Prediction of Microclimate Parameters for Application in Precision Agriculture

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Introduction

planning and management of agricultural production

improvement of crop yields and quality

predicting future values based on historical, time-stamped data.

statistical methods vs. neural networks

data from two different sources used

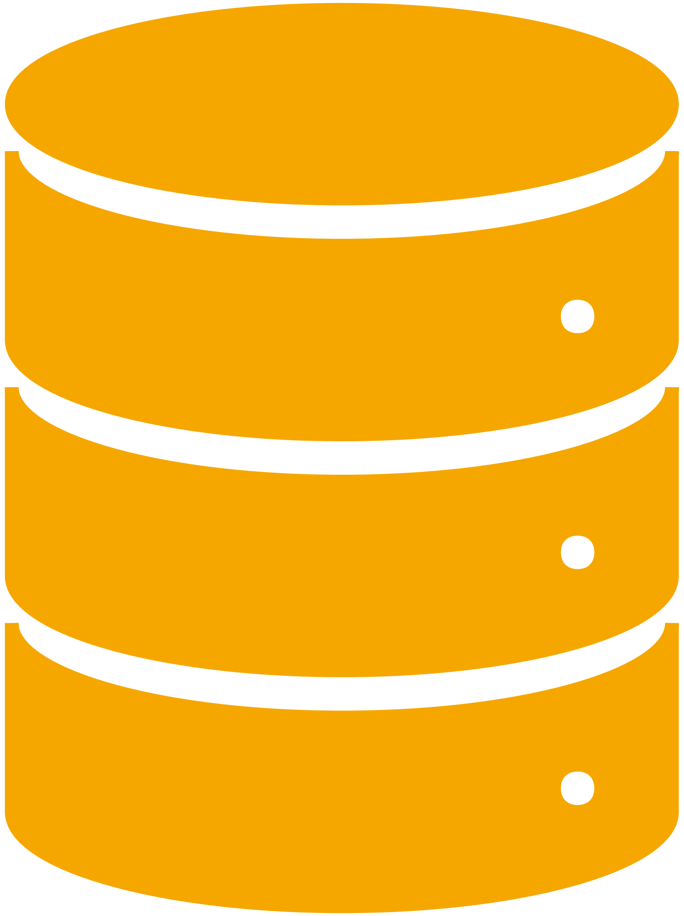
performance evaluation of models for predicting temperature readings

up to the next 48 hours forecast based on historical data for the last n days

Datasets

Copernicus CDS

Pinova Meteo



Datasets

Copernicus CDS

- Copernicus services rely primarily on data from the Sentinel satellites
- In – situ measured data - calibration and verification of the satellite data
- ERA5-Land dataset
- The parameters measured:
    - *air temperature, air humidity, pressure, evaporation, surface solar radiation, snowfall, precipitation…*
- Location Osijek (January 2018 – October 2020)

Pinova Meteo

- Agrometeorological station designed to monitor microclimate conditions
- The parameters measured:
    - *air temperature, humidity, leaf moisture, precipitation, soil temperature, temperature in the plant or leaf zone, soil moisture, global radiation, wind direction and speed*
- Data from 23 sensors
- Jan. 1, 2019 - Dec. 31, 2020
- Sampling frequency: every 10 minutes ~ 2.9 million readings in the database
- Locations:
    - Budimci (Osijek- Baranja County),
    - Skenderovci (Požega-Slavonia County)1

Used parameters

Era5-land parameter used for prediction:

Name	Unit	Description
2m temperature	K	air temperature at 2m above the surface of land, sea or in-land waters

Parameters from the agrometeorological station Pinova used for prediction:

Name	Unit
Air temperature	°C
Air moisture	%
Leaf wetness	%
Leaf temperature	°C
Rainfall	mm
Global radiation	W/m2
Wind speed	m/s

