NeurIPS 2022 Workshop
Tackling Climate Change with Machine Learning

Hybrid Recurrent Neural Network for Drought Monitoring

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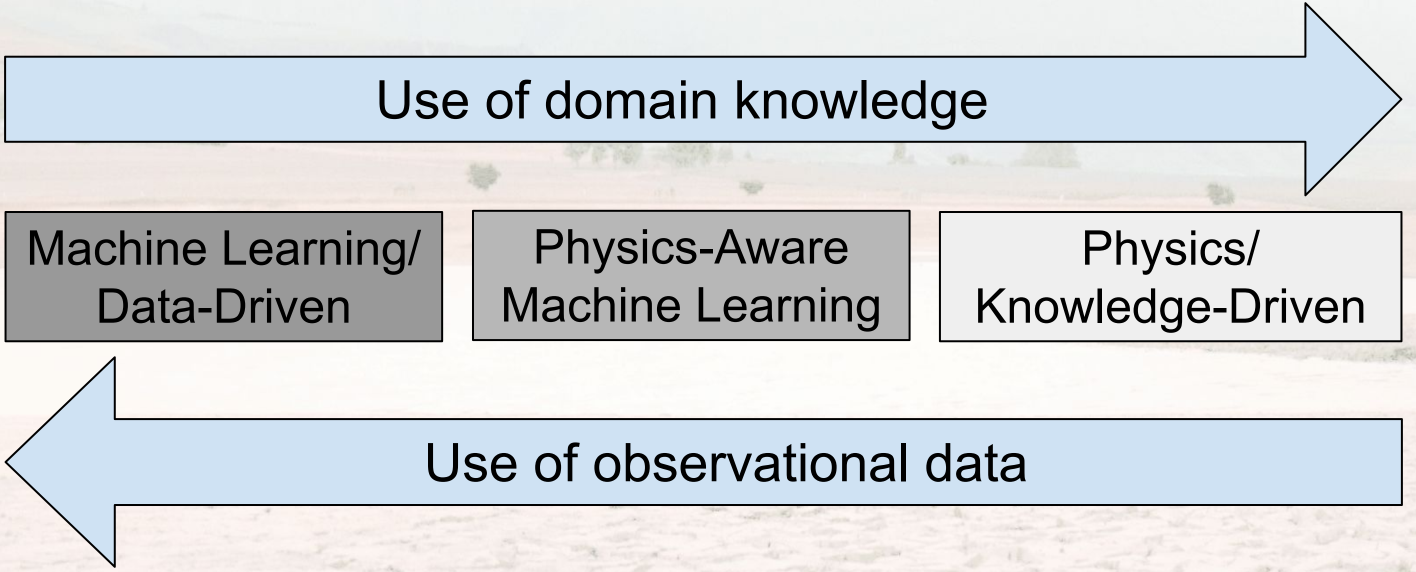
1. Introduction: Hybrid Modeling

Climate Change AI



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1. Introduction: Drought Monitoring

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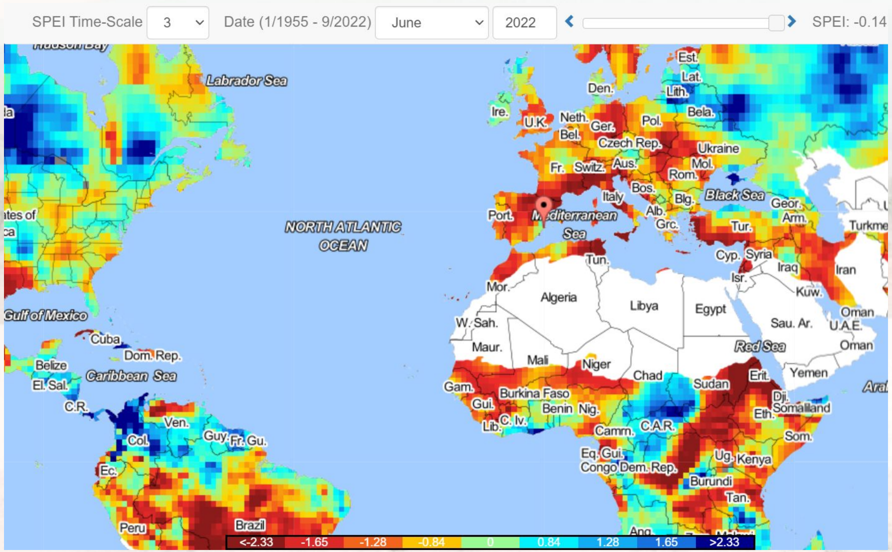

