EGU General Assembly 2020

Comparison of Machine Learning Techniques Powering Flood Early Warning Systems

Application to a catchment located in the Tropical Andes of Ecuador

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Why forecasting floods?

- Hydrological extremes (especially floods) have multiple impacts on society.
- Flood frequency and severity will increase with climate and land use changes!
- Forecasting is an emerging field of research for risk assessment and mitigation
- 263 floods caused more than 400 human losses in Ecuador (1970-2007)

Effect of the El Niño S.O., Ecuador, 2016.
Photo: John Sackton

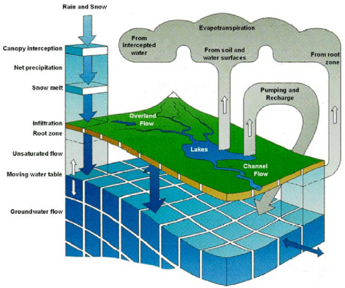
Flood forecasting in mountainous areas is harder...

- The main flood drivers (humid areas) are precipitation, soil humidity and topography.
- Flood forecasting is crucial but limited.
    - Extreme spatio-temporal variability of driving forces
    - Budget constrains
    - Remoteness of monitoring sites
- Temporal information is still limited.

Urban flash-flood in Cuenca, Ecuador, 2012.

Forecast modeling approaches

- Distributed vs. black-box modeling
- Data scarcity and model specificities (overparameterization) often limit the model operational value
- Machine Learning (ML) techniques use have increased in past decades
- ML models can deal with:
  - Missing information
  - Measurement errors
  - Non-stationary problems



MIKE SHE scheme (fully-distributed). DHI©

Research objective

Primary objective

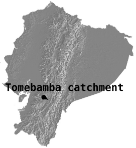
To compare the performance of five Machine Learning (ML) classification techniques for Flood Early Warning Systems (FEWSs) applied in a medium-size mountain catchment representative of the tropical Andes in Ecuador

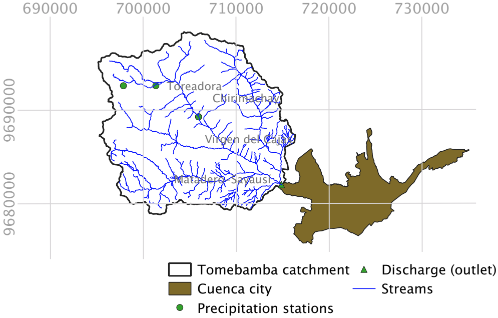
Scope:

1. FEWS alternatives are determined by the ML algorithm used and for varying lead times of 1, 4, 8 and 12 hours
2. Determination of an optimal input-structure construction process for improving forecasts
3. Determination of an appropriate methodology for performance evaluation

The Tomebamba catchment, southern Tropical Andes of Ecuador

- Area≈ 85 km^2, 2800–4400 m.a.s.l.
- Fresh water supplier of the 3rd. largest city in Ecuador (Cuenca).
- Mainly composed by páramo ecosystem.





Hydrological data

- 4 years of hourly precipitation and runoff timeseries (Jan 2015 - Jan 2019)
- Precipitation stations (within the catchment)
  - Toreadora (3955 m a.s.l.)
  - Virgen del Cajas (3626 m a.s.l.)
  - Chirimachay (3298 m a.s.l.)
- Runoff station (outlet)
  - Matadero-Sayausí (2693 m a.s.l.)
- Training: 2015-2017
- Test: 2018

ML techniques for flood classification

ML picked up from different families (classification by similarity in terms of their functionality)

1. Logistic Regression (**LR**) $\rightarrow$ Regression
2. K-Nearest Neighbors (**KNN**) $\rightarrow$ Instance-based
3. Random Forest (**RF**) $\rightarrow$ Decision tree
4. Naive Bayes (**NB**) $\rightarrow$ Bayesian theorem
5. Multi-layer Perceptron (**MLP**) $\rightarrow$ Artificial Neural Networks

