A flood forecasting model for unregulated catchments based on Artificial Neural Networks: the October 2017 flood in Tovdal's catchment

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Summary

Artificial Neural Networks (ANN) data-driven models are used to predict downstream section river`s maximum daily water level in an unregulated catchment. By using the ANN models developed in Yakoub (2018) and Yakoub and Leal (2018) a flood forecasting model is implemented allowing four days ahead forecast based on weather forecast extracted from the Norwegian meteorological institute servers. The flood forecasting model is tested for the extreme event occurred in the 2nd of October 2017. The results show that the ANN models can predict such an extreme flood level, which is well above the range of levels used to train the models. Therefore, this type of data-driven models seems to be a good alternative or complement to traditional physical-based models for flood forecasting purposes.

Sammendrag

Flomprognose modell for uregulerte vassdrag basert på kunstige nevrale nettverk: flomhendelsen i Tovdalsvassdraget i oktober 2017. Datadrevne modeller basert på kunstige nevrale nettverk (ANN) blir brukt til å forutsi maksimal vannstand i ei elv nedstrøms fra et uregulert vassdrag. Gjennom å bruke ANN-modeller utviklet av Yakoub (2018) og Yakoub og Leal (2018) utvikles det en flomprognose modell som muliggjør fire dagers farevarsel basert på værvarslingsdata fra Meteorologisk institutt. Algoritmen ble testet med data for ekstremværet som inntraff 2. oktober 2017 i Agderfylkene. Resultatene viser at ANN-modellen kan forutsi en slik flomhendelse, og det uten at slike ekstreme hendelser var del av treningssettet. Dette indikerer at denne typen datadreven modell er et godt alternativ, eller komplement, til tradisjonelle fysikkbaserte modeller for flomprognose.

Introduction

As a result of the increased danger associated with the climate change, many areas around the globe have witnessed extreme weather events such as intense floods, like the one that occurred in October 2017 in Vest- and Aust-Agder counties in Norway. Therefore, water level forecasting is an important case for river environmental protection, and flood mitigation. Good forecast values associated with sufficient time forecast can reduce flood damages significantly. This damage reduction can be done by having enough time for issuing disaster warnings, which can allow a safe reservoir management and can help habitants and industries to take adequate actions (e.g. evacuation).

Several physical based models have been proposed and developed in the past to address the relationship between water level and other factors (an exhaustive and comprehensive review can be consulted in Paniconi and Putti 2015), but their complexity, calibration difficulty, uncertainty and computational time required create a challenge (Campolo et al. 1999). The need for fast and efficient approaches to solve this problem can be met by an alternative approach based on data-driven models.

Past studies have shown that ANN is a good approach and has a high potential (Hung et al. 2009). The ANN is capable of modeling the relationship without prescribing hydrological processes, in other words, the ANN can catch and solve the complex nonlinear relationship between inputs and outputs without the use of differential equations. The use of Neural Networks in river forecasting has more than two decades. Over that period a lot of different techniques and approaches were used, an overall review of them can be seen in more detail in Abrahart et al. (2012). Regarding the use of ANN, probably the most popular technique, a very thorough review can be consulted in Maier et al. (2010). That study shows that ANN has been applied to predict river water level successfully in several past studies.

Referring to the previous studies done by Yakoub (2018) and Yakoub (2017), several ANN`s models were designed using maximum daily and hourly water level observations from upstream and downstream sections, in addition to total daily precipitations from five gauges with different time lags. In general, Ad-Hoc approaches were used for input selection supported by analytical (Correlation and Average mutual information) approaches. The record was divided into training, test validation and testing sets using an unsupervised approach (Yakoub 2017) and a supervised approach (Yakoub 2018). The structure of the network was optimized based on trial and error method (Ad-Hoc) (Yakoub 2017), while in (Yakoub 2018) the grid search method was used. Several error metrics were used to evaluate the model's performance, including the root mean square error (RMSE) and efficiency index (EI). The results showed the potential of ANN`s models to predict the water level downstream. By using observations of the upstream and downstream maximum daily water level, total daily precipitation and average daily temperature, a full description of the catchment`s state is obtained, associated with reasonable prediction ability up to four days forecast.

