Application and Verification of ECMWF Products 2021

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Turkish State Met. Services (TSMS)

1. Summary of major highlights

TSMS started to apply Non-Homogeneous Gaussian Regression (NGR) to daily 2-meter maximum and minimum temperature forecasts up to 15 days of ECMWF's Ensemble Prediction System (ENS) for 104 stations.

2. Use and application of products

2.1 Direct Use of ECMWF Products

ECMWF products are main source of TSMS forecasting/warning systems and IC/BC of local models. TSMS uses a web-based visualization tool that provides interactive parameterized graphical products to authorized users. The framework is designed to use Magics++ with python for generating products. Java and PHP are also used for interface. This software displays direct model outputs and derivated products of ECMWF's High Resolution Deterministic Model (HRES), ENS and local models.

2.2 Other uses of ECMWF output

2.2.1 Post-processing

Kalman Filtering:

Kalman Filtering is applied to HRES's daily 2- meter maximum and minimum temperature forecasts from D+1 to D+5 for 960 stations including 42 foreign stations. Kalman Filtering scores have been considered %5-%25 better than direct model outputs.

Calibration of ECMWF's Operational ENS Forecasts for Daily Max-Min Temperature:

TSMS recently started using calibrated daily maximum and minimum temperature forecasts up to 15 days of the 00 UTC ENS model by applying Non-Homogeneous Gaussian Regression (NGR) Method. NGR scores have been tested against corresponding observations, ENS mean and Kalman Filtering scores (up to 5 days) in between 17 January and 30 June 2020 for 104 stations. Below is a brief description of what we do and result of comparisons.

The data pairs of ECMWF re-forecast and corresponding observation (20 years backward beginning from previous year) have been used as training data to implement the method. Four weekly (16 days before and 14 days after EPS model run date) re-forecast window was selected considering each ENS model run date. The data remaining in the window was used as training dataset. The re-forecast window slides according to the date of the ENS operational model run. Therefore, when operational ENS model run date moves forward then reforecast window moves accordingly. As the date of the ENS model run changes, the re-forecast dates in the window also change.

The coefficients were calculated with Continuous Ranked Probability Score (CRPS) approach. NGR was implemented using *crch()* package in R programming.

Temperature forecasts of ENS operational and re-forecast models are mostly lower than observations (under estimation). Therefore, NGR tends increasing both forecasts (positive Standard Deviation (stdev)). The method gives good results when there is a similar trend and sufficient spread in operational forecast. The breakdown of this relationship due to errors in the synoptic scale of the ENS model reflects negatively on the results. Similarly, weather events such as cloudiness, precipitation and fog, which occur at the local scale, which affect the maximum and minimum temperatures, also make it difficult to predict temperature by the model.

Results of ENS daily max/min calibration are illustrated below (Figure-1). Bi-linear interpolation was used for all interpolation processes. The graphs compare Root Mean Square Error (RMSE) scores for raw model output (bil-raw: black solid line with star), NGR calibration (bil-ngr: red solid line with star) and Kalman Filtering (KF) (kal: blue dotted line with filled triangle point-up blue). RMSE of calibrated and raw forecast were also computed for nearest grid land point in order to understand possible effect of interpolation (ngp-raw/ngr: black/red dashed line with filled circles black/red). Results look very promising.

The RMSE values at maximum temperature range from 2 to 4 over the 14-day period (likewise minimum temperature range from 2 to 3), which can be considered a good result considering the average of 104 stations. RMSE values of minimum temperature are lower than the maximum temperature is considered that because of the model predicts the minimum temperature better than the maximum temperature. As stated above, NGR provides more correction when ensemble spreads are high. As seen on Figure-1, the temperature predictions have been improved over the period and no breakdown (NGR error amount is less than model over the period) has been occurred. NGR even gives better results than KF in short range where spread is lower.