Source: SPEI Global Drought Monitor
https://spei.csic.es/map/maps.html

Step 1) Difference between precipitation and evapotranspiration
(based on air temperature 2m)

$$D_i = P_i - PE_i$$

Step 2) Standardization of the diff.
(based on a probabilistic approach)

$$f_{pdf}(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1+\left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2}$$

$$Z = F_{ppf}(F_{cdf}(x))$$

Summary

- Pros: Comparable, easy to use, interpretable
- Cons: Linear, stationary, not learn real events

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2. Methodology: Overview

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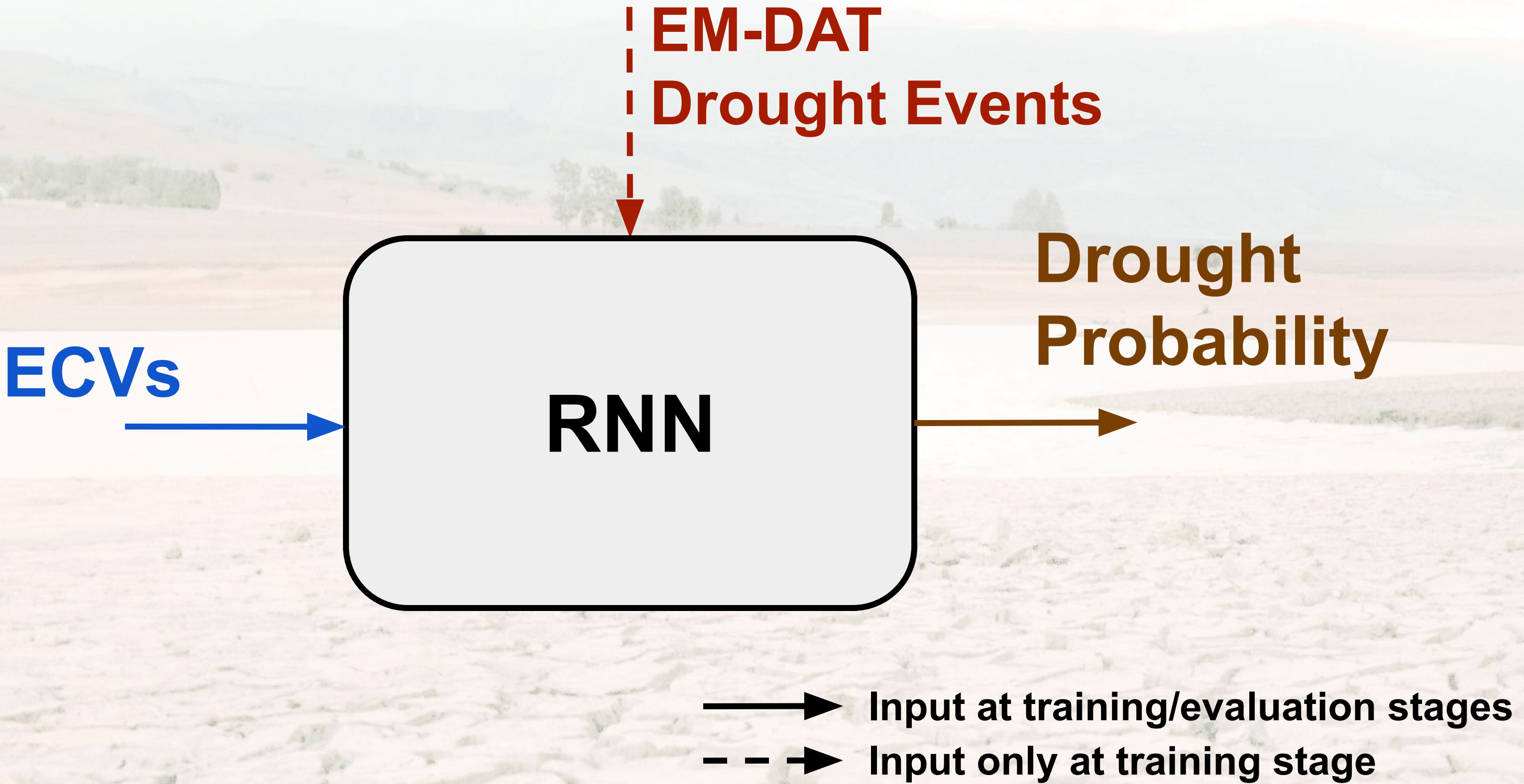

