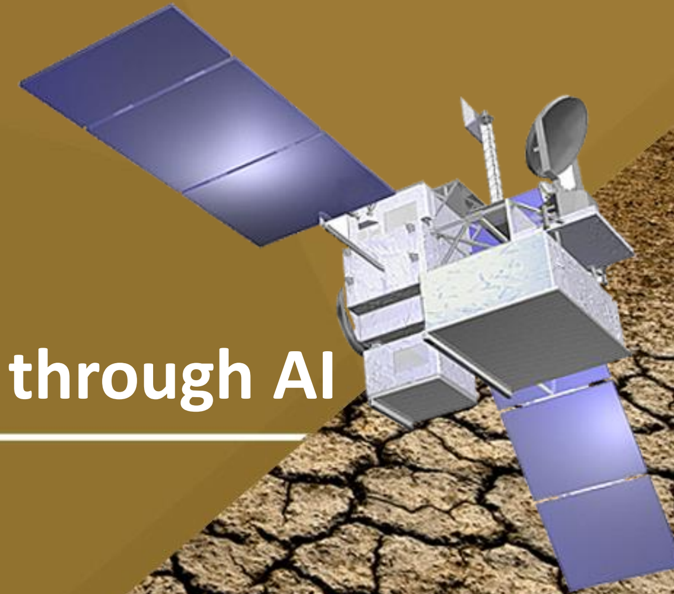
Disaster Monitoring using Satellite through AI



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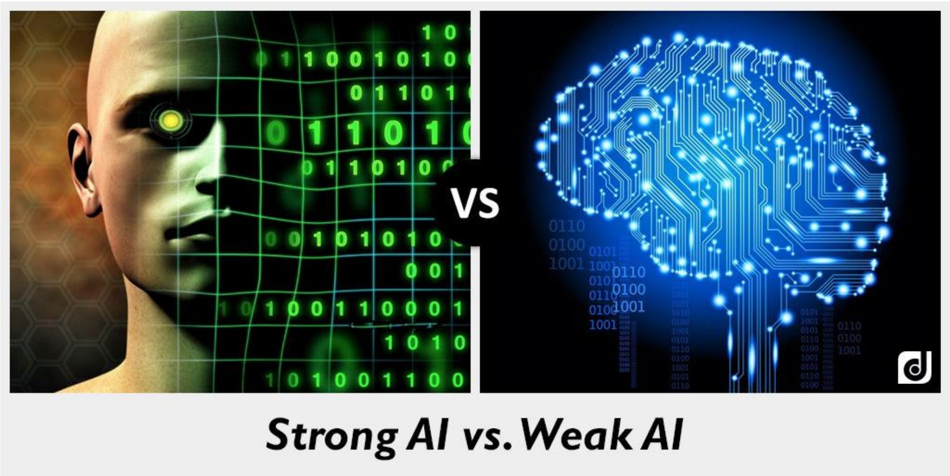
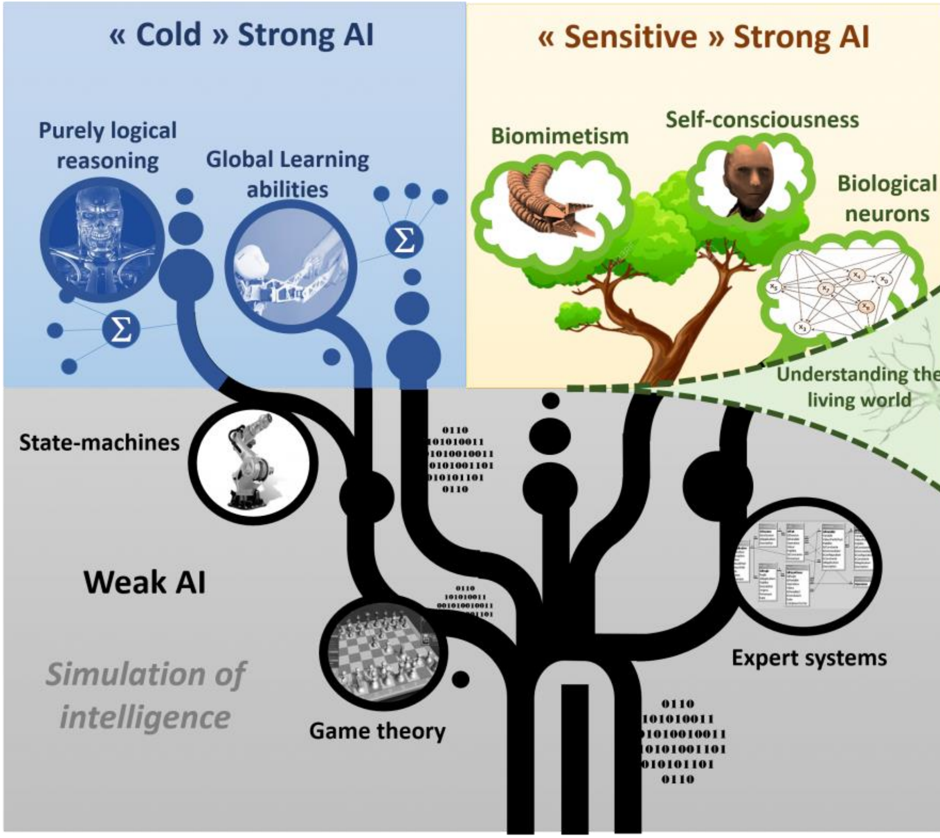
Artificial Intelligence