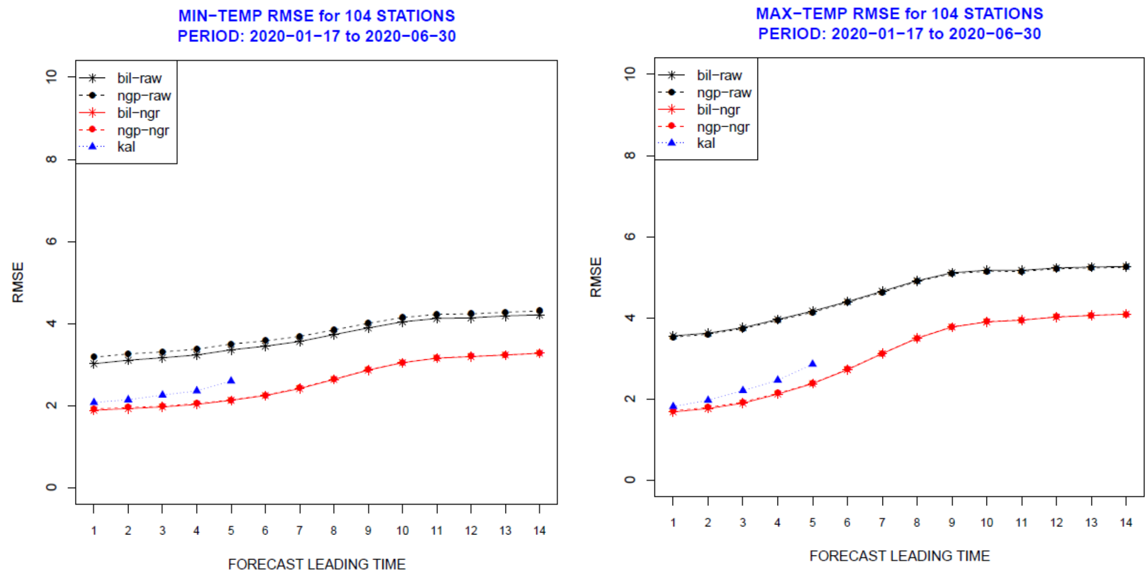


Figure-1: Daily Min/Max RMSE Results (Average of 104 Stations)

In terms of weather forecasting, temperature forecast for places at high altitudes and complex geographical structures in inner and eastern regions of Turkey is more difficult than other regions. The fact that the NGR provides an appropriate improvement for many stations in such regions. This improvement is also better than KF.

Model errors are generally smaller at seaside stations. Using the nearest grid land point instead of bi-linear interpolation at lower altitudes did not reduce the effect of the sea on temperature. This is especially true for minimum temperatures. As a result, the low amount of model error reduces the NGR improvement.

2.2.2 Derived fields

None

2.2.3 Modelling

ECMWF models are used as initial and boundary conditions at TSMS for following local models.

WRF: Coupled with ECMWF hourly HRES. 3km horizontal and 60 vertical layer. It runs 4 times per a day. Forecast range is up to 72 hours.

AROME-Turkey: Surface assimilation cycle of AROME-Turkey is running since Mid-October 2020 after implementation studies (Cengiz and Sezer, 2020). The surface assimilation is running in the pre-operational mode on ecflow and the system produces forecast every 3 hours with a lead time of 24 hours. The horizontal resolution of AROME-Turkey is 1.7 km and it has 72 vertical levels. The time step of the model is 60 seconds and the model is using code version cy43t2-bf10. Lateral boundary condition (LBC) data of the model is obtained from HRES. The LBC data is also used to update the sea surface temperature during the surface assimilation cycle.

The method used for surface assimilation is CANARI-OIMAIN which produces soil and surfex fields (T2M, H2M, TG1, TG2, WG1, WG2) in every analysis. The SAPP system developed at ECMWF (Fucile et al., 2014) is the pre-processing tool used for the preparation of observations, which get in the surface assimilation system of AROME-Turkey (Cengiz et al., 2020).

A-LAEF: TSMS cooperates with RC LACE on A-LAEF system which is coupled to ENS 16 members.

WW3 Wave Model: HRES products are used as initial and boundary conditions. WW3 model runs 2 times per a day with 3km horizontal resolution for whole Mediterranean, Black Sea and Caspian Sea. Forecast range is up to 120 hours.

SWAN Wave Model: It runs at 1 km horizontal resolution in coastal regions of Turkey. The model has a forecast period of 72 hours with 3-hour intervals.

FFGS: HRES precipitation forecasts are used in Flash Flood Guidance System (FFGS). This system provides information on rainfall and hydrologic response in determining the potential for a flash flood.

3. Verification of ECMWF products

TSMS uses A-LAEF products since December 2020, but we have no any comparisons between ENS and A-LAEF systems.