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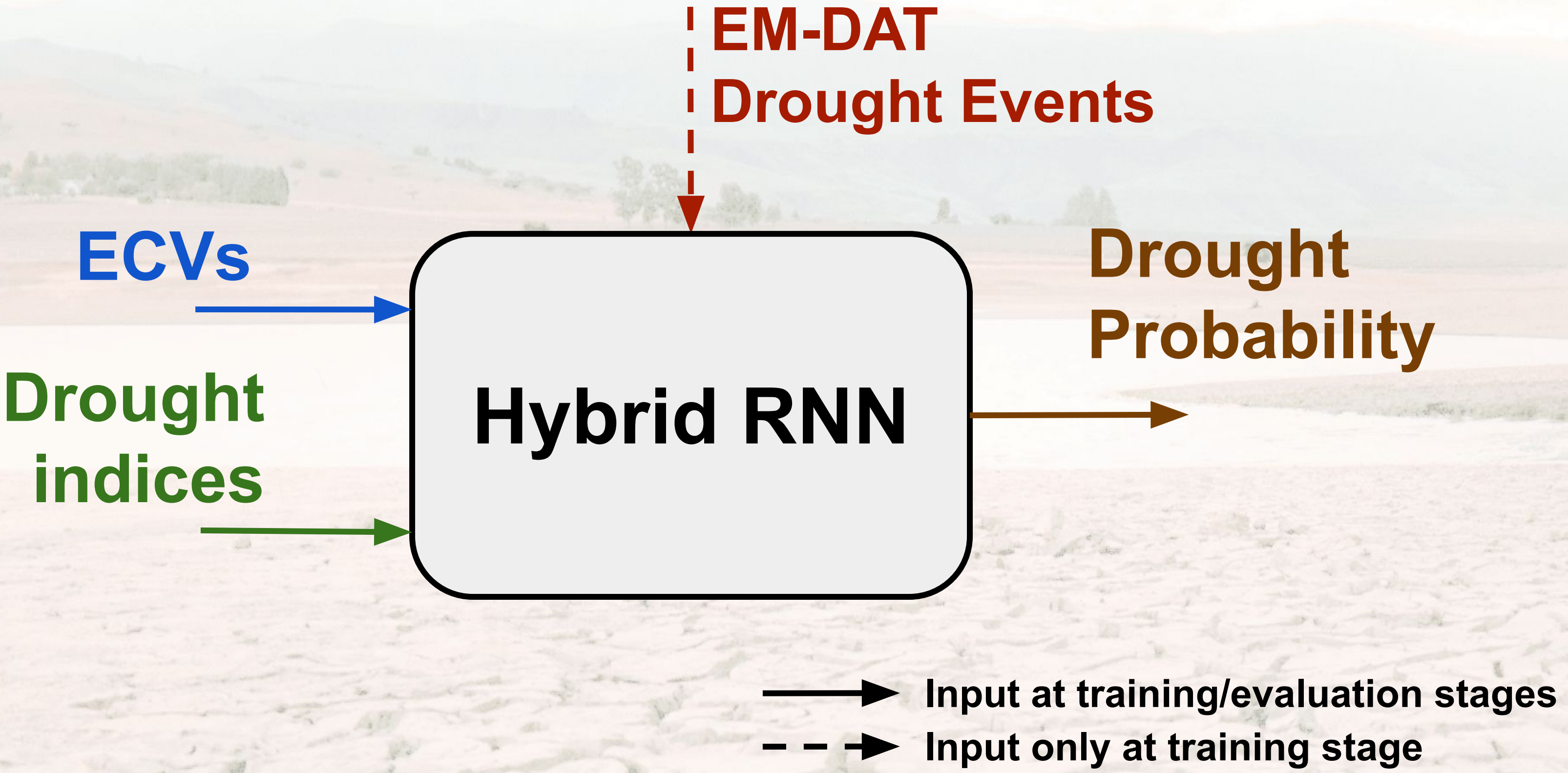

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2. Methodology: Hybrid Recurrent Neural Network