Process for input construction

- Input data composition (Lag analyses)
  - Pearson´s cross-correlations for precipitation (3 stations)
  - Auto- and partial-auto-correlation functions for discharge (1 station at the outlet of the catchment)
- Feature scaling and normalization
- Principal Component Analysis (PCA)
  - Dimension reduction (trimming off correlated features)
- Resampling (under or over) ✗
- Put weights on errors proportional to class imbalance ✓

Output data labeling

- Flood warnings based on measured runoff at the Matadero-Sayausí control station
    - Control station at the entrance of the city
    - 20 years of data
- Flood warning definitions
    - Alarm $\Leftrightarrow$ $Runoff > 50\ \mathrm{m}^3.s^{-1}$
    - Pre-alarm $\Leftrightarrow$ $30 \leq Runoff \leq 50\ \mathrm{m}^3.s^{-1}$
    - No-alarm $\Leftrightarrow$ $Runoff < 30\ \mathrm{m}^3.s^{-1}$

Models' hyper-parameterization

- Each model is a combination of the ML selected and lead time (1, 4, 8 and 12 hours)
- Grid-search (10-fold cross-validation)

Model-hyper-parameters and their search domain for tuning

ML technique	Hyper-parameters				
LR	*C* 0.001 – 1000	*penalty* {'l1','l2'}			
KNN	*n_neighbors* 3 – 75	*weights* {'uniform', 'distance'}	*metric* {'euclidean', 'manhattan', 'minkowski'}	*algorithm* {'auto','ball_tree', 'kd_tree','brute'}	
RF	*n_estimators* 50 –1000	*max_features* {'auto', 'sqrt', 'log2'}	*max_depth* 50 –1000	*min_samples_leaf* 1–500	*min_samples_split* 1–500
MLP	*solver* {'lbfgs'}	*max_iter* 10 – 5000	*alpha* 1 E–9 – 0.1	*hidden_layers* 1 – 16	

Models' performance evaluation

Metrics for dealing with imbalanced and multi-class problems

- F1 score

$$F1_{score} = 2 * Precision * Recall/(Precision + Recall)$$
$$Precision = TP/(TP + FP)$$
$$Recall = TP/(TP + FN)$$

- Geometric mean

$$G_{mean} = \sqrt{TP_{rate} * TN_{rate}}$$
$$TP_{rate} = Recall$$
$$TN_{rate} = TN/(TN + FP)$$

where TP stands for True Positives, TN stands for True Negatives, FP for False Positives and FN for False Negatives

Models' performance evaluation

- Log loss score

$$Logloss_{score} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij}\log p_{ij}$$

  where N is the number of samples, M is the number of classes, y_{ij} is 1 when the observation belongs to class j; else 0, and p_{ij} is the predicted probability that the observation belongs to class j

- Statistical significant test
  - Chi-squared test
  - To prove that the difference in the observed proportions of the contingency tables of a pair of ML algorithms are significant

Imbalanced sample class distribution

The imbalanced data problem was overcame by penalizing misclassifications inversely proportional to class frequencies:

$$w_{No-alert} = 0.01; w_{Pre-alert} = 0.55; w_{Alert} = 0.51$$

Sample class distribution for the entire dataset, and for the training and test subsets

Warning	Complete	Training	Test
No-alert	96.1%	96.2%	95.7%
Pre-alert	2.1 %	1.8 %	3.1 %
Alert	1.8 %	2.0 %	1.2 %

Lag analyses for the timeseries. 1h lead time

- Discharge
  - Dominance of the autoregressive over the moving-average process
  - 8 lags (hours) for the 1-hour lead time case
- Precipitation
  - Max correlation at lag 4 (all stations)
  - Resulting number of lags (correlation threshold of 0.2): 15 for Toreadora, 11 for Virgen and 14 for Chirimachay
- The same analyses were done for the 4, 8 and 12-hour cases

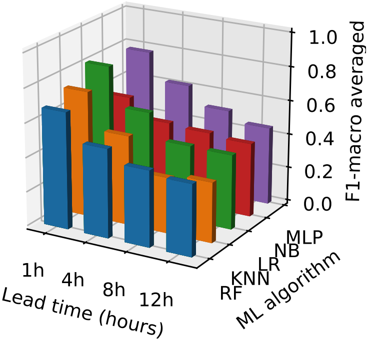
Full details on the followed methodology can be found in *Muñoz et al. (2018)*