3.1 Objective verification

3.1.1 Direct ECMWF model output (both HRES and ENS), and other NWP models

Point Verifications:

All time steps forecasts between T+00 and T+240 and 24 hourly forecasts between T+00 and T+144 of 00 UTC and 12 UTC deterministic model run are operationally verified with standard statistical score of root mean square error. In the verification process of upper level parameters (temperature and geopotential heights), observations of 7 our radio-sonde stations used for calculations. Interpolated model outputs of local weather parameters (maximum, minimum and 12 UTC of 2-meter temperature, mean sea level pressure, and total precipitation) verified against corresponding observations. For this process, suitable time steps of model outputs were used. Verified parameters are given in below:

• Daily Maximum and Minimum Temperature, Mean Sea Level Pressure and 2 m Temperature ; D+1, D+2, ..., D+6;

Scores: RMSE.

• Total Precipitation existence and contingency tables with 6 categories (0, 0.1-1, 1-5, 5-10, 10-20, 20<mm):D+1, D+2, D+3;

Scores: BIAS, PC, POD,FAR, F, KSS, TS, ETS, HSS, OR, ORSS.

<u>Comparison of HRES with Local Models</u>:

Verification of ECMWF-HRES, ALARO (ALR-cy40) and WRF models are performed monthly at TSMS. Harmonie verification package was used to compare these model scores. Verification scores of 2-metre temperature and geopotential in different seasons are given below.

<u>2-Metre Temperature:</u>

Figure 2 shows 2-metre temperature stdev and bias values of three models for 115 stations in summer and winter seasons. There is no big change in the bias values of HRES and WRF between winter and summer periods. HRES scores show that it always has negative biases for summer and winter period. STDEV for all models are lower in summer than winter.

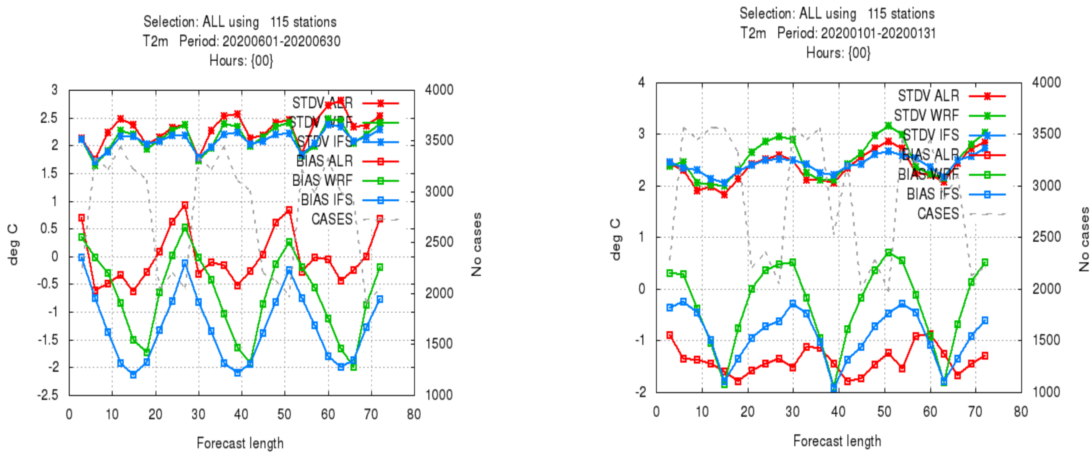


Figure 2: 2-metre Temperature bias and stdev for 2020 winter and summer for HRES, ALR and WRF for 115 stations in Turkey.

<u>Geopotential:</u>

Figure 3 shows RMSE and bias values of geopotential for three models at 7 stations during summer and winter seasons. For both periods, HRES's RMSE at 500 hPa is particularly lower than other models. HRES and WRF generally have negative biases whilst ALR has changeable bias.

<u>3.1.2 Post-processed products and end products delivered to users</u>

e.g. Calibrated ENS probabilities, etc. For lead times up to day 15.

3.1.3 Monthly and Seasonal forecasts

Focus on lead times beyond day 15.