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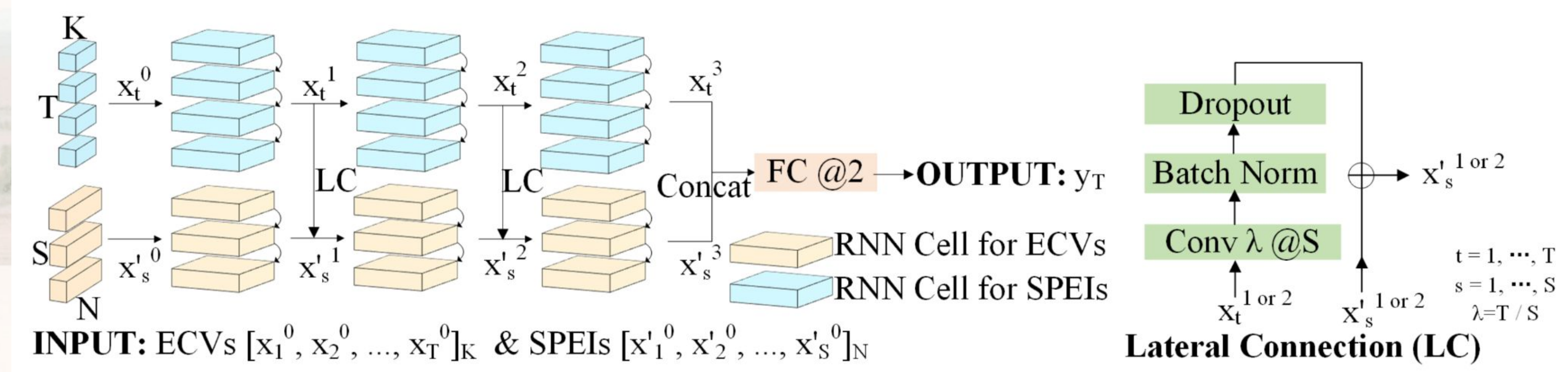

- **Blend time-series of SPEIs and ECVs as network inputs**
- **HRNN**: Dual-branch RNN w/ lateral connections
- **Lateral connections:** 1D conv. + batch norm. + dropout layers

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3. Datasets

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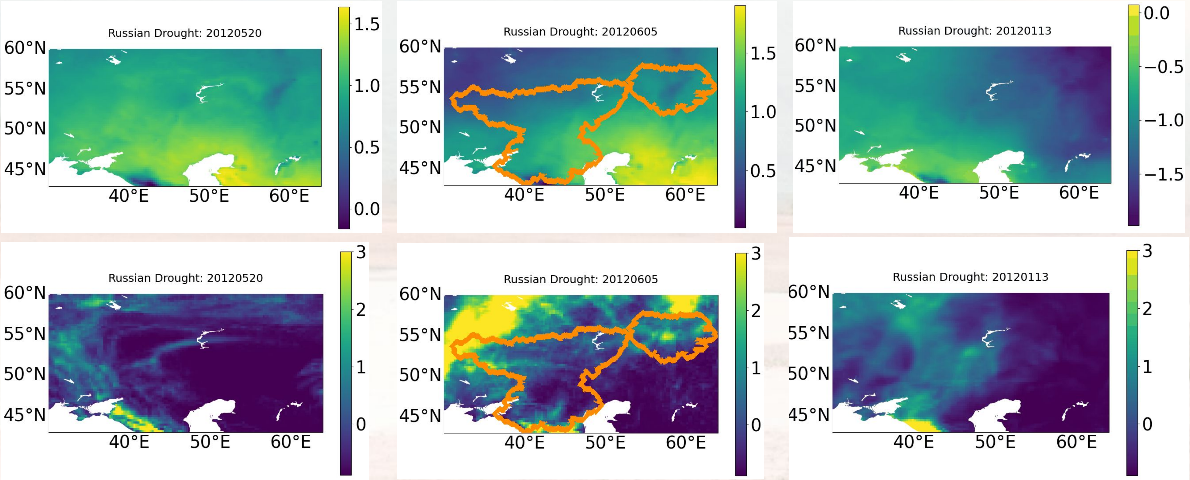
1) Essential Climate Variables (ECVs) Spatio-temporal data, 8-daily, 8 km^2

Mahecha, M. et al., 2020
Earth system data cubes unravel global multivariate dynamics