The present study is aiming to apply the developed ANN models in order to test their ability to cope with the use of weather forecast information (operational mode), as a result achieving a flood forecast model that can utilize weather forecast data extracted from the Norwegian Meteorological Institute servers. To achieve this purpose the most extreme event ever recorded in Tovdal catchment (2nd of October 2017) was chosen as a case study. Therefore, the paper is structured by a following section where the case study is presented, followed by a section with a brief explanation about the ANN models used. In section 4, the flood warning system strategy is described, followed by a section where the main results are presented and discussed.

Case study

The Tovdal river is 150 km long with an average slope of 6.5 m/km and its 1863 km^2 catchment belongs to Aust-Agder county. The catchment is almost unregulated, containing only a small reservoir (Hanefoss). In Tovdal river, large floods occur particularly in Spring and Autumn, though Autumn floods due to intense precipitation are dominant. The watercourse is somewhat regulated, but the regulations are not expected to have significant impact on runoff in flood situations (cf. Pedersen et al. 2005). The catchment has a mean annual precipitation of 1261 mm (around 60% in Autumn and Winter) and an average annual temperature of 4.1 °C. It is covered mostly by forest (74.3 %) with negligible urban occupation (0.1%) and effective storage (0.5%), more information can be seen in Drageset (2003).

Figure 1. Tovdal catchment's location (source: NVE atlas)

The Norwegian Meteorological Institute (MET) operates several meteorological stations. One station for air temperature (Byglandsfjord) and five other stations for precipitation (Tovdal, Mykland, Herefoss, Dovland and Senumstad) were selected to perform the study. These stations are marked with a red circle in Figure 1.

The Norwegian Water Resource and Energy Directorate (NVE) operates two gauging stations (Austenå and Flaksvatn), which are represented by red squares in Figure 1. Nearby Flaksvatn station there is a village (Birkeland) where floods can cause problems due to the proximity to the river, therefore the water level at Flaksvatn is the output of the ANN model. A database of 19 years from 1998 to lately 2017 is collected from available historical records for each of the mentioned stations. For more information see Yakoub (2018).

In what concerns the extreme flood event of the 2nd of October 2017, on Tuesday the 26th of September the atmospheric models ECMWF were already predicting an extreme forecast, where a huge amount of rain was moving towards south Norway. On Thursday 28th of September the models showed that it would be a rain fall of about 250 mm during the next three days, while it was still not possible to predict the exact location.

MET issued the first warning for Agder county on 29th of September at 08:48 o'clock (local time) describing a large amount of rainfall. It was predicted up to 200 mm during the weekend mostly on Saturday (around 100 mm). Several warnings were issued afterwards updating the values and the affected areas. Similarly, NVE had issued a flood red warning on the 30th of September which is the highest warning level for floods.

A distribution of the precipitation amount over the period from 28th of September to the 2nd of October 2017 can be seen in Figure 2. New records have been recorded in different stations, the highest is for Senumstad station with a 173 mm over one day (Gislefoss et al. 2017).

The intense precipitation event resulted in an extreme level on Flaksvatn on the 2nd of October (26.85 m.a.s), which largely overcomes the maximum recorded since 1899 (25.35 m.a.s in November 1959) and the water levels with 100-year and 500-year return periods (24.50 and 25.50 m.a.s, respectively) (Pedersen et al. 2005). As a result, Birkeland industry park was severely inundated and big economic losses occurred, with insurances companies paying a record bill to cover damages.

The ANN models

The development process of the ANN models will be presented briefly here, and more details can be consulted in Yakoub (2018). Reference should be made to the fact that in this process

