On the Generalization of ML-based Agricultural Drought Classification from Climate Data

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Introduction: Droughts

Many changes in the climate system become larger in direct relation to increasing global warming. They include increases in the frequency and intensity of hot extremes (…) agricultural and ecological droughts (…). [(1)]

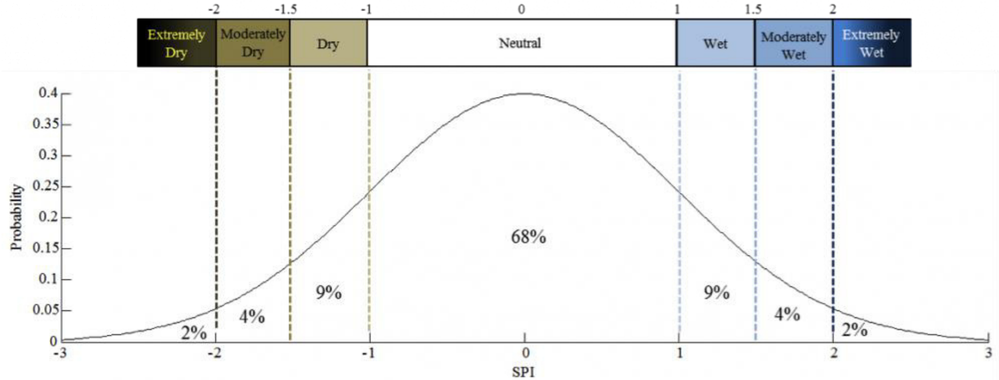
(1) IPCC, 2021: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (eds.)]. Cambridge University Press. In Press

Introduction: Classic drought indices, SPI

Existing drought indices are often relative.

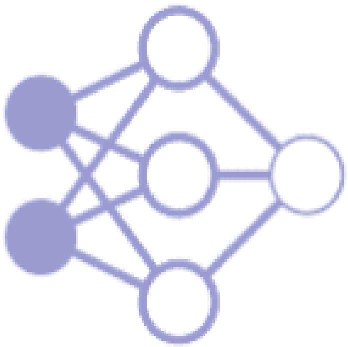
$$SPI = \frac{f(P) - \bar{u}}{d_u}$$

<u>standardized precipitation index (SPI)</u>
is a standardized deviation of **precipitation** in a particular period from the median long-term value of this period (McKee et al. 1993, 1995)



-> If you apply the SPI to a region, it will **<u>always</u>** find droughts.

Research question



How can we develop a ML algorithm to detect, analyze and understand droughts in CMIP climate projections?

Initital study:
ERA5 Land instead of CMIP

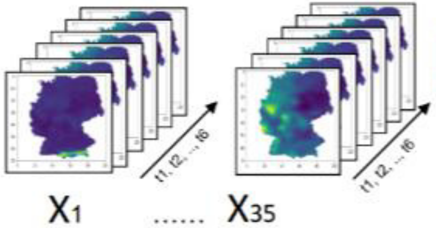
Study region: Germany

XXX

Input Data (X)

35 Input Features:
ERA5-Land: n =12
Land Use (MODIS): n =19
Derived positional
and seasonal encoding: n=4

Sequence of 6 months per pixel



Classification model

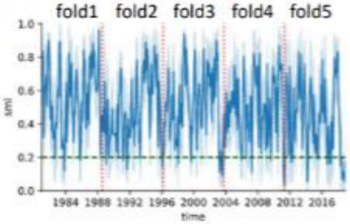
Labels (y) :

binary drought labels,

derived from UFZ - SMI (<0.2)

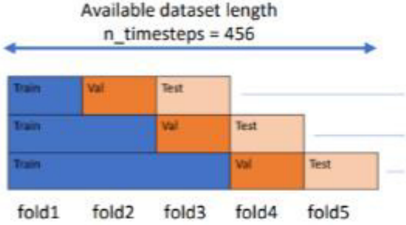
1 label per pixel at the end of the 6 input months sequence as t6

Dataset Split



Split dataset with timesteps n = 456 into folds **k=5**

- good compromise between a sufficient number of folds for a robust estimate of performance
- large enough folds with multiple years of data to account for seasonal and interannual effects



HPO

Hyperparameter optimization on Training Data via raytune on Selection of the parameters on the Validation fold for 4 different model architectures:

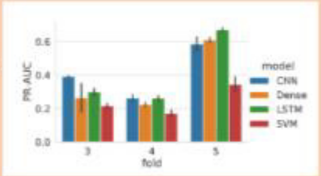
- **M1** SVM
- **M2** MLP
- **M3** CNN
- **M4** LSTM

Models with sequential inductive bias

With best parameters for each Model

Classification model M1 – M4

For the kth split, we train on folds {1...k}, validate on fold k+1 and test on k+2.
Evaluation on PR_AUC and F1 for 5 different random seeds:



Data Preparation: Datasets

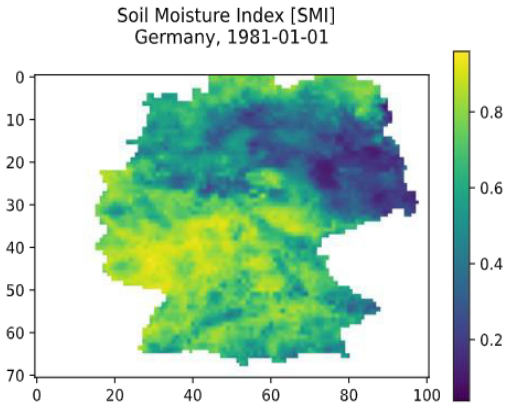
Overview of the variables used in this study. Native resolution of SMI: 4x4km, ERA5-Land:9km, MODIS land use: 500mx500m
Study region: Germany

source	variable	description	unit
Helmholtz	SMI	soil moisture index topsoil (top25cm) via UFZ Drought Monitor	-
ERA5-Land	u10, v10	wind (u + v component at 10m)	ms^{-1}
	tp	total precipitation	m
	sp	surface pressure	Pa
	t2m	temperature	K
	ssrd	surface solar radiation downwards	Jm^{-2}
	d2m	dewpoint temperature	K
	ssr	surface net solar radiation	Jm^{-2}
	str	surface net thermal radiation	Jm^{-2}
	lai_lv, lai_hv	leaf area index high + low vegetation	m^2m^{-2}
	strd	surface thermal radiation downwards	Jm^{-2}
MODIS	land use class	water, evergreen needleleaf forest, Evergreen Broadleaf forest, Deciduous Needleleaf forest, Deciduous Broadleaf forest, Mixed forest, Closed shrublands, Open shrublands, Woody savannas, Savannas, Grasslands, Permanent wetlands, Croplands, Urban and built up, Cropland Natural vegetation mosaic, Snow and ice, Barren or sparsely vegetated, Cropland	Fraction
self-derived	positional encoding	latitude longitude grid	degree
self-derived	seasonal encoding	2D circular encoding of the month	degree

→ The input data is re-gridded to the ERA5-Land regular latitude-longitude grid (0.1×0.1≈(9km)^2)

Binarization of the drought labels

UFZ drought monitor Data



Variable "soil moisture" [SMI]

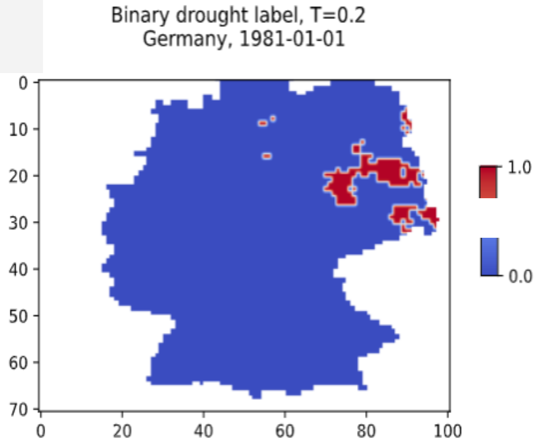
0

0,20 - 0,30 = unusual drought

Threshold T= 0.2

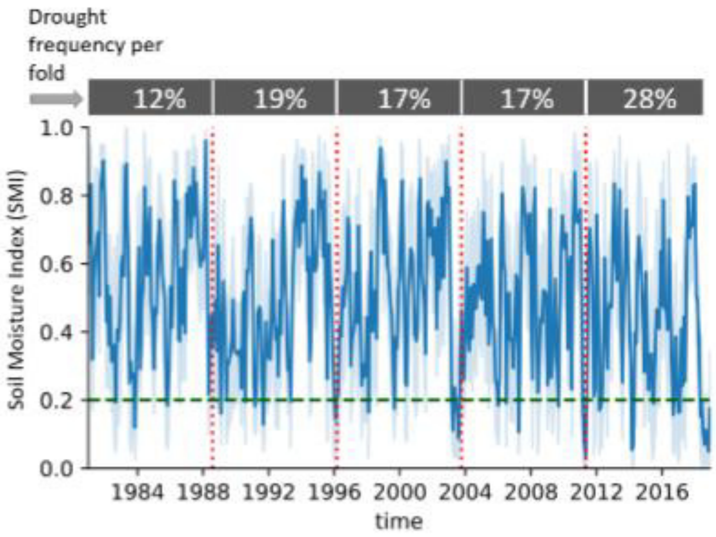
0,10 - 0,20 = moderate drought
0,05 - 0,10 = severe drought
0,02 - 0,05 = extreme drought
0,00 - 0,02 = exceptional drought