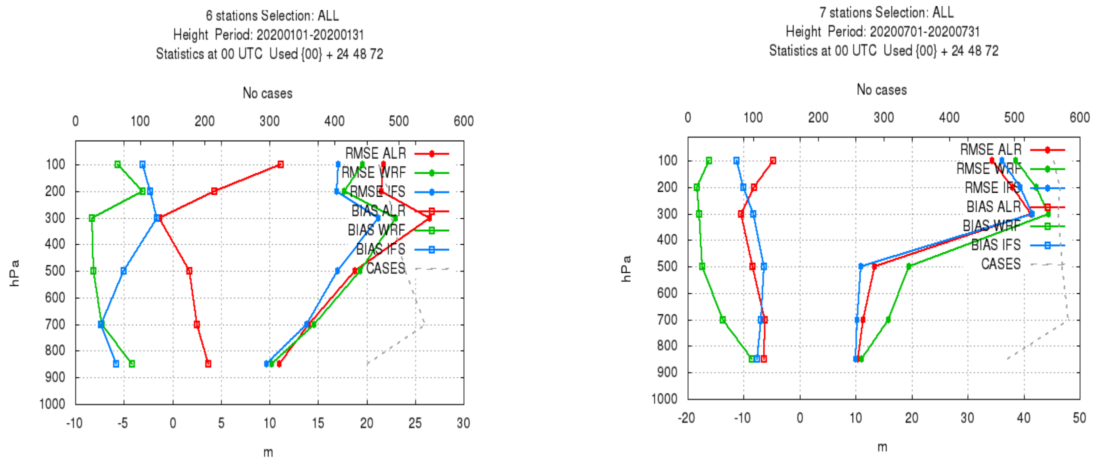


Figure 3: Geopotential bias and RMSE for 2020 winter and summer for IFS, ALR and WRF at İstanbul, Ankara, Erzurum, İzmir, Isparta, Diyarbakır and Samsun.

3.2 Subjective verification

3.2.1 Subjective scores

TSMS prepares monthly (updated twice a week in weekly periods) and seasonal forecasts (updated once a month in monthly periods) using ECMWF extended range and seasonal forecast products. Performance of ECMWF seasonal temperature and precipitation anomaly forecasts for 2020 June and 2020 October have been evaluated subjectively.

June 2020:

In the 01.04.2020 Run forecasts for June 2020, there is a positive temperature anomaly (Figure 4a) in inner and eastern regions, while there is no signal for precipitation anomaly (Figure 4e).

In the 01.05.2020 Run forecasts for June 2020, there is a positive temperature anomaly in inner and western regions (Figure 4b), but there is no significant signal for precipitation anomaly (Figure 4f).

In the 01.06.2020 Run forecasts for June 2020, a positive temperature anomaly is seen in inner and eastern regions (Figure 4c) and a limited positive precipitation anomaly in Central Black Sea region (Figure 4g).

In temperature anomaly map of June 2020 (Figure 4d), there are negative temperature anomalies in western and southern parts, whilst positive temperature anomalies are observed in other regions. Negative temperature anomaly could not be predicted in all three Run forecasts. In precipitation anomaly map of June 20209 (Figure 4h), a negative precipitation anomaly was observed in southern and eastern parts while positive precipitation anomaly was observed in other regions, especially in north-western regions. Positive and negative precipitation anomalies could not be predicted in all three Run forecasts.