Forecasting Methods for Time Series Data

SARIMA

LSTM

Forecasting with the SARIMA Model

extension of an ARIMA model with seasonality taken into account

model parameters must be specified at startup

the grid search for different combinations of parameters

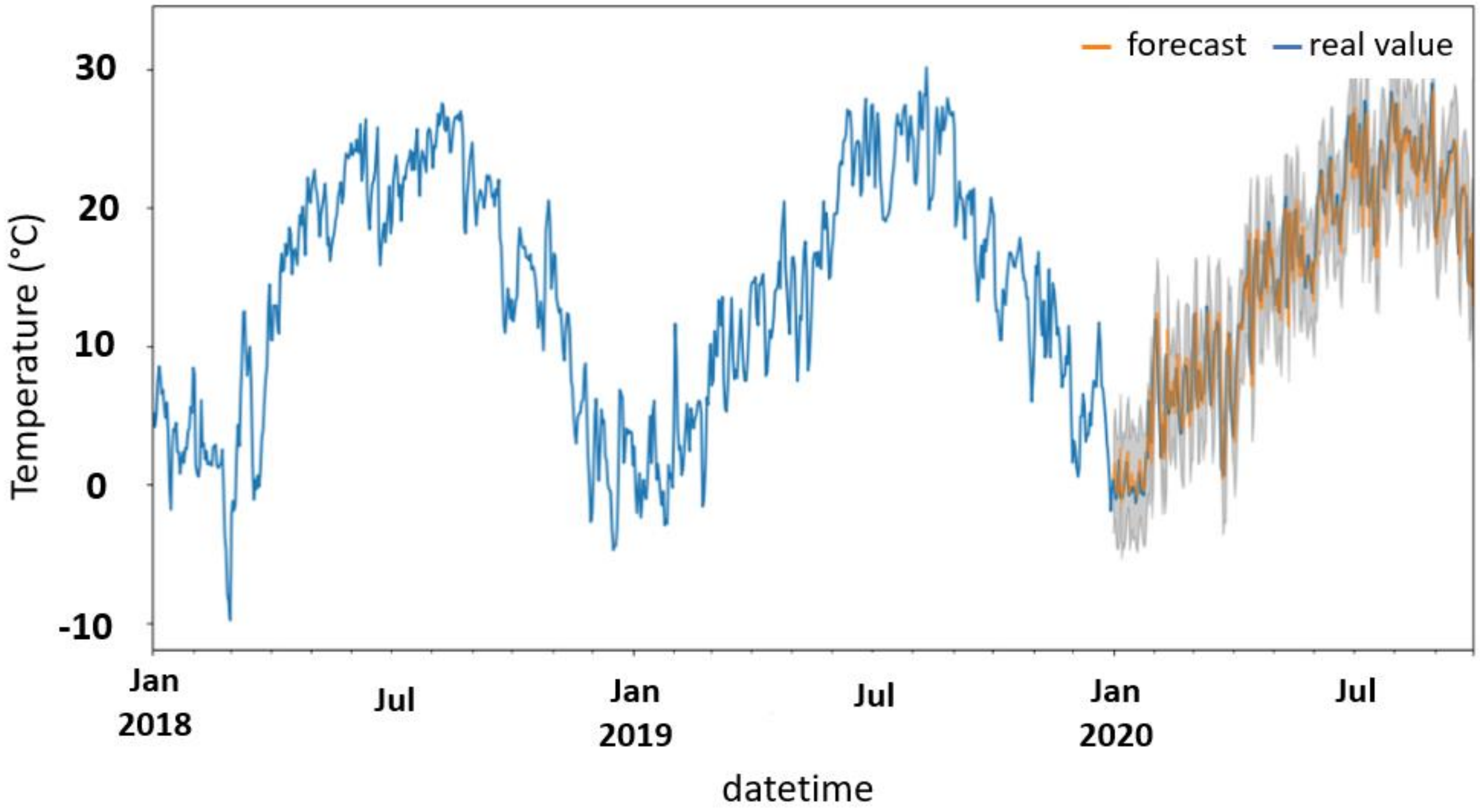
the Akaike Information Criterion (AIC) - an evaluation metric for the grid search

Forecasting with the LSTM

- LSTM *(Long Short-Term Memory)* - a special case of a RNN
- RNNs - problem of vanishing/exploding gradients
- LSTMs - additional gates, control whether information is allowed to passes through or not
- Tensorflow framework, Keras API
- processor with 4 cores running at 1.8 GHz and 8 GB RAM