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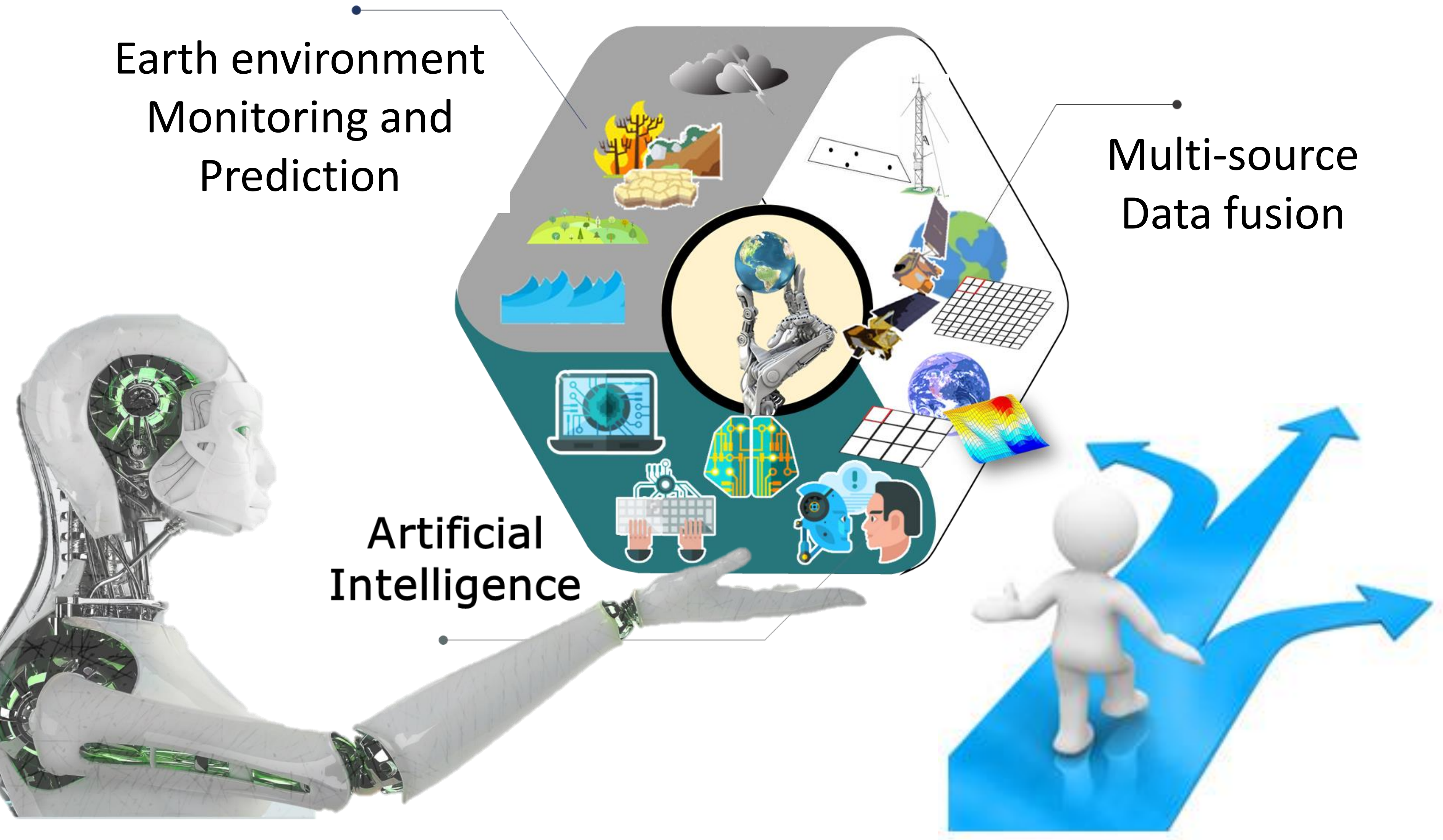

1. Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions

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Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions

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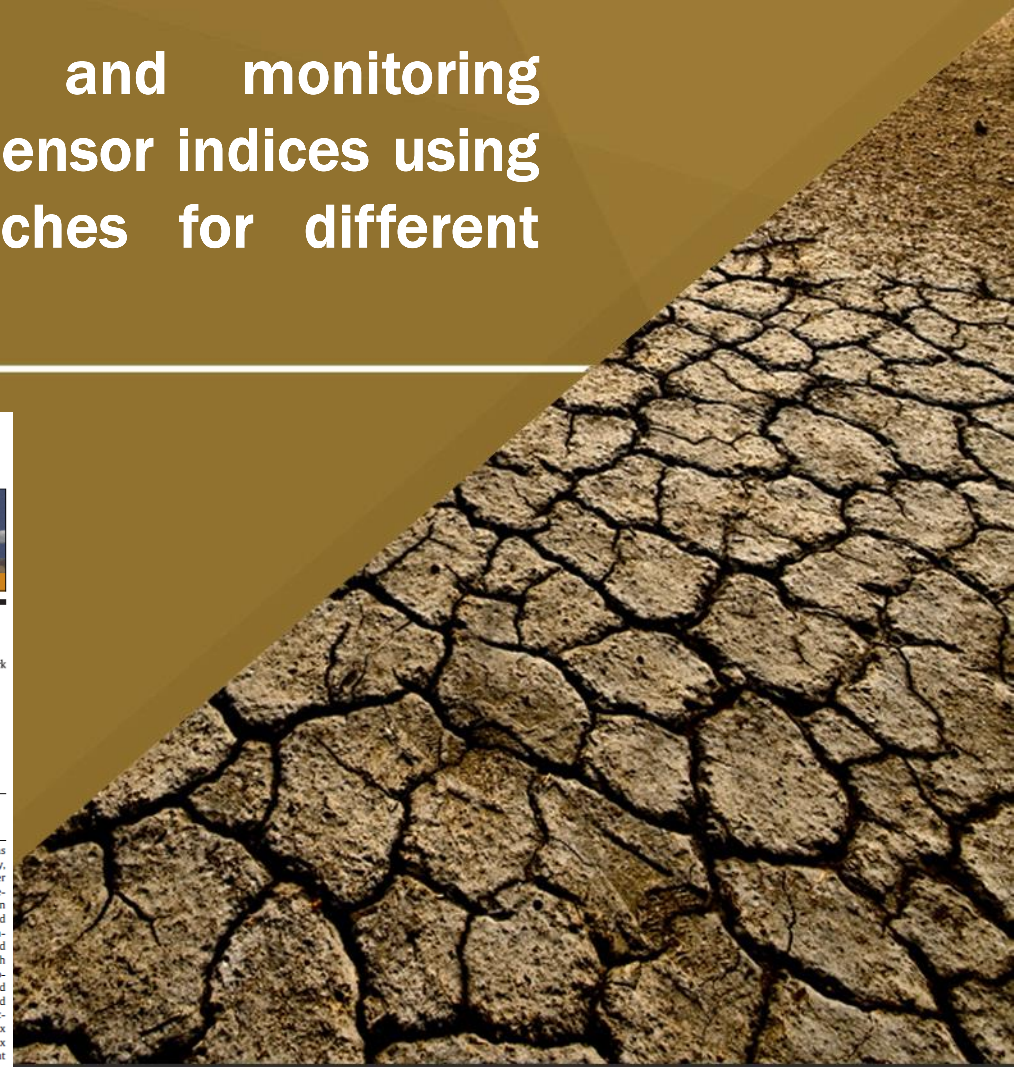
ABSTRACT

