Prognosis of water levels in a moor groundwater system influenced by hydrology and water extraction using an artificial neural network (EGU21-3013)

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Introduction

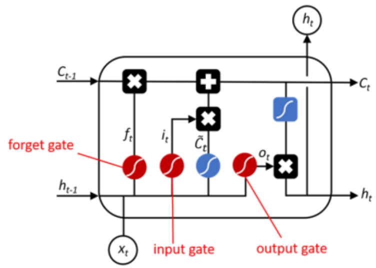
Ecologically sensitive moor influenced by hydrology and water abstraction

Goals:

- Prevent possible negative impacts of water abstraction
- Better system understanding

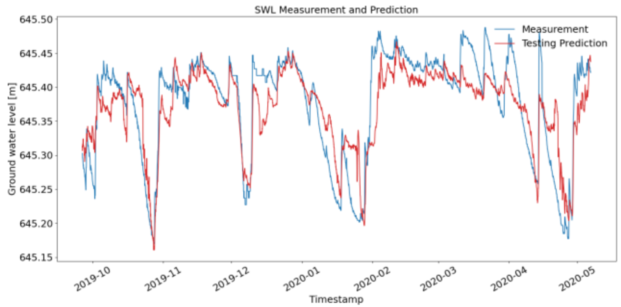
Methods

- Long short-term memory (LSTM)
- Different designs / configurations
- Include physical knowledge



Results

- Inserting preprocessed data leads to better prediction results
- Individual and combined influences can be represented well
- LSTM outperforms MODFLOW
- Scenarios of pumping events party unplausible



Conclusion

- Accurate predictions for a seven days prediction horizon
- More accurate when physical knowledge is included

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Introduction

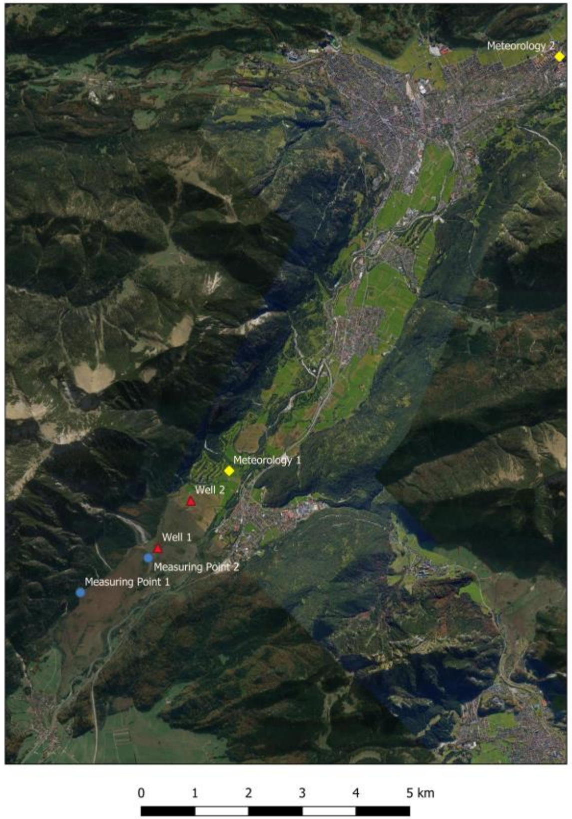
Motivation:

- Ecologically valuable moor → Influenced by hydrology and water abstraction
- Complex aquifer → Difficult to model

→ Forecasts of moor water levels difficult

Goals:

- Determine most efficient LSTM architecture
- Obtain robust, plausible and accurate predictions of the moor water levels
- Better system understanding



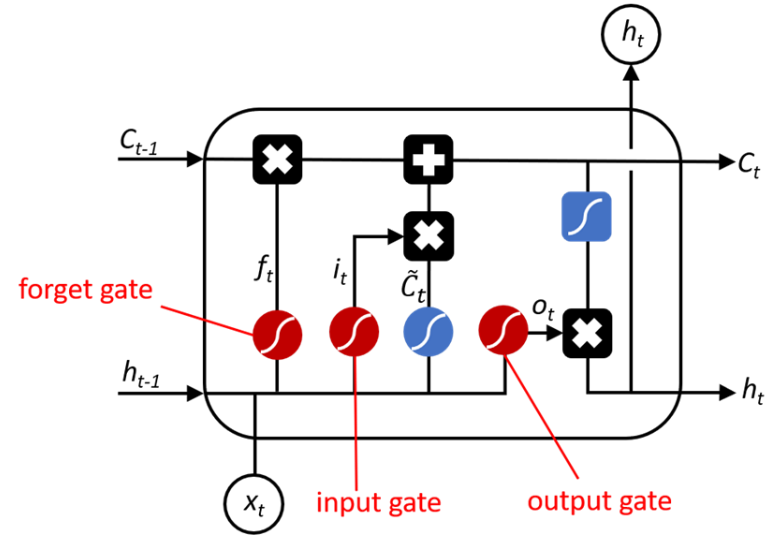
Satellite image: Google-Maps

Methods

- Prepare raw data
- Long short-term memory (LSTM)
- Test metric: Mean squared error
- Different designs / configurations
- Programming language: PyTorch