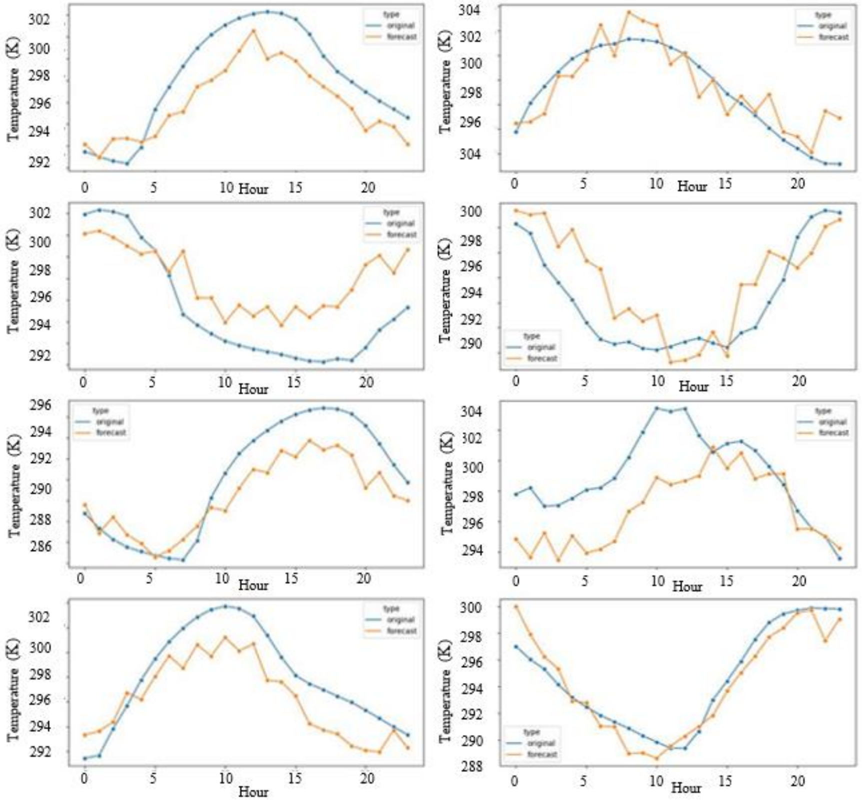
Forecasting with the SARIMA Model

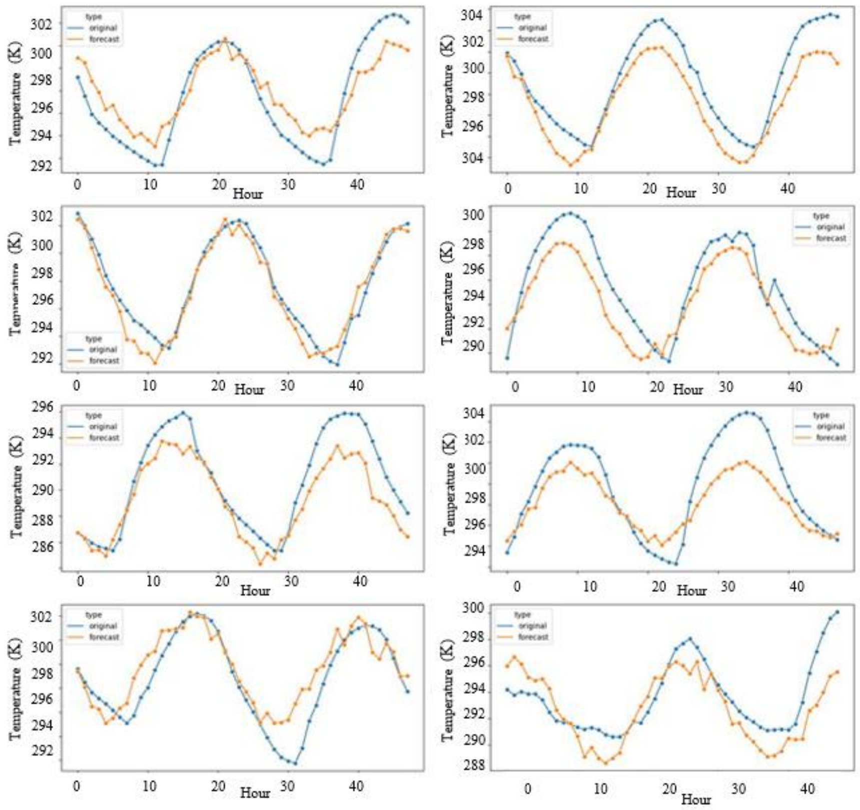
- Training set
  - time series from 2018 and 2019
- Test set
  - time series from 2020
- Dynamic and non-dynamic prediction