Drought triggered by a deficit of precipitation, is influenced by various environmental factors such as temperature and evapotranspiration, and causes water shortage and crop failure problems. In this study, sixteen remote sensing based drought factors from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Tropical Rainfall Measuring Mission (TRMM) satellite sensors were used to monitor meteorological and agricultural drought during 2000–2012 growing seasons for different climate regions in the USA. Standardized Precipitation Index (SPI) with time scales from 1 to 12 months and crop yield data were used as reference data of meteorological and agricultural drought, respectively. The relationship between sixteen remote sensing based drought factors and in situ reference data was modeled through three machine learning approaches: random forest, boosted regression trees, and Cubist, which have proved to be robust and flexible in many regression tasks. Results showed that random forest produced the best performance ($R^2 = 0.93$, RMSE = 0.3) for SPI prediction among the three approaches. Land surface-related drought factors, e.g., Land Surface Temperature (LST) and Evapotranspiration (ET) showed higher relative importance for short-term meteorological drought while vegetation-related drought factors, e.g., Normalized Difference Vegetation Index (NDVI) and Normalized Multi-band Drought Index (NMDI) showed higher relative importance for long-term meteorological drought by random forest. Six drought factors were selected based on the relative importance by their category to develop drought indicators that represent meteorological and agricultural drought by using the relative importance as weights. While TRMM showed higher relative importance for meteorological drought, LST and NDVI showed higher relative importance for agricultural drought in the arid and humid regions, respectively. Finally, drought distribution maps were produced using the drought indicators and compared with the U.S. Drought Monitor (USDM) maps, which showed a strong visual agreement.



Research 1

Drought assessment and monitoring through blending of multi-sensor indices using machine learning approaches for different climate regions

<Research highlight>

- **Multi-sensor data** were used to monitor meteorological and agricultural drought.
- Machine learning approaches were used to examine the **importance of drought factors**.
- The **characteristics of drought factors** were identified depending on the duration of drought in different regions.
- Drought indices were proposed to monitor **meteorological and agricultural drought**.

Purpose

Purpose

✓Understanding the characteristics of drought factors depending on the duration of drought in different climate regions

✓Monitoring meteorological and agricultural drought

Region

- Arid region
- Humid region
- Combined region

Drought duration

- Short-term (1-3 months)
- Long-term (6-12 months)

Machine learning

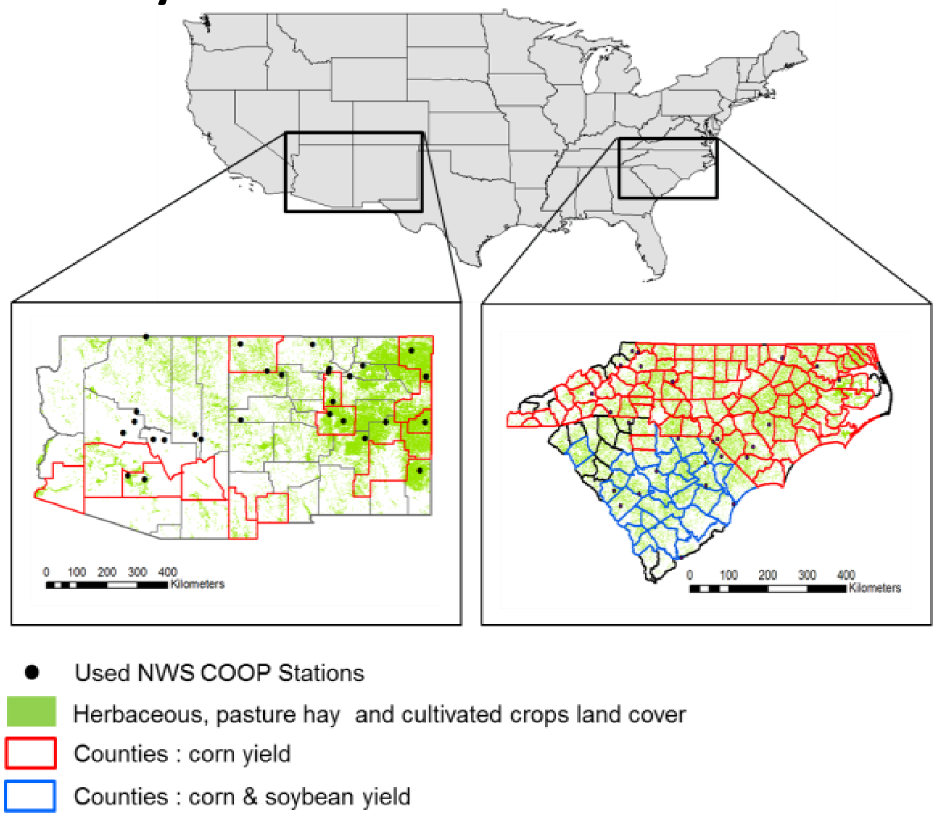
- Random forest
- BRT
- Cubist

Meteorological drought
SPI 1-12 month

Agricultural drought
Crop yield (corn&soybean)