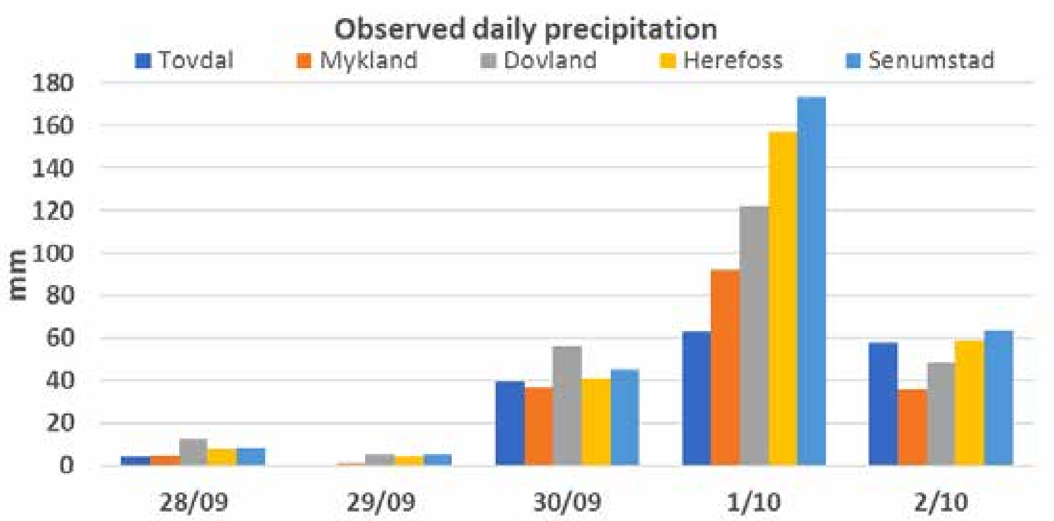

Figure 2. Observed daily precipitation from 28th of September to 2nd of October 2017.

only measured historical data was used and no forecast data was used, since the models should be trained to real data. In general, the development process can be briefly described in several steps.

The output of the models is the maximum daily water level at Flaksvatn. The reason to choose the water level instead of the flow discharge is because the former is the main variable of interest in flood mapping. Although, preliminary tests, show that the ANN models could also be trained with flow discharge values, rendering also good accuracy, the use of flow discharge would require the inclusion of a stage-discharge curve or the use of a physical-based model to transform the flow discharge into water level, which in both cases would add uncertainties associated to extreme events. Moreover, the water level is what is in fact measured at the hydrometric stations, so its use only includes uncertainties and errors corresponding to the measurement procedure, which are assumed to be negligible.

The first step consisted in selecting the high potential inputs and their time lags related to the output variable. For this purpose, two different model-free approaches were used, namely the Pearson's correlation coefficient (linear) approach and the mutual information (non-linear) approach. As a result, it was concluded that all variables had a relationship with the output variable within a time-lag of four days, implying that this will be the maximum forecast time. Moreover, the daily maximum water level at Austenå is the variable that relates better with the daily maximum water level at Flaksvatn, although the daily average temperature and the total daily precipitation in the meteorological stations also contains valuable information. Therefore, four forecast ANN models were developed, corresponding to 4, 3, 2 and 1 days forecasts (see Table 1).

In Table 1, $\boldsymbol{W}$ is the daily maximum water level (which can be obtained from the hourly records, note that the station values are water depths and by summing 18.6 m we can obtain the water levels), $\boldsymbol{P}$ is the total daily precipitation (which is available for each day at 06:00 UTC for the previous 24 hours), $\boldsymbol{T}$ is the daily average air temperature (which can be obtained by averaging the recorded values for each day at 06:00, 12:00 and 18:00 UTC), subscript k represents each of the gauging stations, subscript i represents each of the precipitation stations, subscript B represents the Byglandsfjord station, t stand for the day when the forecast is done, meaning that times higher than t (i.e., $t + 1, \ldots, t + 4$) refer to forecast values and times below t

Table 1. Output and input variables for each forecast ANN model.

ANN model	Output variable	Input variables
4 days forecast	$\boldsymbol{W}_{Flaksvatn}(t+4)$	$\boldsymbol{W}_k(t)$ $\boldsymbol{P}_i(t+4), \boldsymbol{P}_i(t+3), \boldsymbol{P}_i(t+2), \boldsymbol{P}_i(t+1), \boldsymbol{P}_i(t)$ $\boldsymbol{T}_B(t+4), \boldsymbol{T}_B(t+3), \boldsymbol{T}_B(t+2), \boldsymbol{T}_B(t+1), \boldsymbol{T}_B(t)$
3 days forecast	$\boldsymbol{W}_{Flaksvatn}(t+3)$	$\boldsymbol{W}_k(t), \boldsymbol{W}_k(t-1)$ $\boldsymbol{P}_i(t+3), \boldsymbol{P}_i(t+2), \boldsymbol{P}_i(t+1), \boldsymbol{P}_i(t), \boldsymbol{P}_i(t-1)$ $\boldsymbol{T}_B(t+3), \boldsymbol{T}_B(t+2), \boldsymbol{T}_B(t+1), \boldsymbol{T}_B(t), \boldsymbol{T}_B(t-1)$
2 days forecast	$\boldsymbol{W}_{Flaksvatn}(t+2)$	$\boldsymbol{W}_k(t), \boldsymbol{W}_k(t-1), \boldsymbol{W}_k(t-2)$ $\boldsymbol{P}_i(t+2), \boldsymbol{P}_i(t+1), \boldsymbol{P}_i(t), \boldsymbol{P}_i(t-1), \boldsymbol{P}_i(t-2)$ $\boldsymbol{T}_B(t+2), \boldsymbol{T}_B(t+1), \boldsymbol{T}_B(t), \boldsymbol{T}_B(t-1), \boldsymbol{T}_B(t-2)$
1 day forecast	$\boldsymbol{W}_{Flaksvatn}(t+1)$	$\boldsymbol{W}_k(t), \boldsymbol{W}_k(t-1), \boldsymbol{W}_k(t-2),, \boldsymbol{W}_k(t-3)$ $\boldsymbol{P}_i(t+1), \boldsymbol{P}_i(t), \boldsymbol{P}_i(t-1), \boldsymbol{P}_i(t-2), \boldsymbol{P}_i(t-3)$ $\boldsymbol{T}_B(t+1), \boldsymbol{T}_B(t), \boldsymbol{T}_B(t-1), \boldsymbol{T}_B(t-2), \boldsymbol{T}_B(t-3)$

