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Spatio-temporal Forecasting of Meteorological Visibility over Northwest of Morocco using Long Short-Term Memory (LSTM) Network.

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Plan

Background

- Low visibility conditions (LVC)
  - Negative impact on all forms of transport
  - Challenge for weather forecasters, particularly over large domain

Need to improve the spatio-temporal forecasting of low visibility, but how ?

Example of low visibility

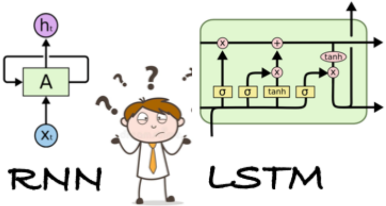
Impact of the low visibility on road traffic

Visibility Forecasting approaches

- Physical modelling with NWP using empiric parameterization such as (Kunkel 1984) or (Gultepe 2006) But,
  - The complexity of the processes driving low visibility makes predictions challenging through a physical parametrization
  - With improved horizontal and vertical resolutions, 3D NWP models are computationally expensive
- AI-based techniques to emulate processes related to visibility (Claxton et al 2018, Bari and Ouagabi 2020) or to build full ML-based models for visibility prediction (Marzban et al 2007, Dutta et al 2015) But,
  - Most of the proposed methods focused on single site or on the spatial dimension. Thus, dealing with both the time and space dimensions is still needed for visibility forecasting over a large domain.

LSTM-Based approaches for Visibility Forecasting

- Recurrent Neural Networks (RNN) and specially LSTM are widely used for time series prediction. (Hochreiter and Schmidhuber 1997)
- It has been used for visibility prediction in many research studies (Salman et al 2018, Deng et al 2019, Miao et al 2020)
- Most of these research studies focused on single site, often an airport.



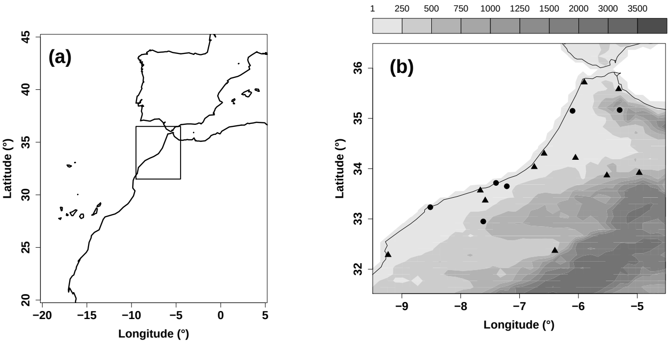
Need for LSTM-based research studies which deal with both space and time dimensions for visibility forecasting.

Objectives

- Evaluate the potential of combining NWP model and LSTM to predict horizontal visibility
- Assess the impact of NWP forecasts unbiasing on the spatio-temporal prediction process.

Study Domain and Datasets

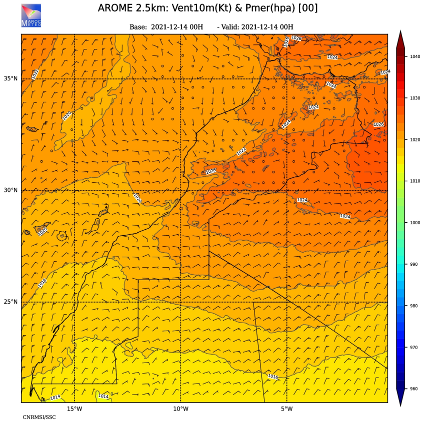
- 17 synoptic stations
- 2 years of hourly forecasts and observations data (from March-2015 to March-2017).
- 6 predictors : T2m, RH2m, MSLP, WS10m, WD10m, and SURFP



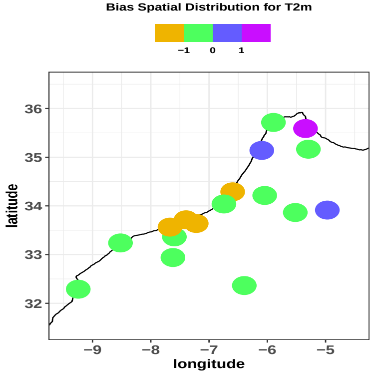
NWP Model AROME

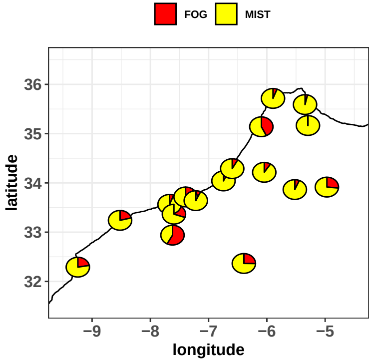
3D AROME NWP features (Seity et al. 2011, Hdidou et al 2020) :

- A non-hydrostatic model
- 2.5km horizontal resolution
- 90 vertical levels, first level starting at about 5m.