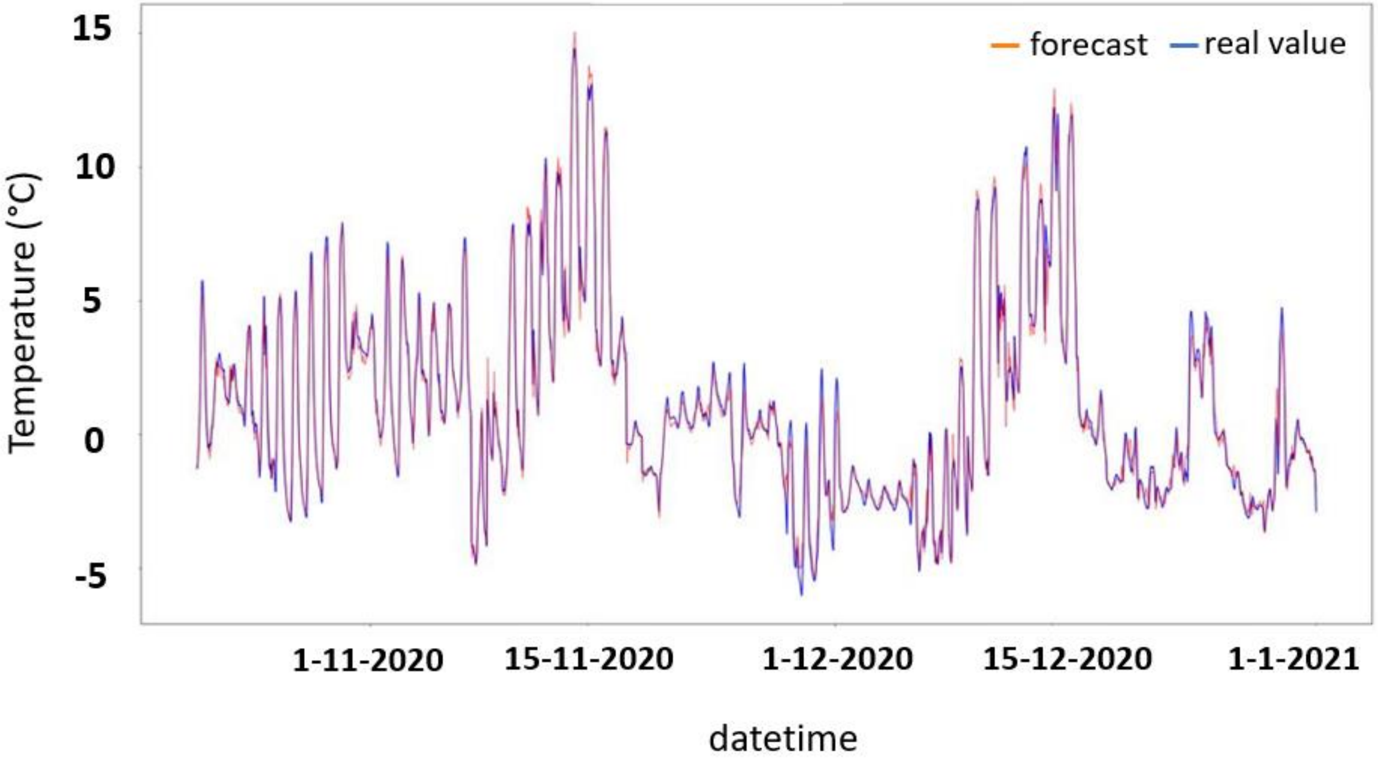
Copernicus data prediction using LSTM

- configuration - a crucial step in time series prediction
- to determine each parameter the network is started 10 times
- Each model was evaluated at the end of each epoch based on the RMSE
- 80% of the data was used for training





Prediction of data from the Pinova agrometeorological station using LSTM



- removed redundant features - air temperature and leaf temperature
- the training set - 70% of the data
- different combinations of neuron values, previous values at the input, the number of hidden layers were explored
- model:
  - 2 hidden layers
  - 50 neurons
  - 24 previous values (1 day)

Results

Baseline model: 2.207 ℃

SARIMA non-dynamic: 2.09 ℃

SARIMA dynamic: 9.85 ℃

LSTM (Copernicus data) 1 h: 0.933 ℃

LSTM (Copernicus data) 24h: 2.161 ℃

LSTM (Copernicus data) 48h: 2.925 ℃

LSTM (Pinova data) 1h: 1.474 ℃

LSTM (Pinova data) 24h: 2.503 ℃

Conclusion and Future Work

Next steps

- using a larger amount of input data
- using a different neural network architecture
- further refinement of the models to increase accuracy and performance of long-term forecasting
- adding additional parameters that affect the weather
- deploying the models on devices with limited resources

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