1

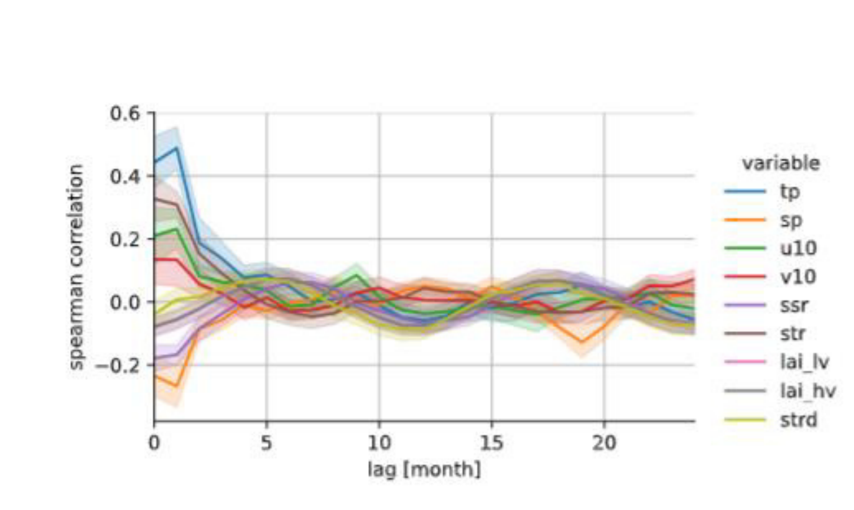


Dataset Analysis

Labels:
Time series of SMI from 1981-2018 from the Helmholtz dataset:



Input Dataset:
Time-lagged Spearman correlation between the selected ERA5-Land input variables and the target variable SMI over 24 months:



Data Preparation: Sequential framing

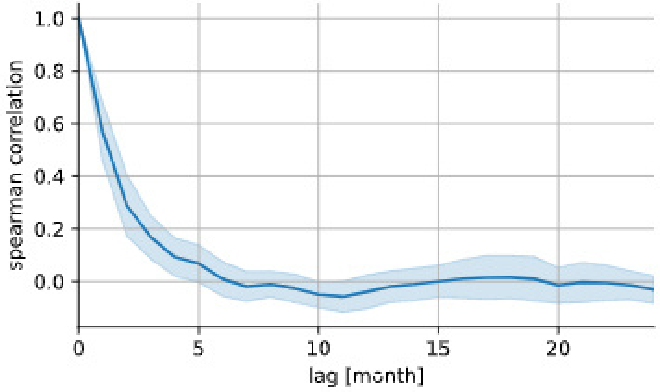


Figure 2. Time-lagged Spearman correlation for the SMI target variable of the same spatial location. The shaded area shows the standard deviation across all locations.

The SMI values for the same location exhibit a noticeable correlation for lags up to 6 month.

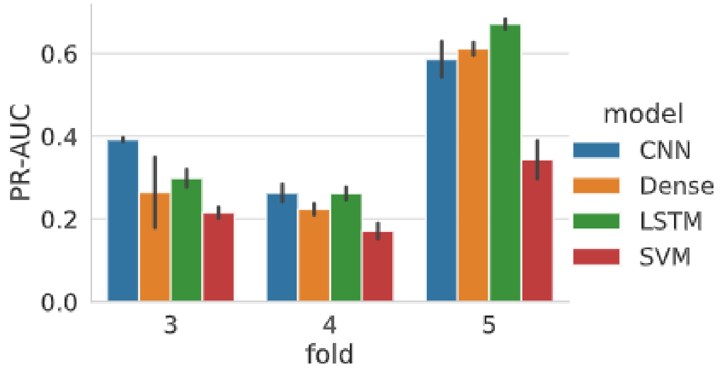
→ A simple random split over data points could therefore lead to data leakage, where memorizing SMI values from train and simple interpolation can lead to misleadingly good results

Results

Model hyperparameters as a result of the random HPO search:

type	HPO fold	hidden	lr	dropout	activation	batchnorm	batch size
LSTM	2	16, 32	1.18e-4	0.1	softplus	False	2208
	3	96, 96	1.00e-4	0.2	relu	False	96
	4	32, 48, 128	2.15e-5	0.0	softplus	True	2592
CNN	2	128, 176, 224, 240	3.53e-5	0.1	softplus	False	32
	3	112, 176	2.40e-5	0.2	softplus	False	64
	4	16, 96, 128	1.29e-2	0.1	ReLu	True	448
Dense	2	32, 48, 96	3.36e-2	0.1	relu	False	769
	3	48, 208, 208, 208	1.66e-2	0.2	softplus	True	192
	4	80, 192	1.02e-5	0.2	ReLu	True	800

Results on PR-AUC of the different models on the test dataset across five different random seeds for drought classification using a window of six months.