Table 2. Optimal configurations setup for each forecast ANN model.

ANN model	Activation function	Optimizer	Batch size	No: epochs	No: Hidden nodes 1st	No: Hidden nodes 2nd	Dropout rate_1	Dropout rate_2	Weight initializer
4 days forecast	Relu	Nadam	32	30	30	25	8%	11%	Normal
3 days forecast				20				10%	
2 days forecast				33	34	27	6%	12%	
1 day forecast				32	36	25		15%	

(i.e., t – 3,…, t – 1) refer to measured values in the prior days.

The second step was data processing, where the unprocessed data, which consists of input and output variables, was scaled to make it in a suitable form for the algorithm.

The third step was data division and resampling. The historical record was divided into three subsets, training set which contains one half of the total dataset, test-validation set, which contains one-sixth of the total dataset, and test set, which contains one-third of the total dataset. The data was randomly sampled times without replacement (i.e. shuffling the lines) and for each randomization the data was divided into three subsets. Nine different randomizations (with three subsets each) were found based on having maximum relative differences of 6% for the statistical properties (the coefficient of variations) of the subsets.

The fourth step was the selection of the model architecture. It was decided to use a feed forward multi-layer perceptron model (MLP), where the back-propagation algorithm is integrated with other technique called Dropout technique to improve the accuracy and increase the generalization.

The fifth step was model structure selection and optimization. A stepwise constructive approach combined with the cross-validation Grid Search algorithm was used to optimize (tune) different hyperparameters. Since each forecast ANN model has a different number of inputs, the model structure selection and optimization were done independently for each case. The optimal configurations setup for each model are presented in Table 2.

Lastly, for the performance evaluation different performance evaluation metrics were used to evaluate the predictive accuracy of the sele-

Table 3. Overview of performance statistics for each forecast ANN model.

ANN model	RMSE			R		
	Training	Test-validation	Test	Training	Test-validation	Test
4 days forecast	0.25 ± 4%	0.27 ± 3%	0.26 ± 3%	0.94 ± 1%	0.92 ± 1%	0.93 ± 1%
3 days forecast	0.21 ± 4%	0.25 ± 3%	0.22 ± 3%	0.96 ± 1%	0.94 ± 1%	0.95 ± 1%
2 days forecast	0.16 ± 6%	0.21 ± 4%	0.18 ± 5%	0.97 ± 1%	0.95 ± 1%	0.96 ± 1%
1 day forecast	0.12 ± 10%	0.16 ± 10%	0.13 ± 10%	0.98 ± 1%	0.97± 1%	0.98 ± 1%

cted models. A resume of those results is presented in Table 3.

The flood forecasting model

For implementing the ANN models described previously an appropriate weather forecast is needed. In this study the weather forecast model system used by MET, described by MEPS (MetCo Op Ensemble Prediction System), is used. The weather forecast model is run in operational routine in cooperation between Norway, Sweden and Finland meteorological institutes. MEPS covers Scandinavia and the Nordic Sea with a horizontal resolution between 1 and 2.5 km, and. The weather model forecasts are updated each 6 hours daily (at time 00:00, 06:00, 12:00, 18:00 UTC) with three-hourly cycling for data assimilation. Boundary data is from ECMWF, and initial perturbations are based on the SLAF method (Scaled Lagged Average Forecasting). The data is offered by the Norwegian meteorological institute and it is freely available to the public for use. For more detailed information it is recommended to review (The Met CoOp ensemble MEPS. 2017). The precipitation and temperature data needed for the ANN models is taken from MEPS by knowing the coordinates of the meteorological stations used in this study (see Figure 1).

