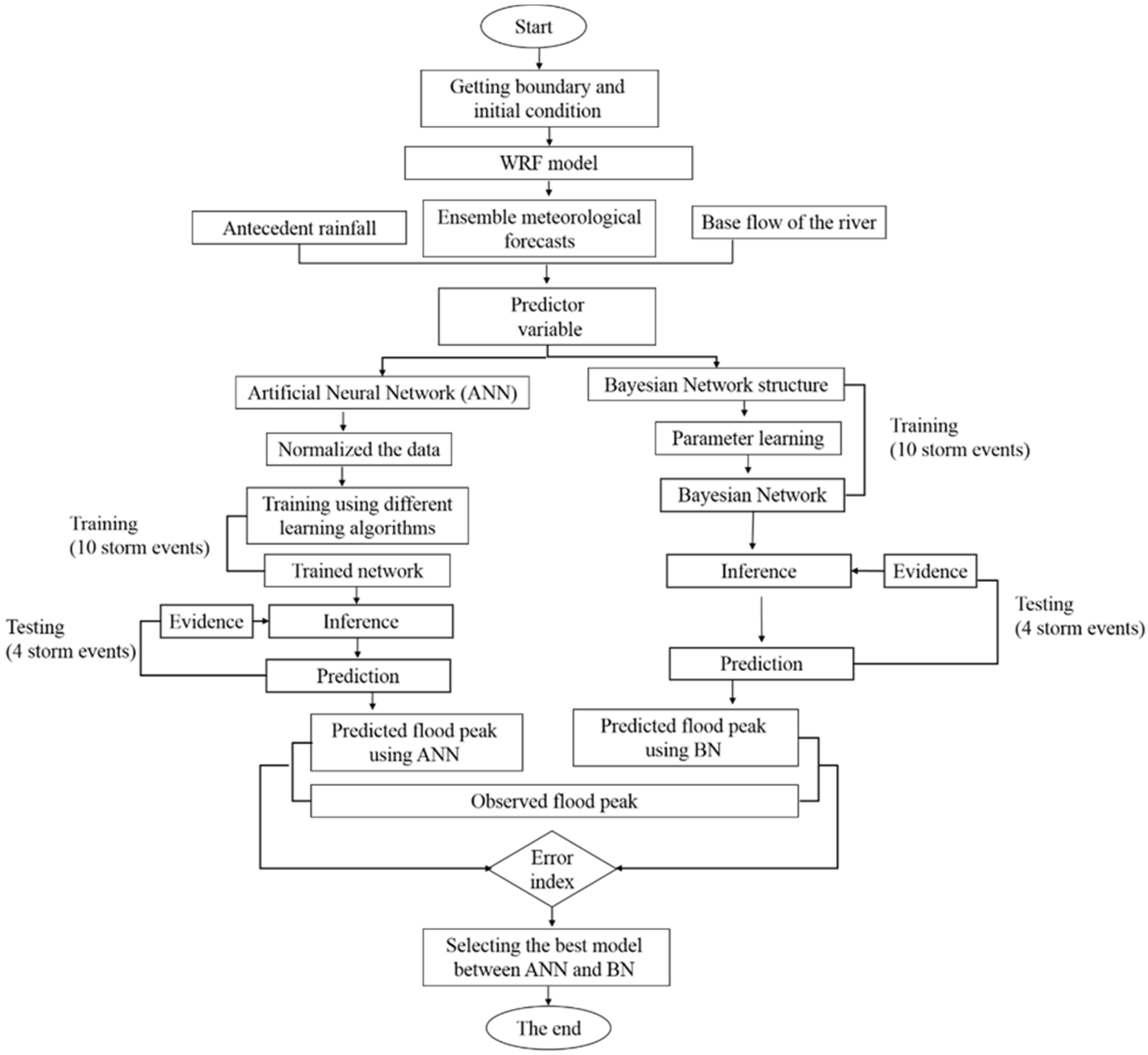

Figure 2. Flow chart of the flood forecast approach in this research.

2.2. The Weather Research and Forecasting model (WRF)

The Weather Research and Forecasting (WRF) model was used to simulate 14 historic heavy precipitation events that caused floods in the study area. In this study, WRF version 3.8 was employed with three domains and one-hour temporal resolution. The horizontal resolutions of the domains are 45 km, 15 km and 5 km, respectively. Figure 3 shows the WRF domain setup using an inter-active nested domain inside the parent domain. The outer (the coarsest) domain covers Iran, the middle domain covers the northern part of Iran and the inner domain covers the study area and only the meteorological information from this domain was used for forecasting of flood in the study basin.