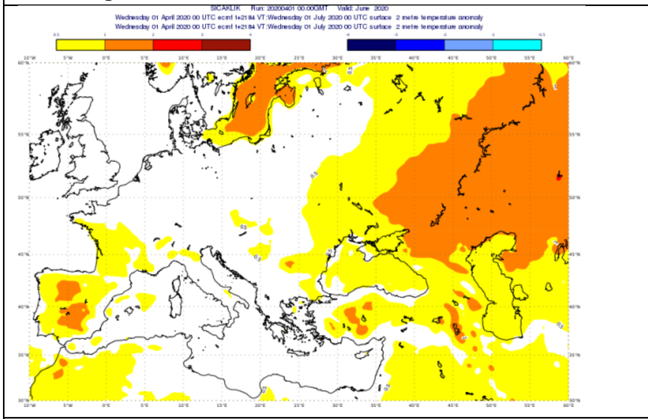
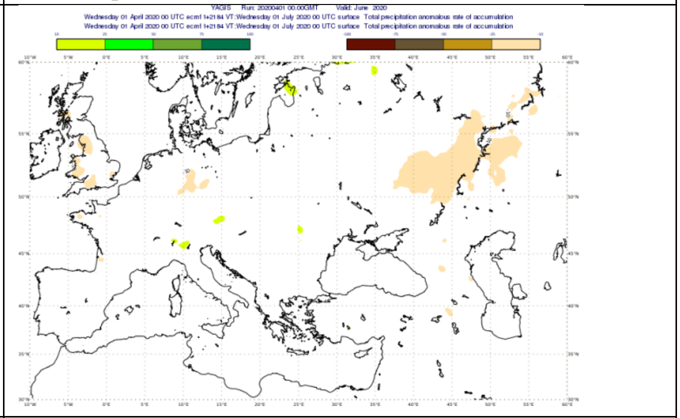
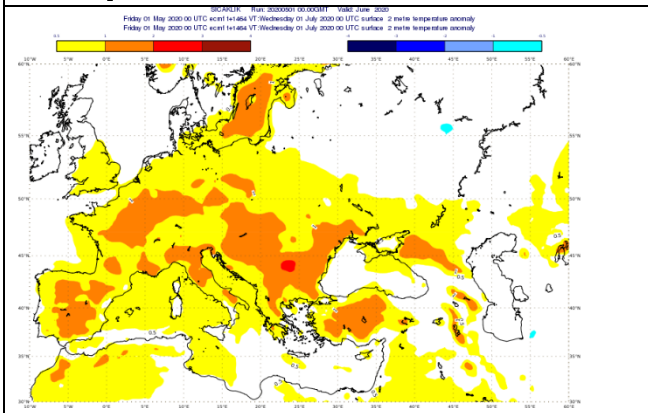
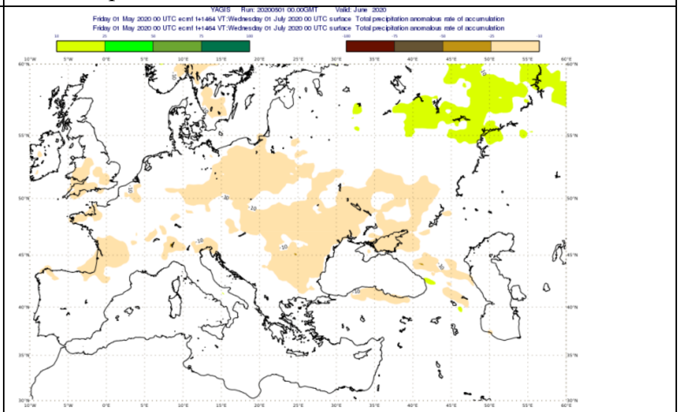
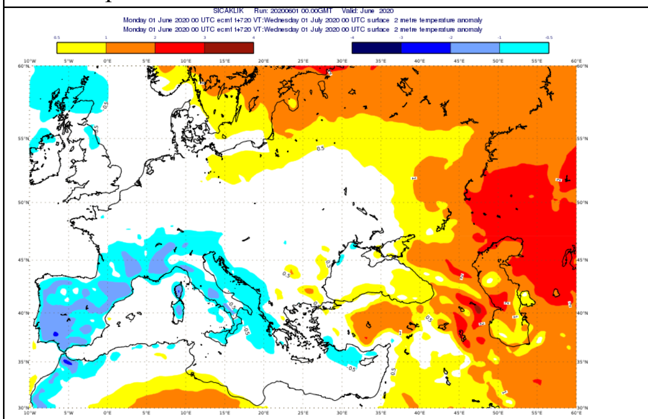
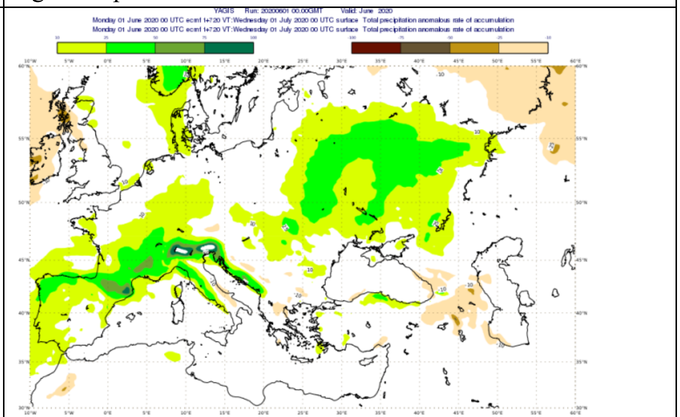
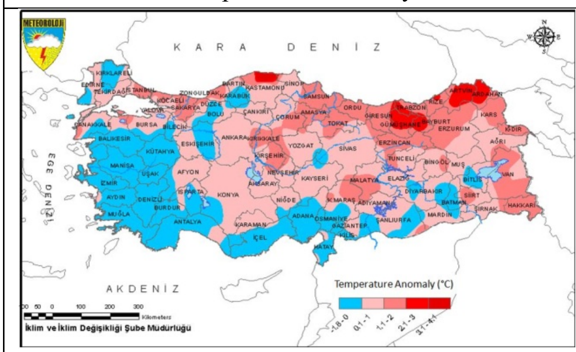
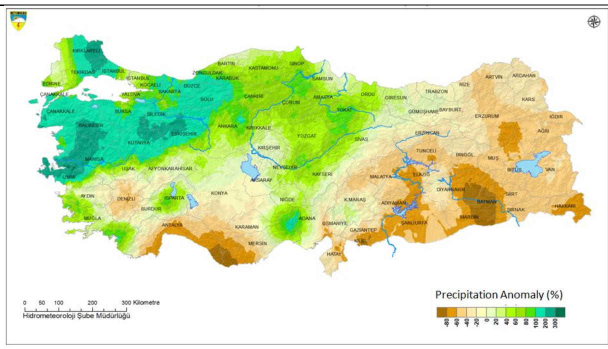
4a. Temperature Run:01/04/2020 Valid:June 2020	4e. Precipitation Run:01/04/2020 Valid:June 2020
	