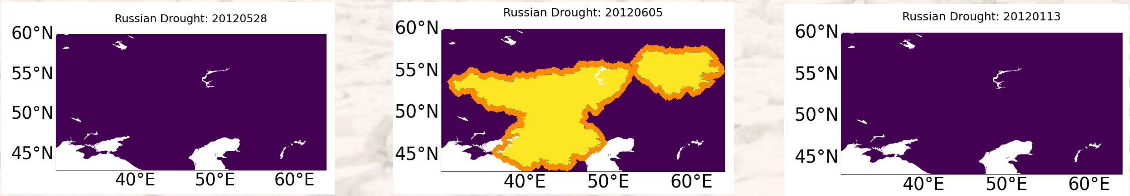
Air Temperature 2m

Precipitation



2) International Disaster Database (EM-DAT) Spatio-temporal location-level data, binary annotations

EM-DAT (2008). EM-DAT:
The International Disaster Database
http://www.emdat.be/



3. Data Analysis

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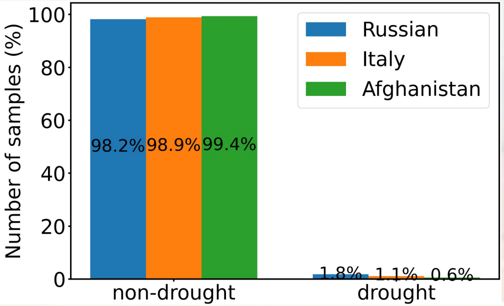
1) Label Distribution (Training and Test)



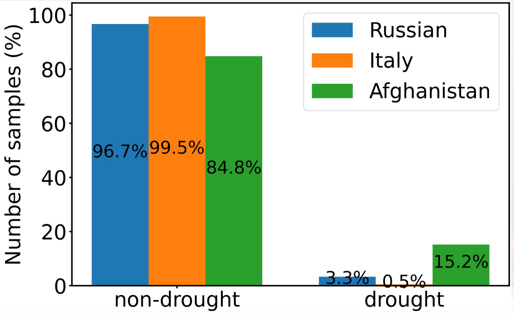


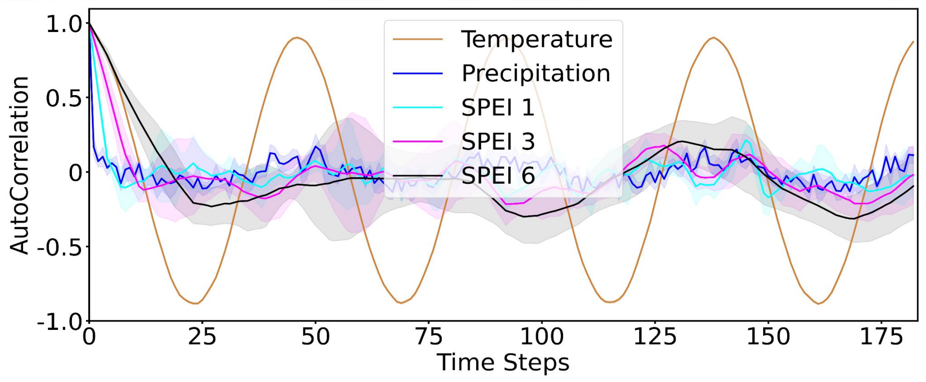
Table 1: Training, validation, and test dataset splits for Russia, Italy, and Afghanistan regions

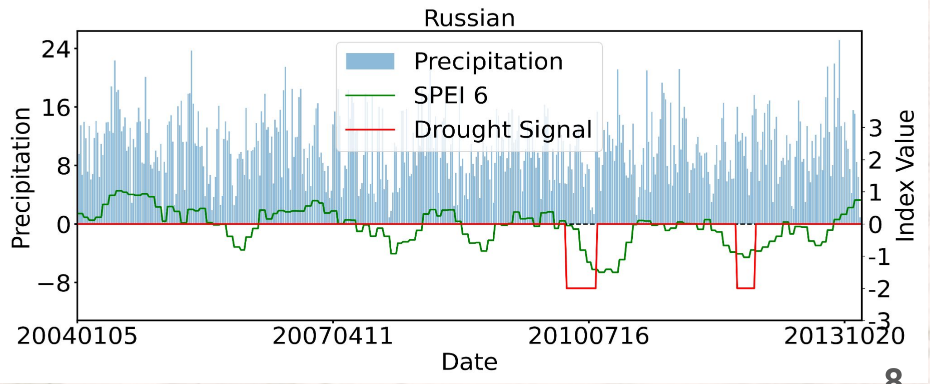
	Training	Validation	Test
Russia	Jan 2004–Jun 2010	Jul 2010–Dec 2011	Jan 2012–Dec 2013
Italy	Jul 2012–Dec 2016	Mar 2011–Jun 2012	Jan 2017–Dec 2018
Afghanistan	Jan 2003–Sep 2008	Oct 2008–Dec 2009	Jan 2010–Dec 2011