Since the flood forecasting model will contain both measured and forecast data, its update must consider the update of that data. Therefore, it is decided to update the flood forecasts four times a day, at 06:00, 12:00, 18:00 and 00:00 UTC. The reason to update the forecast at 06:00 UTC is due to this being the time when new measurements of the total daily precipitation are known from the meteorological stations. All the other updating times correspond to the times when new weather forecast values are available. The implementation of the flood forecast updating strategy along with the corresponding inputs and the ANN model used for 4 days forecast can be seen in the next section for the forecast of the extreme flood event of 2nd of October 2017 (see Table 4).

It should be highlighted that ANN models are stochastic in their nature, which means that it uses randomness (e.g. randomness in sampling and resampling, randomness in initialization, etc.), that leads to having different results for the same data set each time the algorithm is applied. Therefore, to reduce the uncertainty associated to a given result (output), it is recommended to run the ANN model several times and report the results for each run, similar to k-fold cross validation technique, but in this case using the same exact training data set.

Results and discussion

The weather forecast extracted data for the 2nd of October event (Figure 3), was to some extent accurate. The forecast results are consistent and mostly over estimated the observed values (Figure 2), even for four days ahead. It should be mentioned that the data extracted from the meteorological models were based on high estimations.

Based on the weather forecast, on the ANN models presented in section 3 and the flood forecasting model defined in section 4, a forecast updating strategy is implemented along with the corresponding inputs and the ANN model used for forecasting the maximum water

Table 4. ANN model and inputs used in the forecast updating strategy for 2nd October 2017 water level at Flaksvatn.