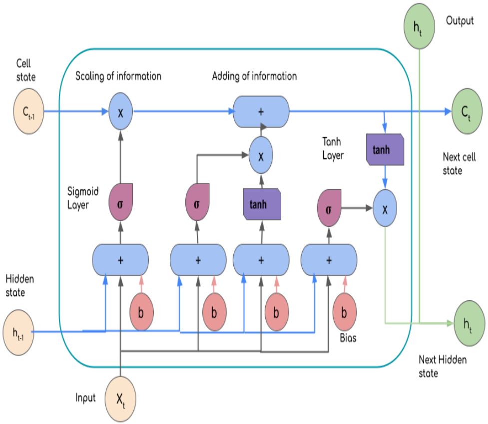
Observed Fog/Mist Frequency and Predictor's Bias over the study domain

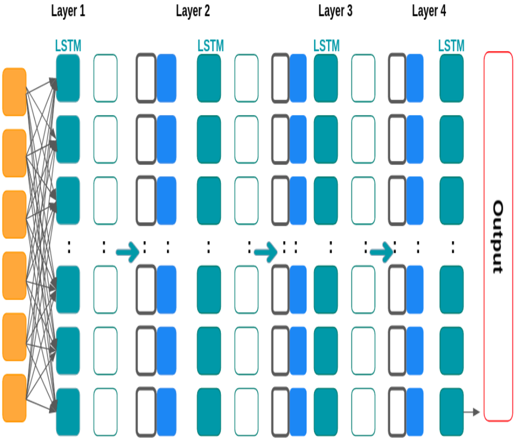




(+) Low Visibility Conditions (Fog and Mist) are frequent on coasts. (+) AROME forecasts have a systematic error which varies as function of the parameter, the lead-time and the geographical position.

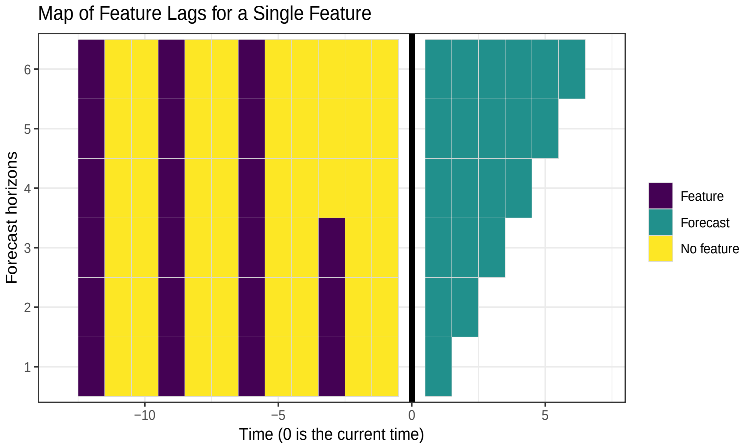
Long Short Term Memory (LSTM) principle and Architecture





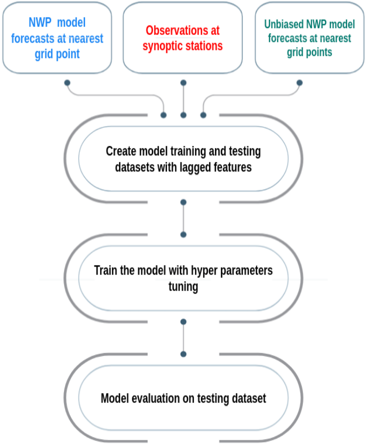
Data preparation : Lagging Data-sets

Depending on the look-back period (3H, 6H, 9H, and 12H), our data-sets are timely lagged for all the features.

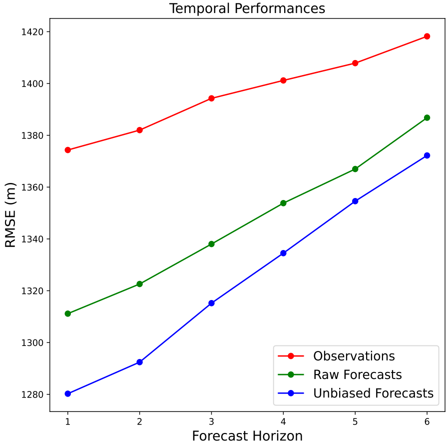


Experimental Design

- **Outcome:** horizontal visibility (m)
- **Lagged Features:** T2m (°C), RH2m (%), FF10m (m/s) DD10m (degrees), MSLP (hPa), and SURFP (hPa)
- **Static Features:** latitude (degrees), longitude (degrees) and altitude (m) of the used observation
- **Forecast:**
  - Build a 6-hours-ahead forecast model using LSTM.
  - Training and validation period : from March-2015 to October-2016.
  - Testing period : from October-2016 to March-2017.