Table A1: Regions and drought events considered for the experiments

	Geospatial coordinates (NSWE)	Drought events
Russia	59.0°N, 43.0°S, 30.0°W, 64.0°E	Apr.–Aug. 2010; June–Aug. 2012
Italy	48.0°N, 35.0°S, 6.0°W, 19.0°E	June–Oct. 2012; July 2017
Afghanistan	38.0°N, 32.0°S, 63.0°W, 70.0°E	Oct. 2008; Jan.–Aug. 2011

2) Feature Autocorrelation (Time-Lag Persistence)





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4. Experiments: Quantitative Results

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Quantitative measures:

- **ROC-AUC**
- **F1 score**
- **PR-AUC score**
- ROC Curves

Table 2: ROC-AUC scores for the different models and the three regions considered in this study

	SPEI 6	MLP	RNN	CMLP	DRNN	HRNN
Russia	0.740	0.711±0.002	0.764±0.009	0.702±0.006	0.717±0.008	**0.778±0.006**
Italy	0.797	0.871±0.001	0.895±0.009	0.917±0.011	0.935±0.007	**0.937±0.009**
Afghanistan	0.820	0.575±0.013	0.420±0.003	0.795±0.004	0.742±0.030	**0.825±0.004**

Table A3: Macro F1 and PR-AUC scores obtained for the different models and the three regions considered in this study

	SPEI 6	MLP	RNN	CMLP	DRNN	HRNN
1) Russia						
Macro F1	0.131	0.105±0.005	0.156±0.009	0.137±0.005	0.167±0.038	**0.230±0.015**
PR-AUC	0.066	0.069±0.003	0.083±0.004	0.080±0.001	0.089±0.018	**0.145±0.010**
2) Italy						
Macro F1	0.017	0.037±0.001	0.047±0.002	0.054±0.004	0.060±0.003	**0.066±0.005**
PR-AUC	0.015	0.018±0.000	0.023±0.005	0.030±0.005	**0.043±0.006**	0.041±0.009
3) Afghanistan						
Macro F1	0.365	0.246±0.002	0.162±0.004	**0.405±0.005**	0.354±0.024	0.377±0.013
PR-AUC	0.307	0.184±0.002	0.121±0.001	0.315±0.003	0.287±0.016	**0.348±0.002**

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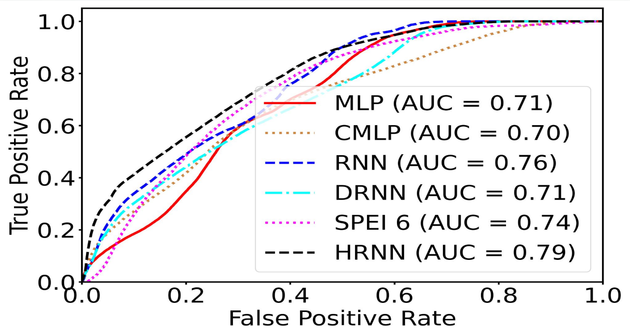
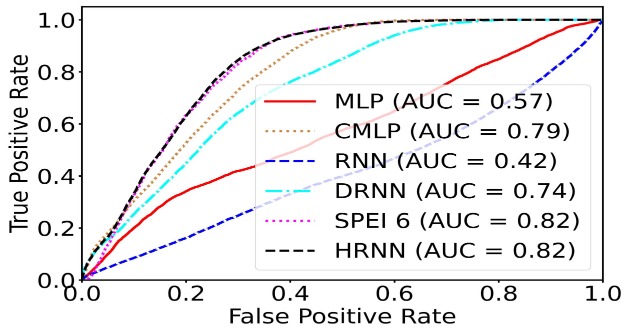
4. Experiments: Quantitative Results

Quantitative measures:

- ROC-AUC
- F1 score
- PR-AUC score
- **ROC Curves**

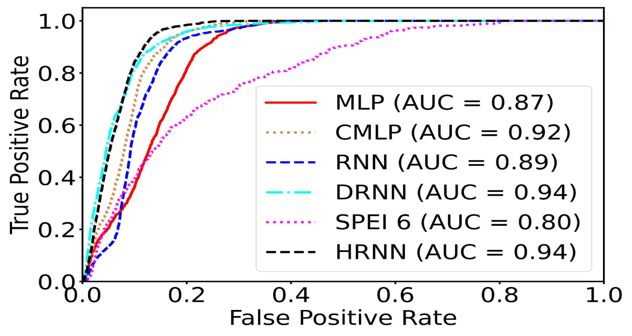
Russia





Afghanistan

Italy



4. Experiments: Qualitative Results

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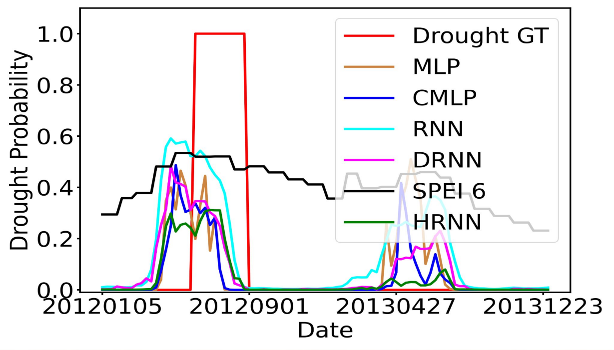
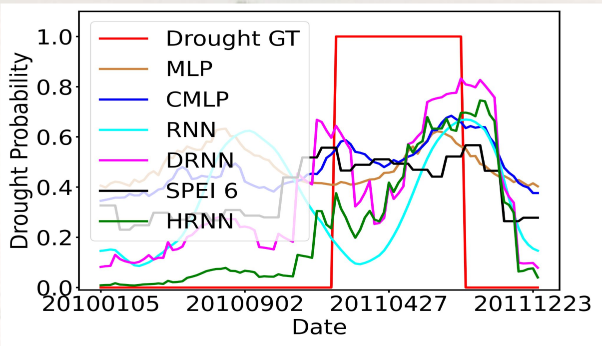
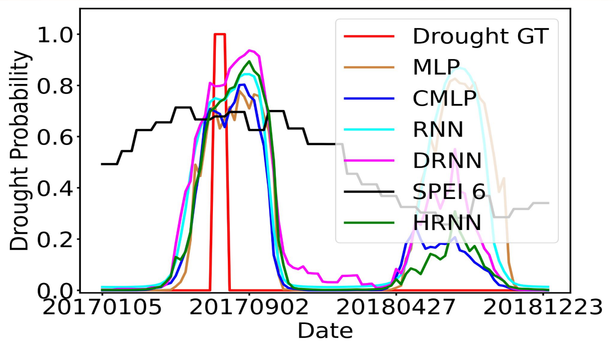
- **Drought Detection Signals**
- Drought Monitoring Maps