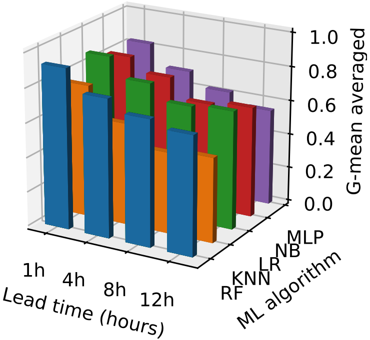
Training subset

Lead time (hours)	Performance's ranking (best → worst)				
	$F1_{macro-score}$				
1	MLP	LR	KNN	NB	RF
4	MLP	LR	KNN	NB	RF
8	MLP	KNN	LR	NB	RF
12	MLP	LR	NB	KNN	RF
	$G_{mean-macro}$				
1	RF	MLP	NB	LR	KNN
4	RF	LR	NB	MLP	KNN
8	LR	RF	MLP	NB	KNN
12	RF	LR	NB	MLP	KNN
	$Logloss_{macro-score}$				
1	MLP	KNN	RF	LR	NB
4	KNN	MLP	RF	LR	NB
8	KNN	MLP	NB	RF	LR
12	MLP	KNN	LR	RF	NB

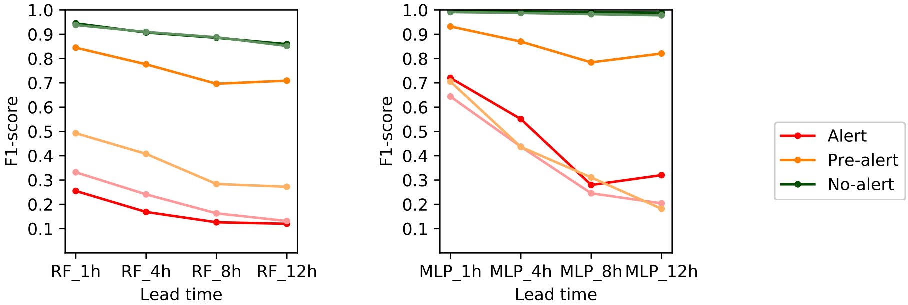
All improvements and degradations are statistically significant

Test subset


1.0
0.8
0.6
0.4
0.2
0.0
F1-macro averaged
1h
4h
8h
12h
Lead time (hours)
RF
KNN
LR
NB
MLP
ML algorithm


1.0
0.8
0.6
0.4
0.2
0.0
G-mean averaged
1h
4h
8h
12h
Lead time (hours)
RF
KNN
LR
NB
MLP
ML algorithm

A more detailed (individualized) assessment...

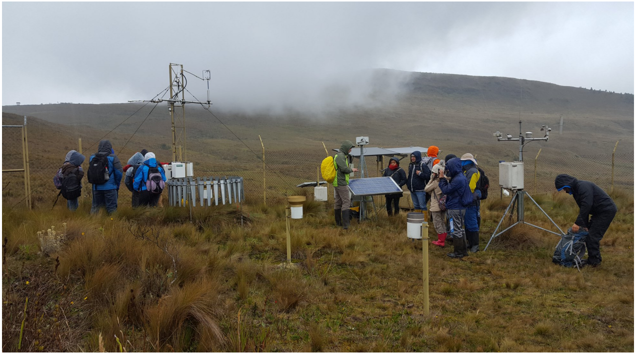


Conclusions and remarks

- The most effective model (F1-macro score and Log-loss score) was based on the MLP technique, followed by LR
- Individual F1-scores unraveled the difficulties when forecasting the Pre-alert and specially the Alert classes
- Deep exploration on the effect of input data composition and the architecture of the MLP might improve models' performance and even to extend the lead time
- The MLP can be used for the first FEWS of the city of Cuenca
- Future efforts should be put on the development of a website and/or mobile application as a tool to boost the preparedness against floods

Interested in collaborating with us?

We study the tropical Andes, the most diverse hotspot of the planet and early indicator of global change



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