The NCEP Global Forecasting System (GFS) Final analysis (FNL) data was used as the initial conditions of the WRF. The model settings were based on the Noah land surface model (Chen and Dudhia, 2001), the Rapid Radiative Transfer Model (RRTM) longwave radiation scheme (Mlawer et al., 1997), the Dudhia shortwave radiation model (Dudhia, 1989), the Yonsei University (YSU) planetary boundary layer scheme (Hong et al., 2006) and the WRF Single-Moment (WSM) 3-class microphysics scheme (Hong et al., 2004). Because of the importance of cumulus parameterization for hydrological purpose, an ensemble was created by using five cumulus schemes including KF, BMJ, GR3D, MSKF and GDE cumulus scheme. The atmospheric ensemble forecasts were fed into the Bayesian Network to estimate flood peak flow.

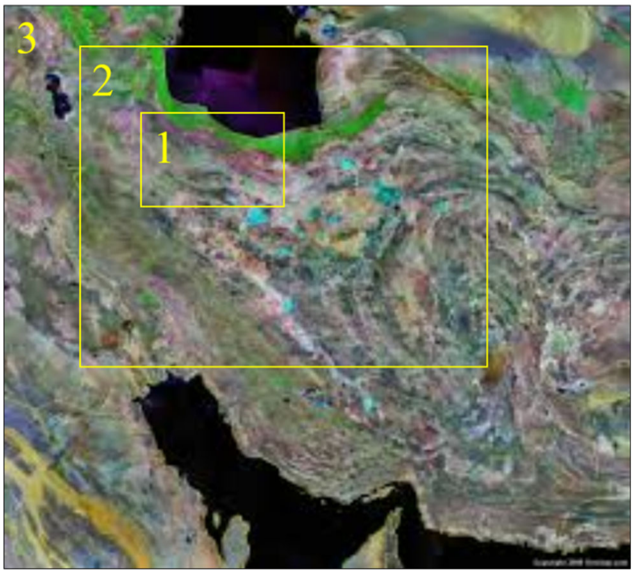

Figure 3. WRF domain setup using an inter-active nested domain inside the parent domain.

2.3. Bayesian Network

This study proposes a probabilistic model to generate the flood forecasts and to estimate the flood magnitude based on Bayesian networks (BN) for an ensemble forecasting. BNs are a class of probabilistic graphical models composed by a set of random variables and directed acyclic graphs (DAG) to show the potential dependence between variables (Scutari, 2017). The node at the start of an arrow is casual or preceding event that is called parent node and the node at the head is an outcome event that is called child node. Each node is labelled with a conditional probability table (CPT) based on prior information or statistically observed correlations that shows the strengths of the influences of the parent nodes on the child node. In general, assuming random variables with domain size d, the conditional probability table of a child node with n parents needs one to specify dn+1 probabilities (Li et al., 2011).

The goal is to calculate the posterior conditional probability distribution of each of the possible unobserved causes given the observed evidence, i.e. P [Cause ǀ Evidence].

However, in practice we are often able to obtain only the converse conditional probability distribution of observing evidence given the cause, P [Evidence ∣ Cause]. The whole concept of Bayesian networks is built on the Bayes theorem, which helps us to express the conditional probability distribution of cause given the observed evidence using the converse conditional probability of observing evidence given the cause as Eq (1):

$$\mathrm{P}\,[\mathrm{Cause} \mid \mathrm{Evidence}] = \mathrm{P}[\mathrm{Evidence} \mid \mathrm{Cause}]\,\frac{\mathrm{P}\,[\mathrm{Cause}]}{P[\mathrm{Evidence}]} \qquad (1)$$

Any node in a Bayesian network is always conditionally independent of its all non-descendants given that node's parents. The conditional probabilities are represented in the form of Conditional Probability Distribution (CPD) if the nodes represent a continuous variable or Conditional Probability Table (CPT) if the nodes represent a discrete variable. The joint probability (P_b) can be defined as the product of the local conditional distributions as given in Eq (2):

$$P_b(x_1.x_2.\ldots.x_n) = \prod_{i=1}^{n} P_b(x_i \mid x_{i+1}.\ldots.x_n) \qquad (2)$$