4b. Temperature Run:01/05/2020Valid:June 2020	4f. Precipitation Run:01/05/2020Valid:June 2020
	
4c. Temperature Run:01/06/2020 Valid:June 2020	4g. Precipitation Run:01/06/2020 Valid:June 2020
	
4d. June 2020 Temperature Anomaly	4h. June 2020 Precipitation Anomaly
	

Figure 4: June 2020 Seasonal Forecast Verifications

October 2020:

In 01.08.2020 Run forecasts for October 2020, only weak positive temperature anomaly in Thrace (Figure 5a) and weak negative precipitation anomaly throughout the country (Figure 5e).

In 01.09.2020 Run forecasts for October 2020, there is a positive temperature anomaly over Turkey (Figure 5b), while there is a weak negative precipitation anomaly in the southern parts (Figure 5f).

In 01.10.2020 Run forecasts for October 2020, there is a strong positive temperature anomaly over Turkey (Figure 3c), while there is a negative precipitation anomaly all over Turkey (Figure 5g).

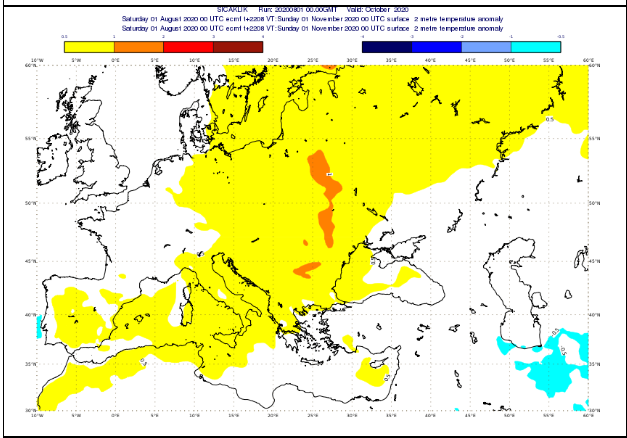
In temperature anomaly map of October 2020 (Figure 5d) shows that a positive temperature anomaly was observed all over Turkey, being more effective in the inner parts. Positive temperature anomaly in whole Turkey was estimated in the last two forecasts (01.09.2020 and 01.10.2020 Run).

In the precipitation anomaly map of October 2020) (Figure 5h), It is seen that strong negative precipitation anomaly is observed in the southern and eastern regions. However, weak positive precipitation anomalies in western parts and strong negative precipitation anomalies in southern and eastern regions could not be predicted (Figure 5h).