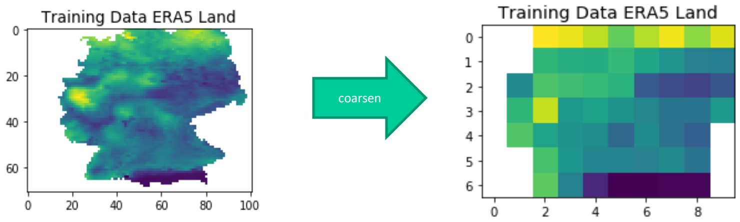


Ablation: Coarsening the Data Resolution

Data Example on coarsened resolution:

Germany, 0.1 degree resolution

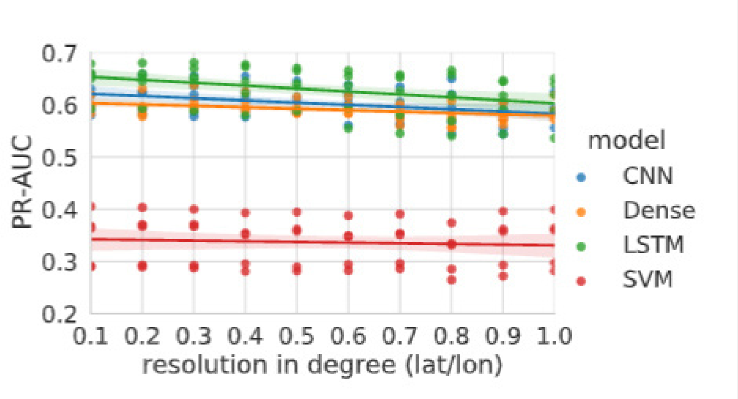
Germany, 1 degree resolution



Training data per feature:
3,384,712 samples over 39y
7171 samples/month
Drought examples:
0.18%

Training data per feature:
33,040 samples over 39y
70 samples/month
Drought examples:
0.06%

Inference on models trained on high resolution given input with decreasing resolution. Evaluation on five different random seeds using a window of six months:



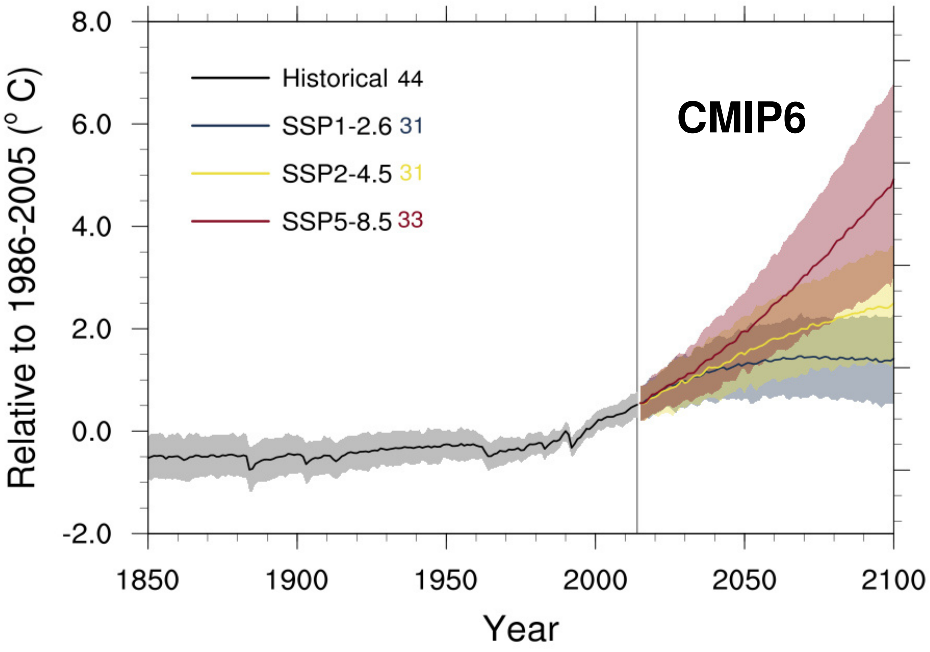
Summary

1. We are the first to compare several ML models in their **capability of classifying agricultural drought in a changing climate based** on soil moisture index (SMI).

2. We provide an **ablation study regarding a transfer to coarser input data** resolution, demonstrating that the model capabilities are transferable to lower resolution when trained in higher resolution

Outlook:

- Transfer to Climate Model Data (CMIP6)
- Add location-aware models
- Add different sources of ground truth data (e.g. SMAP satellite data)
- Expand the study region globally



Tebaldi, Debeire, Eyring et al., ESD (2020)