In a BN, a node x_i is independent of all other nodes except its parents (Sharma and Goyal, 2016). A simple example of BN is presented in Figure 4. The joint probability for this simple network can be defined as Eq (3):

$$\boldsymbol{p(a.b.c) = p(a) \times p(b \mid a) \times p(c \mid a.b)} \qquad (\mathbf{3})$$

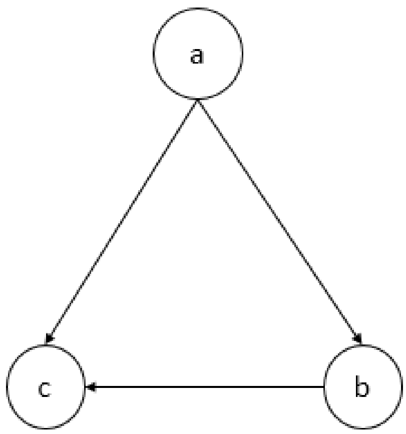

Figure 4. An example of a graphical Bayesian network.

The graph containing nodes and arrows is called BN structure (BS). Learning a Bayesian Network includes two aspects: structure learning and parameter learning.

Structure Learning: The purpose of structure learning is to determine the best structure, which maximizes the conditional probability P(BS|D), where BS is the BN structure and D is the given data (Sharma and Goyal, 2016). Structure learning consists in finding the DAG that encodes the conditional independencies present in the data. This has been achieved in the literature with constraint-based, score-based and hybrid algorithms (Scutari, 2017). Some common structure learning techniques are K2 algorithm (Cooper and Herskovits, 1992; Amirkhani and Rahmati, 2015) and MCMC algorithm (Madigan et al., 1995). However, BS can be easily defined if the relationship between child nodes and parent nodes is known. In the present study, the flood is influenced by atmospheric ensemble forecasts, base flow of the river and antecedent rainfall, so the BS is known.

Parameter Learning: Bayesian network conditional probability tables (CPTs) can be learned when the BN structure is known. Different parameter learning algorithms have been presented, including expectation maximization, Markov Chain Monte Carlo methods such as Gibbs sampling, and gradient descent methods (Reed and Mengshoel, 2014). In this study, Expectation Maximization (EM) was used for Bayesian Network parameter learning. The EM algorithm is an iterative method that performs a number of iterations, each of which calculates the logarithm of the probability of the data given the current joint probability distribution. This quantity is known as the log-likelihood, and the algorithm attempts to maximize likelihood estimators (Bergmann and Kopp, 2009). In the HUGIN software (further developed from original work of Lauritzen and Spiegelhalter, 1988), convergence is achieved when the difference between the log-likelihoods of two consecutive iterations is less than or equal to the numerical value of a log-likelihood threshold times the log-likelihood. Alternatively, the user can specify an upper limit on the number of iterations to ensure that the procedure terminates.

Our proposed ensemble forecasting using a BN model has the following four steps:

1. Selecting relevant variables and spatial units,
2. Creating training data set for the model,
3. Learning the model using the HUGIN software (version 8.3) and
4. Evaluating the performance and accuracy of the model.

In the present study, the flood peak is the response variable that is influenced by some predictor variables including ensemble rainfall forecasts, base flow of the river and antecedent soil moisture. Base flow of the river is the normal day to day discharge. Antecedent recharge flow was used as the base flow of the river. The catchment's antecedent soil moisture represents the relative wetness prior to the flood event and can have an important influence on flood response. Because of the lack of soil moisture data in the Kan basin, antecedent rainfall was used to represent the soil moisture. Antecedent rainfall is the total precipitation amount that occurred in the 24 hours before the start of the event. This study was performed on 14 historical storms. It should be noted that approx. 70% of the available data (10 storm events) is allocated for training and the remaining (4 storm events) data are used for validation. The data sample is relatively small due to the following reasons:

1. NCEP (GFS - FNL) data are not available for some historical storms.
2. During the above-mentioned period, a small number of actual flood events occurred in the study area, since the basin is located in a semi-arid region.
3. There is a lack of flood data because of the flood damages to hydrometry equipment in some floods.