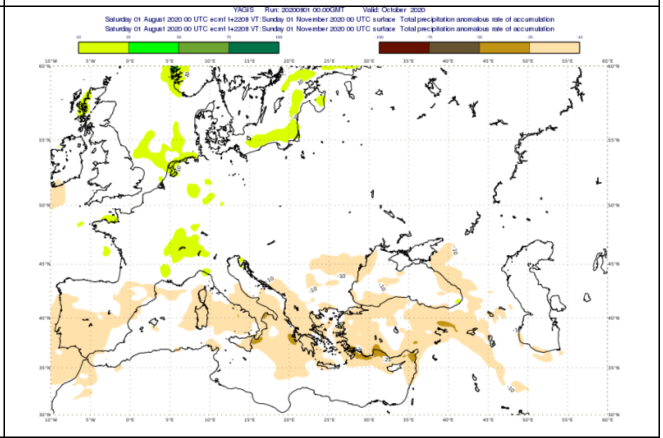
General Evaluation:

- Especially in the transitional seasons (April to June), consecutive predictions show great differences and the accuracy of the forecast decreases.
- When long-term convective precipitation occurs in the inner and western regions in May and June, the precipitation that occurs more than normal cannot be predicted.
- In the autumn months, when the hot weather is higher than the normal, there are no transitions of Middle Mediterranean cyclone. Especially in southern and eastern regions, strong negative precipitation anomaly occurs.

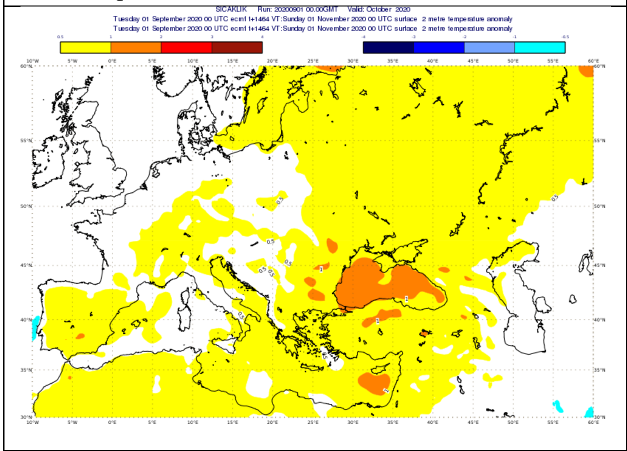
5a. Temperature Run:01/08/2020 Valid:October 2020



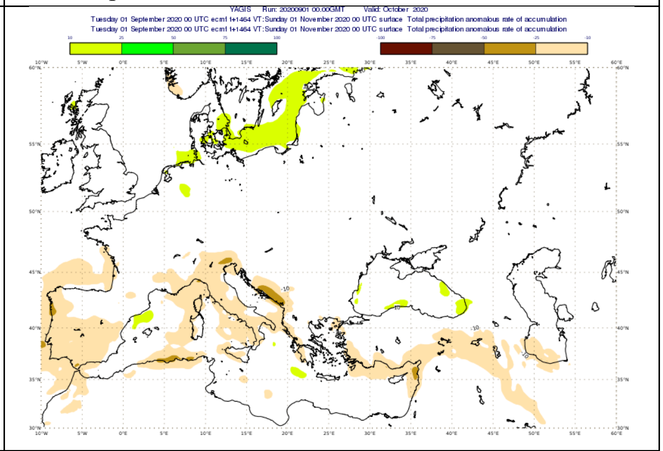
5e. Precipitation Run:01/08/2020 Valid:October 2020



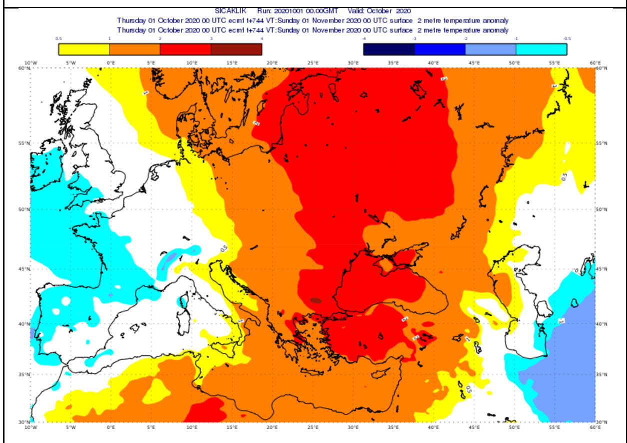
5b. Temperature Run:01/09/2020 Valid:October 2020