→ Prognosis for two measuring points

LSTM-Cell



Following [1]

Methods

External data input

Measuring point 1
(No influence of pumping wells)

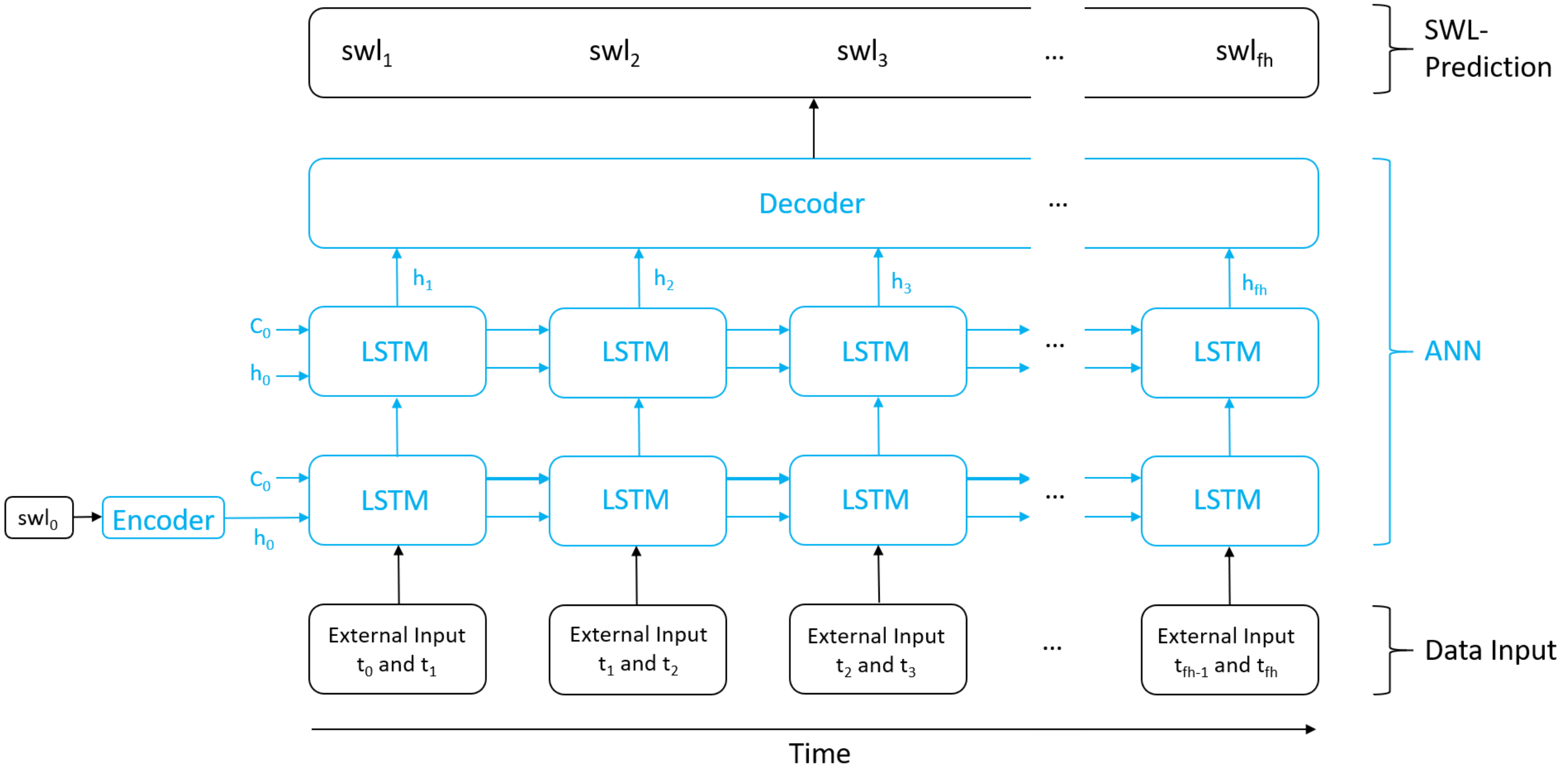
- Swamp water level (t=0)
- Precipitation (t=0, …, t=fh)
- Evapotranspiration (t=0, …, t=fh)