Considering the relatively small sample size, we proposed using the BN that is less sensitive to small data set size in comparison with ANN. Some advantages of BN are:

1. *Suitable for small and incomplete data sets:* A very useful advantage of BN is that there are no minimum sample data sizes needed to perform the analysis, and BN take into account the complete data set (Myllymaki et al., 2002). In addition, Kontkanen et al. (1997) demonstrate that BN can show good accuracy of prediction even with rather small data set. Furthermore, Zhang and Bivens (2007) showed that BN is less sensitive to small data set size in comparison with ANN.
2. *Structural learning possible:* It is possible to use data and also subject matter knowledge to learn the structure of BN. This is an aspect of active research, and though the statistical theory is well understood, the techniques are still under development (Jensen, 2001).
3. *Fast responses:* Since BN is analytically solved, it can provide fast responses to requests once the model is compiled. The compiled form of a BN comprises a conditional probability distribution for each combination of variable values, and thus can provide any distribution instantly, in contrast to the other simulation models in which the results need to be simulated, which can take very long (Uusitalo, 2007). Thus, BN are recommended for operational ensemble forecasting in particular in fast reacting basins, where a high number of forecasts must be simulated within a short time.

2.4. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are used as an alternative of statistical models in different aspects including clustering analysis, estimation, sample recognition etc. (Mammadov et al, 2005). An ANN model is basically an engineering method of biological neurons. It is constructed by input, output and hidden layers. ANN consist of a large number of simple processing elements, which are interconnected with each other and also layered (Sharma et al, 2012).

Typically, there are four distinct steps in developing an ANN model. The first step is data transformation or scaling. The input and output variables are first normalized linearly in the range of 0 and 1 using the following equation:

$$\bar{X} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (4)$$

Where $\bar{X}$ the normalized value of the X. X_{min} and X_{max} are the minimum and maximum of data, respectively. The main purpose for standardizing the data is that the variables are usually measured in different units. By normalizing the variables in dimensionless units, the arbitrary effect of similarity between objects is removed (Aichouri et al., 2015).

The second step is the network architecture definition in which the number of hidden layers, the number of neurons in each layer, and the connectivity between the neurons are determined. The number of neurons and hidden layers is problem dependent and is estimated by the trial and error technique or expert experience. A synaptic weight is allocated to each link to represent the relative connectivity strength of two nodes at both ends in predicting the input-output relationship (Raju et al., 2011). A typical ANN architecture is presented in Figure 5. In this study, the output from the model is the flood peak and the input variables are atmospheric ensemble forecasts, base flow of the river and antecedent rainfall. The third step is using a learning algorithm to train the network to predict correctly to the set of inputs. There are several learning algorithms. In the present study, the most widely used feed forward error back propagation algorithm was used for training because of the good performance of this algorithm in previous studies (Raju et al., 2011; Banihabib et al., 2015; ASCE, 2000; Sarkar and Kumar, 2012). The success of an ANN application depends on the quality and also the quantity of the available data (Cheng et al., 2017). The final step is the validation, in which the performance of the trained ANN model is evaluated using statistical criteria (Sarkar and Kumar, 2012).

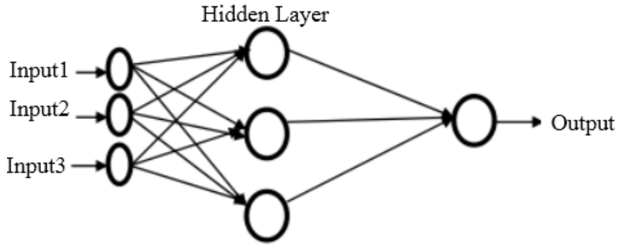

Figure 5. Typical ANN architecture.

2.5 Statistical criteria for validation

In the present study, Mean Absolute Relative Error ($MARE$), Mean Relative Bias Error ($MRBE$) and regression coefficient (r) were used for performance evaluation of the model as given in the following equations:

$$MARE = \frac{1}{n}\sum\frac{|O_i - F_i|}{O_i} \tag{6}$$

$$MRBE = \frac{1}{n}\sum\frac{O_i - F_i}{O_i} \tag{7}$$

$$r = \frac{n(\sum OF) - (\sum O)(\sum F)}{\sqrt{[n\sum O^2 - (\sum O)^2][n\sum F^2 - (\sum F)^2]}} \tag{8}$$

O_i is the observed value, F_i is the predicted value and n is the total number of data sets.