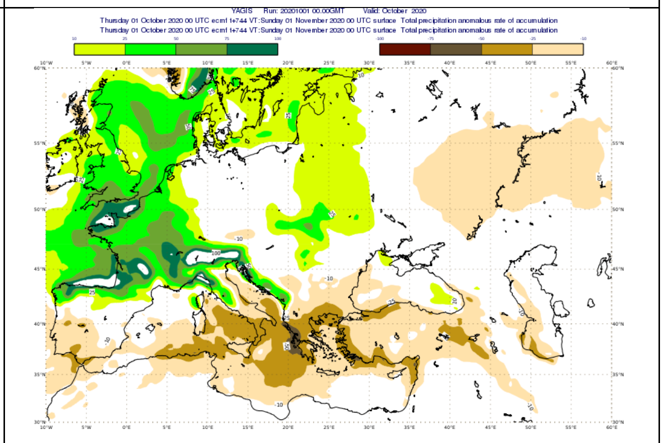
5f. Precipitation Run:01/09/2020 Valid:October 2020



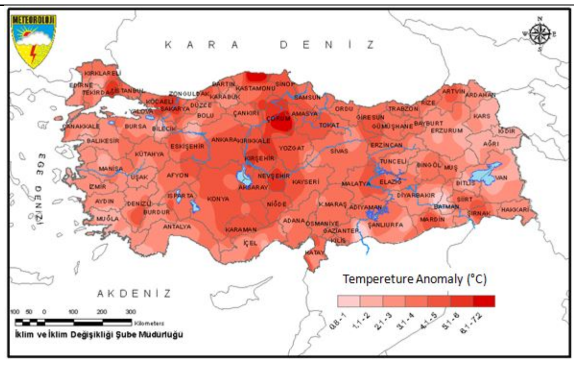
5c. Temperature Run:01/10/2020 Valid:October 2020



5g. Precipitation Run:01/10/2020 Valid:October 2020



5d. October 2020 Temperature Anomaly



5h. October 2020 Precipitation Anomaly

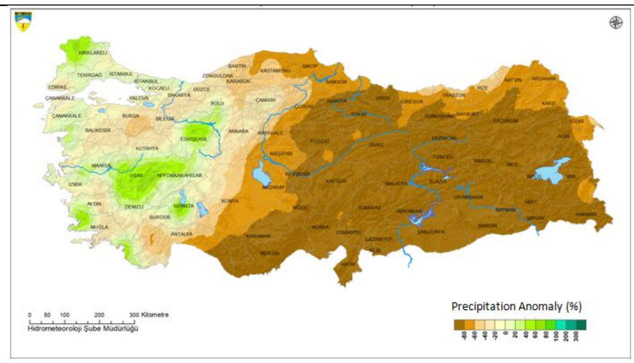


Figure 5: October 2020 Seasonal Forecast Verifications

3.2.2 Case studies

None

4. Requests for additional output

As stated in section 2.2.1, TSMS applies NGR to ENS max/min temperature forecasts up to D+15. It also tests calibration of ENS precipitation forecast. Quality and quantity of training data plays a crucial role in calibration. Precipitation requires larger training data and it is much more sensitive to quality. Since the number of re-forecasts run, which is currently twice a week, looks insufficient to generate necessary number of training sample, additional methods to enlarge sample size are needed. Additional methods are usually more complicated to apply and they may cost reduction in quality. Therefore, taking into account widening usage of AI and ML in weather forecasting and increasing demand on more accurate precipitation forecast in short and medium range, it should be considered increasing number of re-forecast run. It would be much better to seek opportunities for daily re-forecast run which might yield generating almost perfect training dataset.

5. References to relevant publications

Cengiz, Y. and Sezer, M. (2020, January). Implementation of CANARI in AROME TURKEY. ALADIN-HIRLAM Newsletter, No 14, 151-153. https://www.umr-cnrm.fr/aladin/IMG/pdf/nl14.pdf

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Fucile, E. et al., 2014:SAPP: a new scalable acquisition and pre-processing system at ECMWF. ECMWF Newsletter No. 140 – Summer 2014, pp. 37–41. doi: 10.21957/3ylomoa6. https://www.ecmwf.int/sites/default/files/elibrary/2014/17341-sapp-new-scalable-acquisition-and-pre-processing-system-ecmwf.pdf