Measuring point 2
(Influence of the pumps exists)

- Swamp water level (t=0)
- Precipitation (t=0, …, t=fh)
- Evapotranspiration (t=0, …, t=fh)
- Pumping rates well 1 (t=0, …, t=fh)
- Pumping rates well 2 (t=0, …, t=fh)

Methods

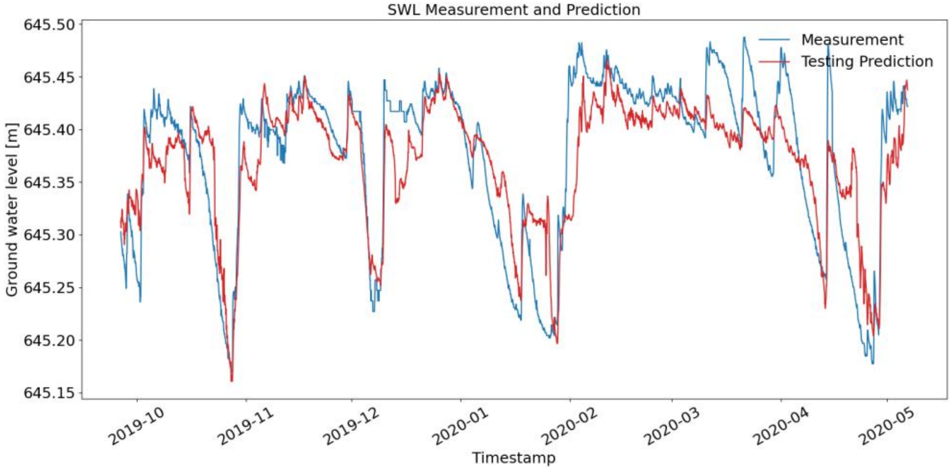
Architecture



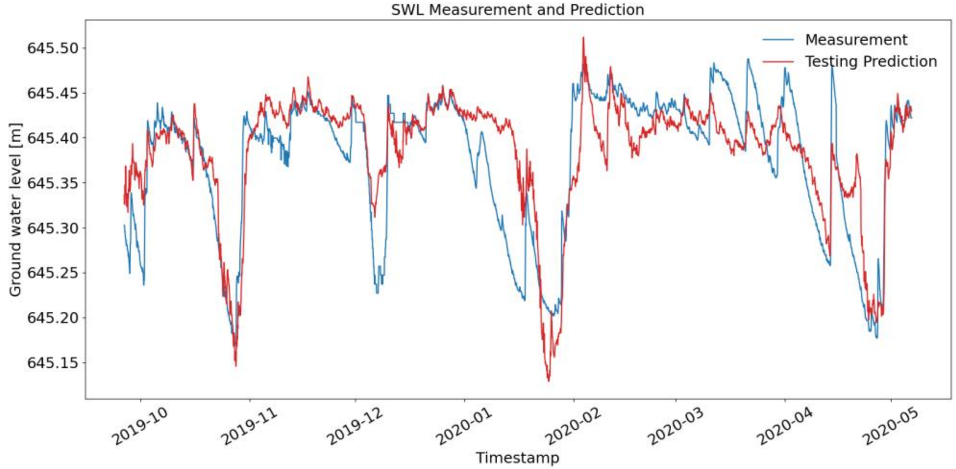
Results

Inserting preprocessed data – Measuring point 2

Evapotranspiration
(Preprocessed)



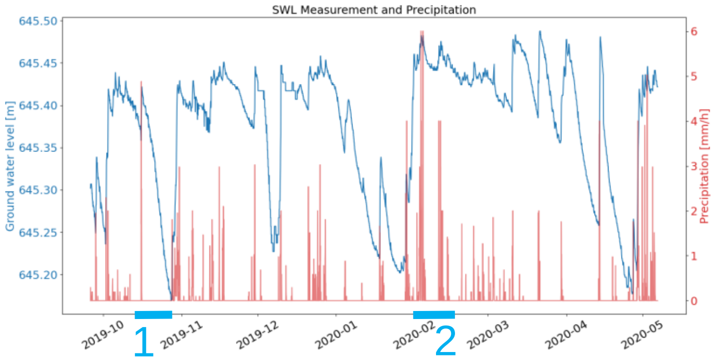
Raw data
(Air temperature, Sun duration, Relative humidity, Wind velocity)