3. Results and discussion

3.1. Rainfall verification using the WRF model

In this section, the comparison between the observed and predicted precipitation obtained from the WRF model is addressed. As mentioned earlier, the WRF model was used to simulate 14 historic precipitation events and the results for some events are presented here. Figure 6 illustrates the predicted cumulative rainfall and the observed cumulative rainfall for these events. In general, the results show that the WRF model was able to capture the heavy rainfall events. The uncertainties in the predicted rainfall lead to a large spread of the ensemble members and this is why the uncertainty in rainfall forecasting becomes important.

The ensemble precipitation illustrates that both overestimation and underestimation of precipitation occurs using various schemes. Overestimation is very noticeable for the early hours of forecasting while for the last period of the event, underestimation occurs in some schemes.

From the case study, the results of precipitation forecast using different cumulus schemes by the WRF model can be significantly different. Therefore, it is necessary to forecast precipitation by implementing various physics schemes, especially different microphysical schemes. Furthermore, it can be inferred that the difference between observed and predicted rainfall is mainly caused by the initial condition in the NWP models, thus the atmospheric ensemble forecasts can be produced also by perturbing the initial conditions.

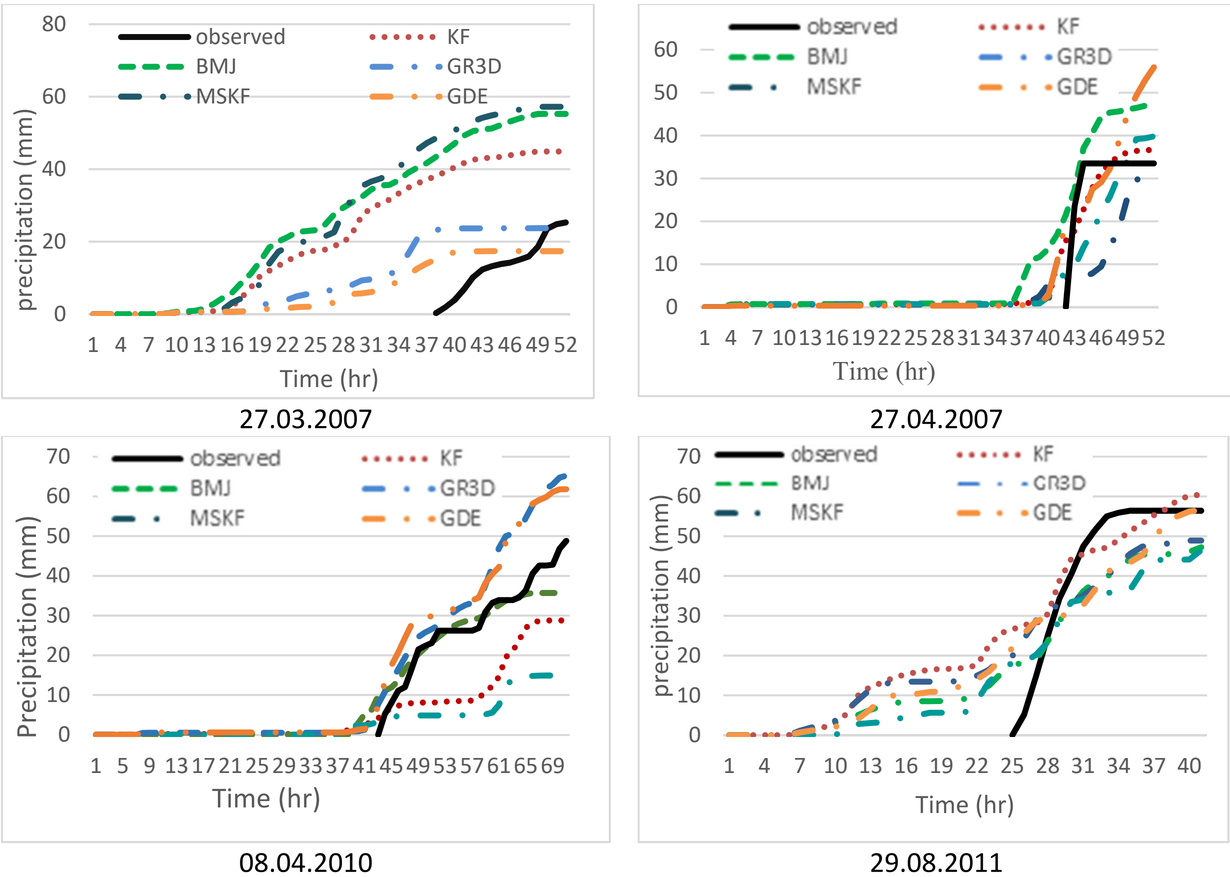

Figure 6. The ensemble forecasted precipitation and the observed cumulative precipitation.