Russia



Italy

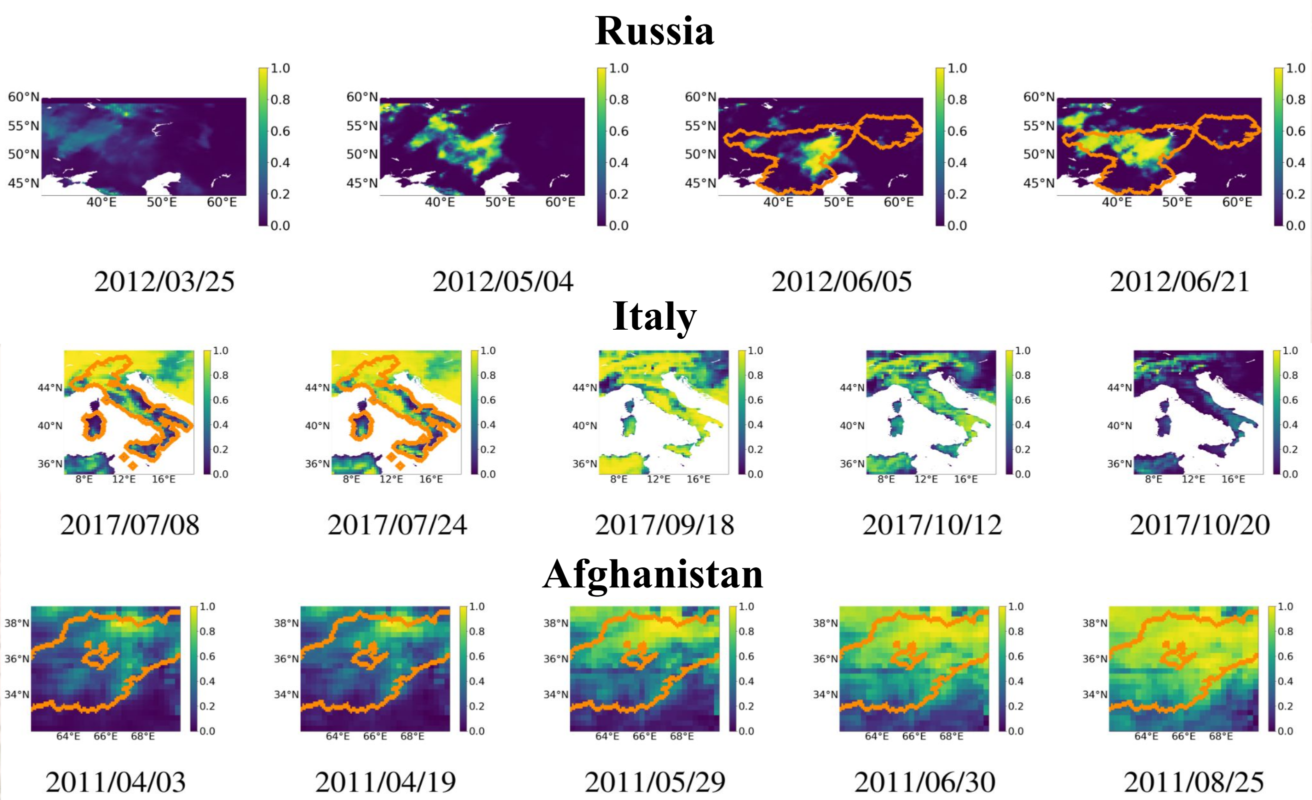




Afghanistan

4. Experiments: Qualitative Results

- Drought Detection Signals
- **Drought Monitoring Maps**



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4. Experiments: Ablation Study

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- **HRNN** is the **best hybrid model** variant
- **Variable standardization** is the most essential step **when computing SPEIs**

Table A4: Ablation study based on different HRNN and SPEIs variants, considering the three regions in this study

	HRNN	HRNN†	HRNN‡	HRNN§	SPIs	SPEIs†	SPEIs‡	SPEIs§
1) Russia								
Macro F1	0.230±0.015	0.240±0.014	0.242±0.010	0.215±0.020	0.158±0.023	0.213±0.027	0.098±0.028	0.233±0.020
PR-AUC	0.145±0.010	0.143±0.017	0.152±0.021	0.121±0.022	0.110±0.016	0.144±0.015	0.068±0.011	0.152±0.022
ROC-AUC	0.778±0.006	0.715±0.022	0.825±0.025	0.813±0.010	0.773±0.024	0.810±0.030	0.667±0.039	0.800±0.031
2) Italy								
Macro F1	0.066±0.005	0.064±0.004	0.045±0.003	0.059±0.005	0.069±0.002	0.066±0.003	0.036±0.004	0.071±0.004
PR-AUC	0.041±0.009	0.038±0.005	0.050±0.005	0.044±0.011	0.049±0.006	0.047±0.008	0.020±0.003	0.053±0.014
ROC-AUC	0.937±0.009	0.932±0.007	0.944±0.005	0.938±0.005	0.938±0.006	0.938±0.008	0.862±0.013	0.940±0.008
3) Afghanistan								
Macro F1	0.377±0.013	0.287±0.009	0.336±0.021	0.317±0.008	0.373±0.040	0.359±0.056	0.083±0.003	0.371±0.018
PR-AUC	0.348±0.002	0.285±0.002	0.265±0.011	0.263±0.005	0.402±0.037	0.327±0.034	0.128±0.002	0.364±0.007
ROC-AUC	0.825±0.004	0.771±0.002	0.716±0.020	0.703±0.013	0.823±0.037	0.795±0.045	0.445±0.004	0.807±0.010

HRNN: proposed method combining convolutional lateral connections with the last concatenation

SPEIs‡: variant of SPEI removing the variable standardization step

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5. Conclusions and Future Work

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- **Hybrid deep learning model** that blends data and indices: **HRNN**

- **HRNN outperforms both indices and data-driven models**

- Great potential of **hybrid frameworks for drought monitoring**

- **Future work**
    - Fusion within the inner loop of a RNN cell
    - SPEI as regularizer for DL models
    - Indices parameterization via end-to-end optimization

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