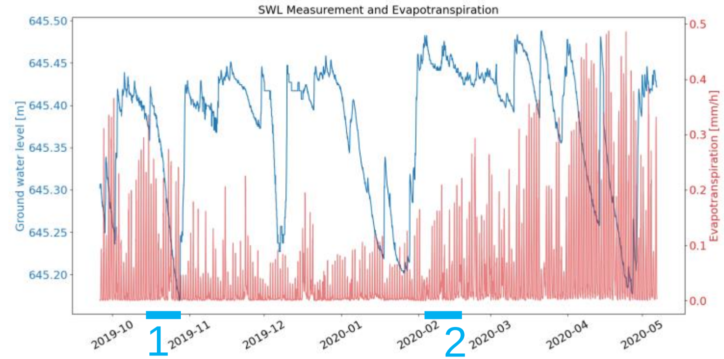


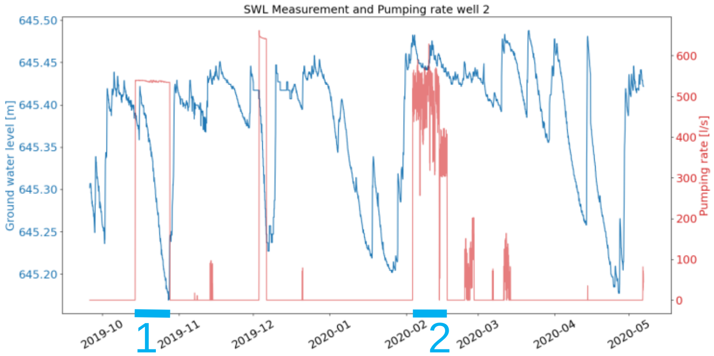
→ Inserting physical knowledge leads to better prediction results

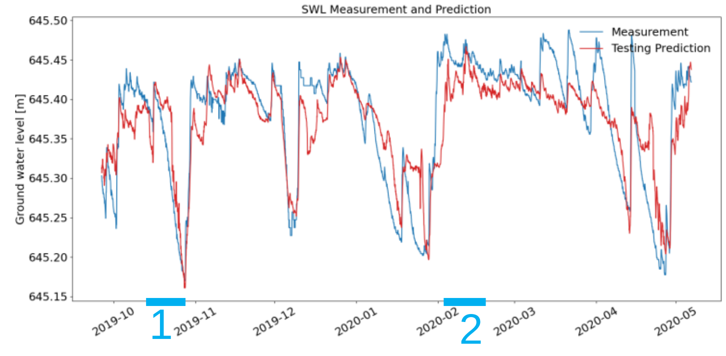
Results

Individual and combined influences – Measuring point 2









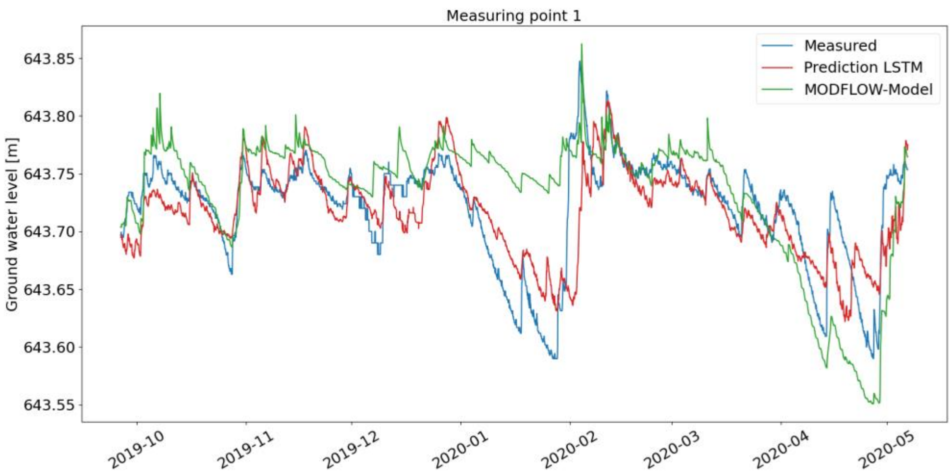
Pumping event 1: Low precipitation, High evapotranspiration → Drop in the SWL