<table>
<tr><th rowspan="3">Flood fore-cast</th><th rowspan="3">ANN model</th><th colspan="14">INPUTS</th></tr>
<tr><th colspan="3">28/09</th><th colspan="3">29/09</th><th colspan="3">30/09</th><th colspan="3">01/10</th><th colspan="2">02/10</th></tr>
<tr><th>W_k (m)</th><th>P_i (mm)</th><th>T_B (ºC)</th><th>W_k (m)</th><th>P_i (mm)</th><th>T_B (ºC)</th><th>W_k (m)</th><th>P_i (mm)</th><th>T_B (ºC)</th><th>W_k (m)</th><th>P_i (mm)</th><th>T_B (ºC)</th><th>P_k (mm)</th><th>T_B (ºC)</th></tr>
<tr><td>28/09 (06:00)</td><td>4 days forecast</td><td>MS 28/09 (≤ 06:00)</td><td rowspan="3">MS 28/09</td><td>MS 28/09 WF2 28/09</td><td rowspan="4">–</td><td colspan="2">WF2 28/09</td><td rowspan="8">–</td><td colspan="2">WF2 28/09</td><td rowspan="12">–</td><td colspan="4">WF2 28/09</td></tr>
<tr><td>28/09 (12:00)</td><td>4 days forecast</td><td>MS 28/09 (≤ 12:00)</td><td>MS 28/09 WF3 28/09</td><td colspan="2">WF3 28/09</td><td colspan="2">WF3 28/09</td><td colspan="4">WF3 28/09</td></tr>
<tr><td>28/09 (18:00)</td><td>4 days forecast</td><td>MS 28/09 (≤ 18:00)</td><td>MS 28/09 WF4 28/09</td><td colspan="2">WF4 28/09</td><td colspan="2">WF4 28/09</td><td colspan="4">WF4 28/09</td></tr>
<tr><td>29/09 (00:00)</td><td>4 days forecast</td><td colspan="3" rowspan="13">MS 28/09</td><td colspan="2">WF1 29/09</td><td colspan="2">WF1 29/09</td><td colspan="4">WF1 29/09</td></tr>
<tr><td>29/09 (06:00)</td><td>3 days forecast</td><td>MS 29/09 (≤ 06:00)</td><td rowspan="3">MS 29/09</td><td>MS 29/09 WF2 29/09</td><td colspan="2">WF2 29/09</td><td colspan="4">WF2 29/09</td></tr>
<tr><td>29/09 (12:00)</td><td>3 days forecast</td><td>MS 29/09 (≤ 12:00)</td><td>MS 29/09 WF3 29/09</td><td colspan="2">WF3 29/09</td><td colspan="4">WF3 29/09</td></tr>
<tr><td>29/09 (18:00)</td><td>3 days forecast</td><td>MS 29/09 (≤ 18:00)</td><td>MS 29/09 WF4 29/09</td><td colspan="2">WF4 29/09</td><td colspan="4">WF4 29/09</td></tr>
<tr><td>30/09 (00:00)</td><td>3 days forecast</td><td colspan="3" rowspan="9">MS 29/09</td><td colspan="2">WF1 30/09</td><td colspan="4">WF1 30/09</td></tr>
<tr><td>30/09 (06:00)</td><td>2 days forecast</td><td>MS 30/09 (≤ 06:00)</td><td rowspan="3">MS 30/09</td><td>MS 30/09 WF2 30/09</td><td colspan="4">WF2 30/09</td></tr>
<tr><td>30/09 (12:00)</td><td>2 days forecast</td><td>MS 30/09 (≤ 12:00)</td><td>MS 30/09 WF3 30/09</td><td colspan="4">WF3 30/09</td></tr>
<tr><td>30/09 (18:00)</td><td>2 days forecast</td><td>MS 30/09 (≤ 18:00)</td><td>MS 30/09 WF4 30/09</td><td colspan="4">WF4 30/09</td></tr>
<tr><td>01/10 (00:00)</td><td>2 days forecast</td><td colspan="3" rowspan="5">MS 30/09</td><td colspan="4">WF1 01/10</td></tr>
<tr><td>01/10 (06:00)</td><td>1 day forecast</td><td>MS 01/10 (≤ 06:00)</td><td rowspan="3">MS 01/10</td><td>MS 01/10 WF2 01/10</td><td colspan="2">WF2 01/10</td></tr>
<tr><td>01/10 (12:00)</td><td>1 day forecast</td><td>MS 01/10 (≤ 12:00)</td><td>MS 01/10 WF3 01/10</td><td colspan="2">WF3 01/10</td></tr>
<tr><td>01/10 (18:00)</td><td>1 day forecast</td><td>MS 01/10 (≤ 18:00)</td><td>MS 01/10 WF4 01/10</td><td colspan="2">WF4 01/10</td></tr>
<tr><td>02/10 (00:00)</td><td>1 day forecast</td><td colspan="3">MS 01/10</td><td colspan="2">WF1 02/10</td></tr>
</table>

MS stands for Measurements at Station
WF stands for Weather Forecast, being WF1, WF2, WF3 and WF4 the daily forecasts at 00:00, 06:00, 12:00 and 18:00, respectively

level at Flaksvatn on 2nd of October 2017 (see Table 4).

In this study, the model was run several times to get a reliable maximum, minimum and averaged output envelop of the forecast daily maximum water level at Flaksvatn. These runs are not particularly computationally intensive, since the optimal hyperparameters remain unchanged (see Table 2).

In Figure 4, the maximum, minimum and averaged values of the output are presented for several number of runs of 4 days forecast ANN model aiming at forecasting the maximum water level at Flaksvatn on the 2nd of October 2017.