3.2. Bayesian Network Verification

The atmospheric ensemble forecasts were fed into the BN to estimate flood peak flow. Ten various models were developed using various combinations of predictors. In all of the combinations, flood-peak discharge is the predicting variable. Table 3 shows the accuracy of the model for different combinations of predictors to compare the performance of the prediction. The performance of the model was evaluated by MARE and R^2. It is clear from Table 3 that maximum hourly rainfall outperformed accumulated rainfall as predictor variable (No. 2 in Table 4). It shows for the relatively short concentration-time basin, Kan basin, that cumulative precipitation is not a good indicator to predict the flood peak and maximum hourly rainfall provides better results. Thus maximum hourly rainfall was used in combinations of other predictor variables. This can also be seen by comparing combination No. 5 and 9 that there is no considerable decrease in accuracy by deleting the Multi-scale Kain-Fritsch scheme, consequently it can be concluded that MSKF is the least accurate cumulus scheme. It was also found that by deleting the Kain-Fritsch scheme in combination (No. 6 in Table 3) the accuracy is significantly decreased. Thus, the Kain-Fritsch is the most efficient cumulus parameterization scheme in the study area. Other studies on precipitation prediction have also shown similar results. Pennelly et al. (2014) showed that the Kain-Fritsch cumulus parameterization schemes is the most accurate in simulating heavy precipitation across three summer events. Liang et al. (2004) showed that the Kain-Fritsch scheme works better in the Southeast of United States where convection is largely governed by the near-surface forcing.

According to Table 3, the best results were obtained for combination No. 5. The proposed structure of this combination is composed of eight nodes as shown in in Table 4. Atmospheric ensemble forecasts, base flow of the river and antecedent rainfall are the parent nodes and flood peak is the child node. It can also be seen that the base flow is influenced by antecedent rainfall. Mean absolute relative error was calculated 0.076 for the validation data set in the combination No. 5. The coefficient of determination (R^2) is another criterion for testing and it is seen from Table 3 that it's values are close to unity. We should compare our study to similar studies to determine whether our R-squared is in the right ballpark. Khan and Coulibaly (2006) used a Bayesian learning approach to train a multilayer feedforward network for daily river flow and reservoir inflow simulation. Their result also showed a high R-squared value. The results showed that the BN is an efficient method for modeling and combining the ensemble flood forecasts prediction. The proposed BN approach in this study predicts flood peak flow. Since the Kan River in the studied reach is a mountainous river without any flood plain storage, the peak discharge is almost not reduced by flood routing along the river, and so we can use the peak flood instead of routing the flood hydrograph. However, in our study, we consider peak flow as the variable of interest. In other fields of application, flow volume or time to peak might be of interest.

Moreover, Bayesian cluster analysis could also provide probabilistic results for flood early warning, but since the data sample is relatively small in this study, cluster analysis cannot be achieved. This method can be also tested in basins with sufficient historical hydrological data in future works.

Table 3. Performance of Bayesian Network for different combinations of predictor variables.

Combination No.	predictor variables	R2	MARE
1	Maximum hourly rainfall	0.99	0.16
2	Accumulated rainfall	0.74	1.06
3	Maximum hourly rainfall, Base flow of the river	0.99	0.18
4	Maximum hourly rainfall, Antecedent rainfall	0.99	0.12
5	Maximum hourly rainfall, Base flow of the river, Antecedent rainfall	0.99	0.076
6	Maximum hourly rainfall (deleting KF) , Base flow of the river, Antecedent soil moisture	0.58	0.46
7	Maximum hourly rainfall (deleting BMJ) , Base flow of the river, Antecedent rainfall	0.99	0.23
8	Maximum hourly rainfall (deleting GR3D) , Base flow of the river, Antecedent rainfall	0.99	0.15
9	Maximum hourly rainfall (deleting MSKF) , Base flow of the river, Antecedent rainfall	0.99	0.087
10	Maximum hourly rainfall (deleting GDE) , Base flow of the river, Antecedent rainfall	0.99	0.10

Table 4. The cause-effect relationships among the variables in the proposed structure of the Bayesian network.