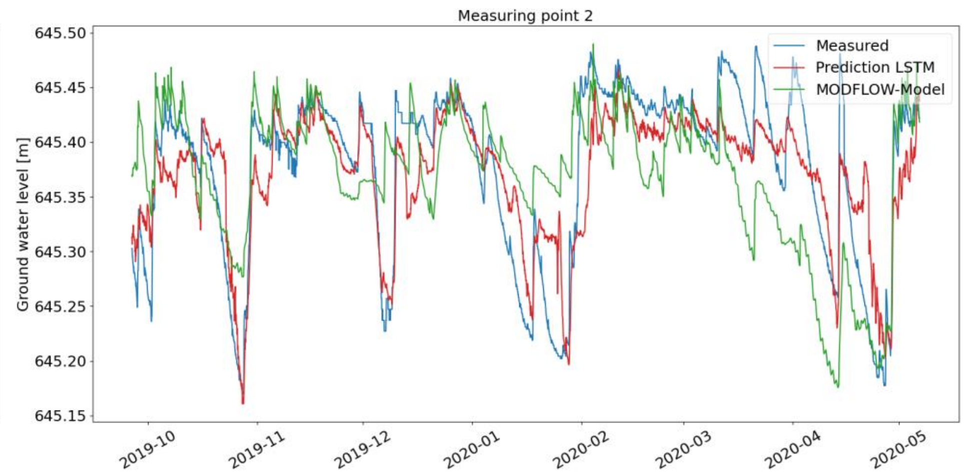
Pumping event 2: High precipitation, Low evapotranspiration → Stable SWL

→ LSTM can identify this situations → Predicts the less pronounced fall of the SWL

Results

LSTM and MODFLOW-Model



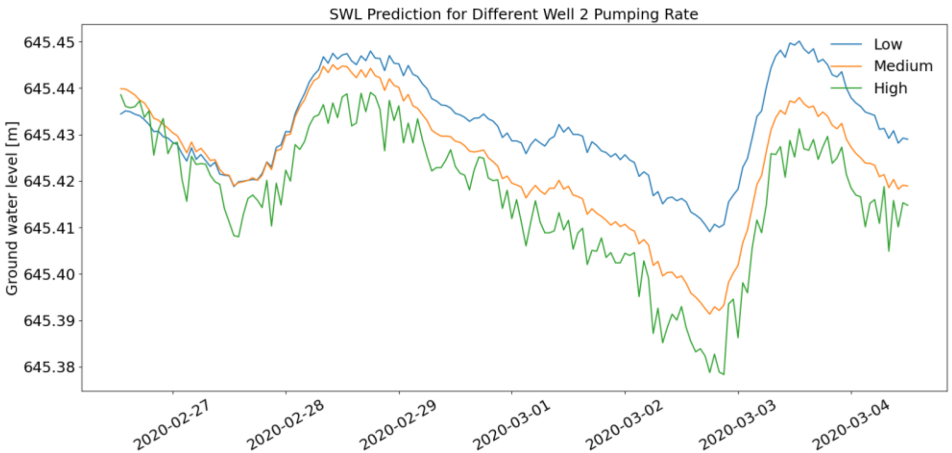


→ LSTM outperforms the MODFLOW-Model

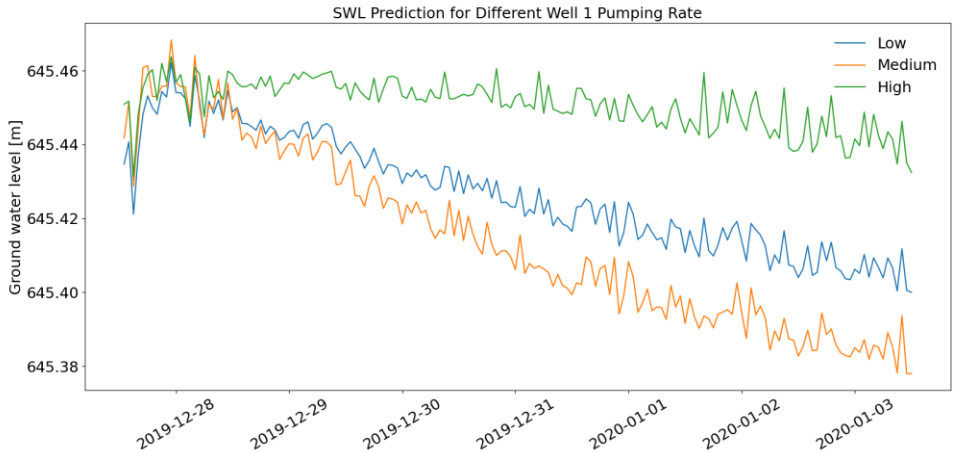
Results

Scenarios of pumping events

Plausible



Unplausible



→ Currently adding physical constraints to counteract this

References & Acknowledgement

FYI: We are currently working on a paper and some additional experiments (Include constraints, amount of data necessary for good results, preselection of possible input data)

References:

- [1] https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21
- Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*(8), 1735-1780.
- Petneházi, G. (2019). Recurrent neural networks for time series forecasting. *arXiv preprint arXiv:1901.00069*.

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