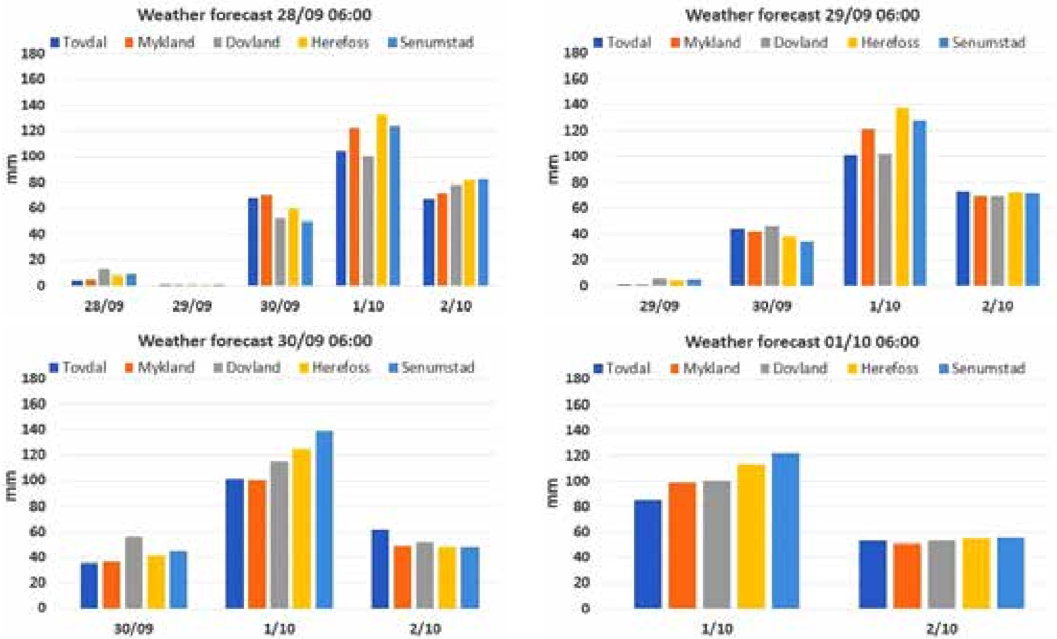

Figure 3. Weather forecast precipitation values between 28/09 and 02/10 for the selected stations.

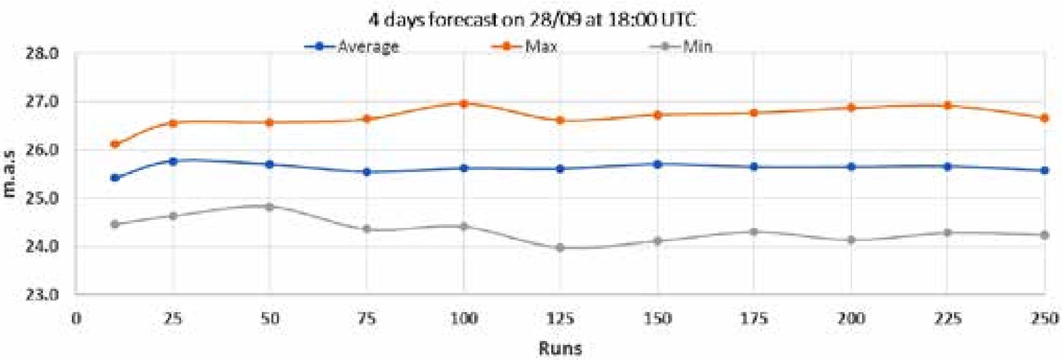

Figure 4. Maximum, minimum and averaged output results of 4 days forecast ANN model for several number of runs.

From that figure one can conclude that 100 runs are enough to get an acceptable convergence of those values associated with an affordable computation time taking around 20 minutes in a standard laptop.

The water level flood forecast results on 2nd of October 2017, using the above implementation, are shown in Table 5.

Figure 5 shows the water level forecast variations for the 2nd of October, corresponding to inputs and ANN model updates (see Table 4) during the period of 28th of September at 06:00 UTC to the 2nd of October at 00:00 UTC. In the figure the real water level on the 2nd of October (26.85 m.a.s) and the water levels corresponding to 100-year and 500-year return periods, respectively 24.50 and 25.50 m.a.s (Pedersen et al. 2005), are also presented. It is clear that the real flood level overpass the outdated 500-year return period flood level. It is also clear that the flood forecasting model presented here, would be able to forecast 4 days ahead values similar to the real

Table 5. The predicted water level downstream for the 2nd of October 2017 extreme event.

Forecast date (time)	Predicted Water level at Flaksvatn on 02/10/2017		
	Average [m.a.s]	Max [m.a.s]	Min [m.a.s]
28/09 (06:00)	26.38	27.96	25.03
28/09 (12:00)	26.15	27.63	24.87
28/09 (18:00)	25.62	26.96	24.41
29/09 (00:00)	25.37	26.63	24.43
29/09 (06:00)	25.49	26.51	23.87
29/09 (12:00)	25.30	26.29	23.87
29/09 (18:00)	25.75	26.96	23.89
30/09 (00:00)	25.36	26.40	23.94
30/09 (06:00)	25.68	26.68	24.83
30/09 (12:00)	26.07	26.93	25.26
30/09 (18:00)	26.39	27.29	25.55
01/10 (00:00)	26.89	27.86	26.00
01/10 (06:00)	27.14	27.98	26.26
01/10 (12:00)	27.29	28.16	26.37
01/10 (18:00)	27.43	28.32	26.48
02/10 (00:00)	27.58	28.50	26.61

one. This shows that the ANN models, with accurate weather forecast as it was in the real event (compare Figures 2 and 3), were able to predict the flood level with quite good accuracy.