Parent ID	Entity Name	Child ID	Child Name
n1	Predicted rainfall using KF cumulus parameterization scheme	n8	Flood peak
n2	Predicted rainfall using BMJ cumulus parameterization scheme	n8	Flood peak
n3	Predicted rainfall using GR3D cumulus parameterization scheme	n8	Flood peak
n4	Predicted rainfall using MSKF cumulus parameterization scheme	n8	Flood peak
n5	Predicted rainfall using GDE cumulus parameterization scheme	n8	Flood peak
n6	Base flow	n8	Flood peak
n7	Antecedent rainfall	n6/ n8	Base flow/ Flood peak

The performance of the BN model is compared with the results obtained from an ANN model as a benchmark. The comparison is conducted using the same data set for training and validation. These results are presented in section 3.3.

3.3. Artificial Neural Network Verification

The first step in developing an ANN model is to determine the input and output variables. The output from the model is the flood peak discharge magnitude, and the input variables have been selected the same of the best combination of predictor variables in BN that has been used in this study (Table 3, combination No. 5). The feed forward error back propagation algorithm has been employed as the training algorithm in this study. The difficult task in working with ANN contains selecting parameters such as the number of hidden nodes. There is no established algorithm until now to determine how many hidden nodes are required to approximate any given function. Here, we use the common trial and error method to choose the number of hidden nodes, which are varied from 2 to 6 according to previous studies (Banihabib et al., 2015). Error index is usually used to select the best performance of the network model compared to observed data. The accuracy of the model for different numbers of nodes in the hidden layer is presented in Table 4. It was found that four hidden nodes give the best results. The mean absolute relative error (MARE) was calculated as 0.39 for the validation data set while this index was calculated 0.076 in BN. The comparison shows that BN offers better accuracy. Although our data set was relatively small, the result of BN model was accurate enough. Therefore, it seems that BN is less sensitive to small data set size, so it is more suited for rare events such as floods, where the available data are limited due to the high return period of such events.

Table 4. MARE and R^2 of Artificial Neural Network in the verification phase.

Number of nodes in hidden layer	MARE	R^2
2	1.14	0.44
3	0.74	0.92
4	0.39	0.77
5	0.51	0.93
6	1.23	0.12

4. Conclusions

This study proposed a probabilistic model to address the uncertainties of flood forecasts using the Bayesian networks (BN) and to estimate the flood peak in an ensemble flood forecasting. This is the first attempt to use BN in ensemble flood forecasting. The Weather Research and Forecasting (WRF) model was used to simulate some historic precipitation rainfall events using five various cumulus parameterization schemes. The results showed that there is no considerable decrease in accuracy by deleting the Multi-scale Kain-Fritsch scheme, thus it can be concluded that is the least accurate cumulus scheme. It also was found that Kain-Fritsch is the most efficient cumulus parameterization scheme. Atmospheric ensemble forecasts were coupled with the Bayesian Network to estimate the flood magnitude in an ensemble forecasting. Results of the BN are compared with the results obtained from an artificial neural network as a widely used model to show the performance of BN. The comparison is conducted using the same data set for validation and training. The results showed that the BN is an efficient method for flood forecasting based on ensemble rainfall forecasts and offers better accuracy than ANN. We showed that BN is less sensitive to small data set size in comparison with other models, thus it is more suited for rare events such as floods. The results of this study indicate that BN might be a suitable tool for a fast computation of peak flow and flood warnings from numerical ensemble weather predictions. Our study is a proof of concept at the current stage that flood warnings can be done by evaluating hydrological pre-conditions and meteorological ensembles by a trained BN instead of a hydrological model. However, further studies are required to confirm the applicability of BN. The present study was conducted with a lead time of one day before the observed event in a small basin. Future studies may test BN for other catchments and for larger lead-times.

Code/Data availability. For this study, we used the software HUGIN Educational, version 8.5 (https://www.hugin.com/). NCEP FNL Operational Model Global Tropospheric Analyses, continuing from July 1999. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory. https://doi.org/10.5065/D6M043C6, accessed 2017. Model data are available from the authors upon request.

Author contributions. LG had a role in the following in this study: conceptualization, formal analysis, investigation, methodology and writing of the original draft. MEB performed the conceptualization, supervision and validation. AR and JD were involved in the conceptualization and advising. All authors were involved in the writing, review and editing processes.

Competing interests. The authors declare that they have no conflict of interest.

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