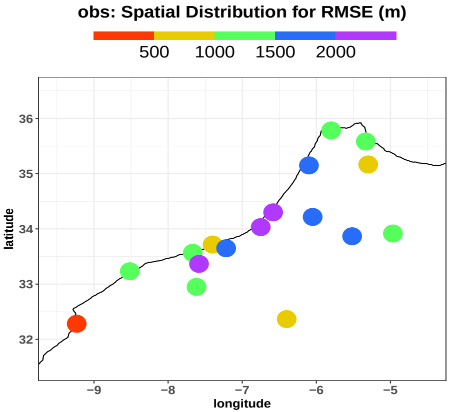


Temporal Performance per forecast horizon for 9H look-back period



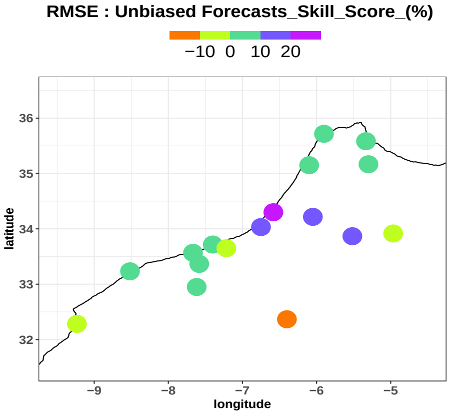
- (+) Performance decreases as forecast horizon increases.
- (+) Observation-based configurations are the worst.
- (+) Unbiasing improves the performance.

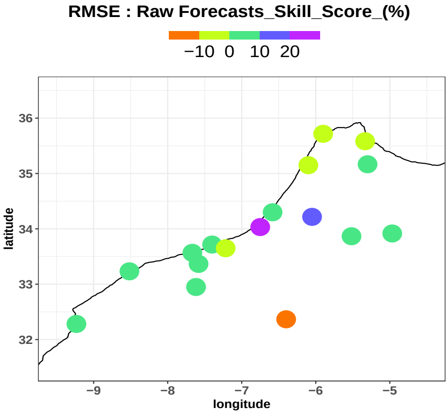
Spatial Scores *RMSE* : Observations-base Config.



(+) The worst RMSE is found over the foggy areas (Grand Casablanca region) while these scores are better elsewhere.

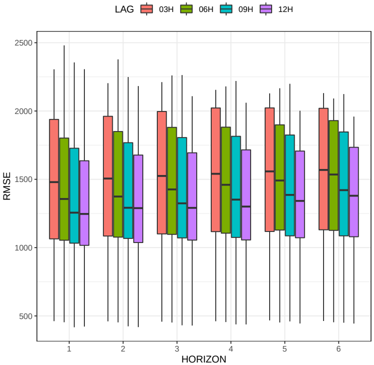
Spatial *RMSE* Skill Scores (SS_{RMSE}) : Raw vs Unbiased Forecasts





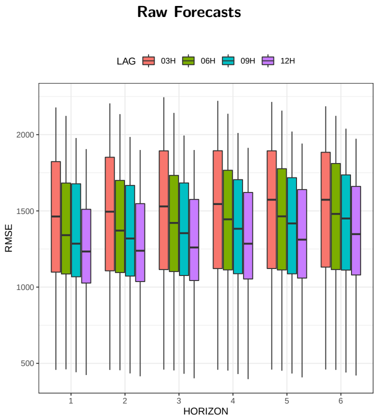
(+) Removing the systematic NWP model error from predictor's forecasts improves the RMS error in visibility forecasting over the foggy area. The observation-based configuration is the benchmark.

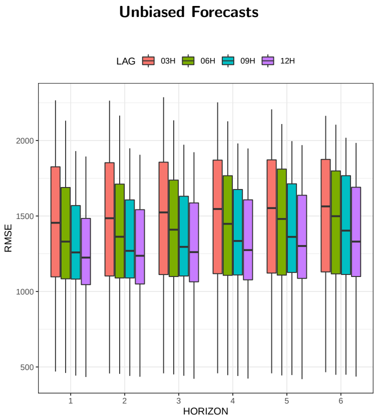
RMSE Scores per Look-back periods : Observations



Performances get better with higher look-back periods.

Scores by Look Back periods : Raw vs Unbiased Forecasts





Comparing the size of the boxplot (RMSE spatial distribution) and the median : the best scores are for the Unbiased Forecasts-based configurations.

Summary

- Combining NWP model outputs and LSTM has shown a promising results for spatio-temporal forecasting of visibility over a large domain (Northwest of Morocco).
- Performances get worst with higher forecast horizons and also with lower look-back periods
- The performance of the NWP-ML developed model is geographically dependent
- Removing the NWP model systematic error from predictor's forecasts has positive impact on the NWP-ML developed model performance.

Future work

- Extend the size of the training dataset
- Extend the size of the study domain to cover the whole country of Morocco
- Include other meteorological parameters that are physically linked to visibility
- Assess the potential of using other AI techniques like the decision tree-based ones (XGBoost, Random Forest, etc.) and compare them to LSTM performance.


THANK YOU :)

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