Moreover, the ANN models seem to be able to forecast the water level due to an intense precipitation event (typical of Autumn floods) and, although the previous day water level was found has a key input during the ANN model development, the results for the first forecast (28/09 at 06:00 UTC) show that even starting with a low water level (in that forecast it was 1.90 and 1.21 m water depth for Flaksvatn and Austenå, respectively) the model is able to produce an exceptionally high and accurate water level. This indicates that this type of models can be also

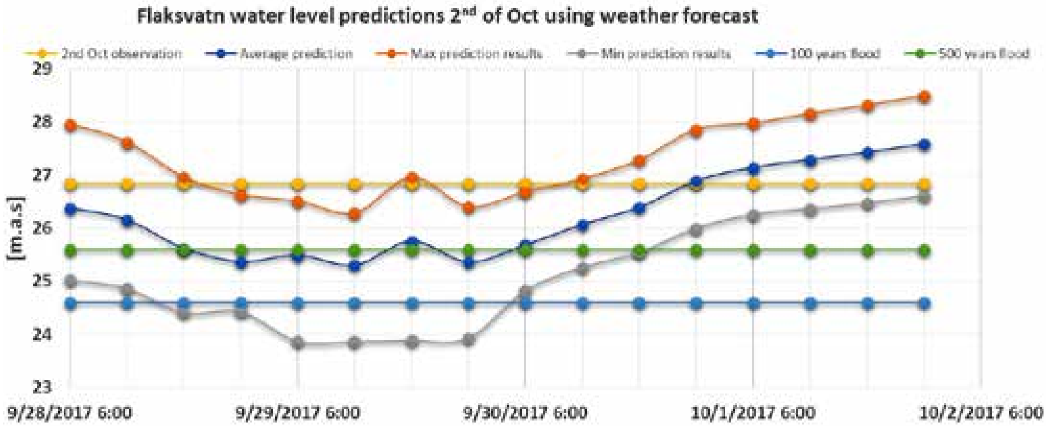

Figure 5. Water level prediction for the 2nd of October based on weather forecast

Figure 6. Flood inundation maps for the 2nd of October 2017: 100-year return period, real flood and maximum 4 days forecast flood.

used in catchments where no upstream water level measurements exist.

Figure 5 shows that the forecasted water level decreases during the period between 29/09 and 30/09, the reason for this is that the weather forecast in that period had slightly smaller precipitation values (see Figure 3). As the forecast approaches the 2nd of October the water level prediction starts to increase and becomes more accurate because prior days data are now included, namely the precipitation and the water levels in the used stations.

To have a better overview of the impact that the proposed flood forecasting model would have, in Figure 6 the flood inundation maps for the 100-year return period, the real flood and the maximum flood level forecast 4 days ahead are presented. From the maps, one can conclude that for 4 days ahead the proposed flood forecasting model would anticipate the overtopping of the Fv41 road and that a big area in the Northeast of the reservoir would be flooded (see red and dark blue areas in Figure 6), including the Birkenes Fire Station and several workshops and industries (like 3B Fibreglass AS).

Conclusion

This study shows that data-driven techniques, like ANN, can be an alternative or complement to traditional physical-based models for flood forecasting. Moreover, due to their low computational demand they can easily be incorporated into real-time flood warning systems. Also, even though they are developed based on historical data, they don't require the establishment of a return period, which is difficult in nowadays under a climate change scenario.

The most impressive outcome of this study is that ANN models based on 19 years data records were able to forecast 4 days ahead an extreme event (water level of 26.85 m.a.s, highest ever recorded in Flaksvatn) for which the models have not been trained for (highest water level in the training data set was 24.30 m.a.s). This points out that these models can give good predictions even if they are used outside the range for which they were developed, as long as the weather forecast is also accurate.

It was also an impressive result that the 4 days forecast ANN model was able to predict such a high water level, taking into consideration that the input water level was low (normal). This indicates that although the water level is a relevant input, it is possible that the models would give good results just based on precipitation and temperature data.

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