Study area and Data

➢ Study area



- **Arid region**

- Arizona & New Mexico states
- Annual rainfall: 323mm
- Small farmland (<4% of area)

- **Humid region**

- North & South Carolina states
- Annual rainfall: 1,105mm
- rich soil ideal for agriculture

✓ **Study period** : 2000 – 2014 (May-Sep)

MODIS (Moderate Resolution Imaging Spectroradiometer)

MODIS Product	Resolution
MOD11A2 (LST)	1 km, 8 days
MOD13A3 (NDVI)	1 km, Monthly
MOD09A1 (Surface reflectance)	500 m, 8 days
MOD16A2 (ET)	1 km, Monthly

TRMM (Tropical Rainfall Measuring Mission)

- Rainfall data (3B42)
- 0.25°, Daily

➢ Reference Data

- Meteorological drought

  The Standardized Precipitation Index (SPI)

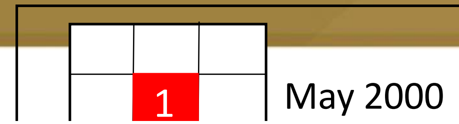
- Agricultural drought

  Crop yield data (corn, soybean)

Methodology

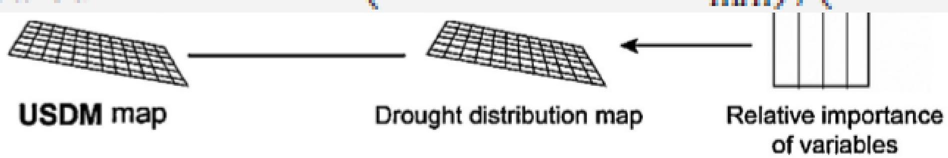
- Flow chart of the processes

MODIS TRMM



Remote sensing variable	Formula
NDVI (500 m)	$(\rho_{\text{band 2}} - \rho_{\text{band 1}})/(\rho_{\text{band 2}} + \rho_{\text{band 1}})$
NMDI	$(\rho_{\text{band 2}} - (\rho_{\text{band 6}} - \rho_{\text{band 7}}))/(\rho_{\text{band 2}} + (\rho_{\text{band 6}} - \rho_{\text{band 7}}))$
NDWI	$(\rho_{\text{band 2}} - \rho_{\text{band 5(or 6 or 7)}})/(\rho_{\text{band 2}} + \rho_{\text{band 5(or 6 or 7)}})$
NDDI	$(\text{NDVI} - \text{NDWI})/(\text{NDVI} + \text{NDWI})$
Scaled LST	$(\text{LST}_{\text{max}} - \text{LST})/(\text{LST}_{\text{max}} - \text{LST}_{\text{min}})$
Scaled NDVI (= VCI)	$(\text{NDVI} - \text{NDVI}_{\text{min}})/(\text{NDVI}_{\text{max}} - \text{NDVI}_{\text{min}})$
Scaled NMDI	$(\text{NMDI}_{\text{max}} - \text{NMDI})/(\text{NMDI}_{\text{max}} - \text{NMDI}_{\text{min}})$ for the arid region
	$(\text{NMDI} - \text{NMDI}_{\text{min}})/(\text{NMDI}_{\text{max}} - \text{NMDI}_{\text{min}})$ for the humid region
Scaled NDWI	$(\text{NDWI} - \text{NDWI}_{\text{min}})/(\text{NDWI}_{\text{max}} - \text{NDWI}_{\text{min}})$
Scaled NDDI	$(\text{NDDI}_{\text{max}} - \text{NDDI})/(\text{NDDI}_{\text{max}} - \text{NDDI}_{\text{min}})$
Scaled TRMM	$(\text{TRMM} - \text{TRMM}_{\text{min}})/(\text{TRMM}_{\text{max}} - \text{TRMM}_{\text{min}})$

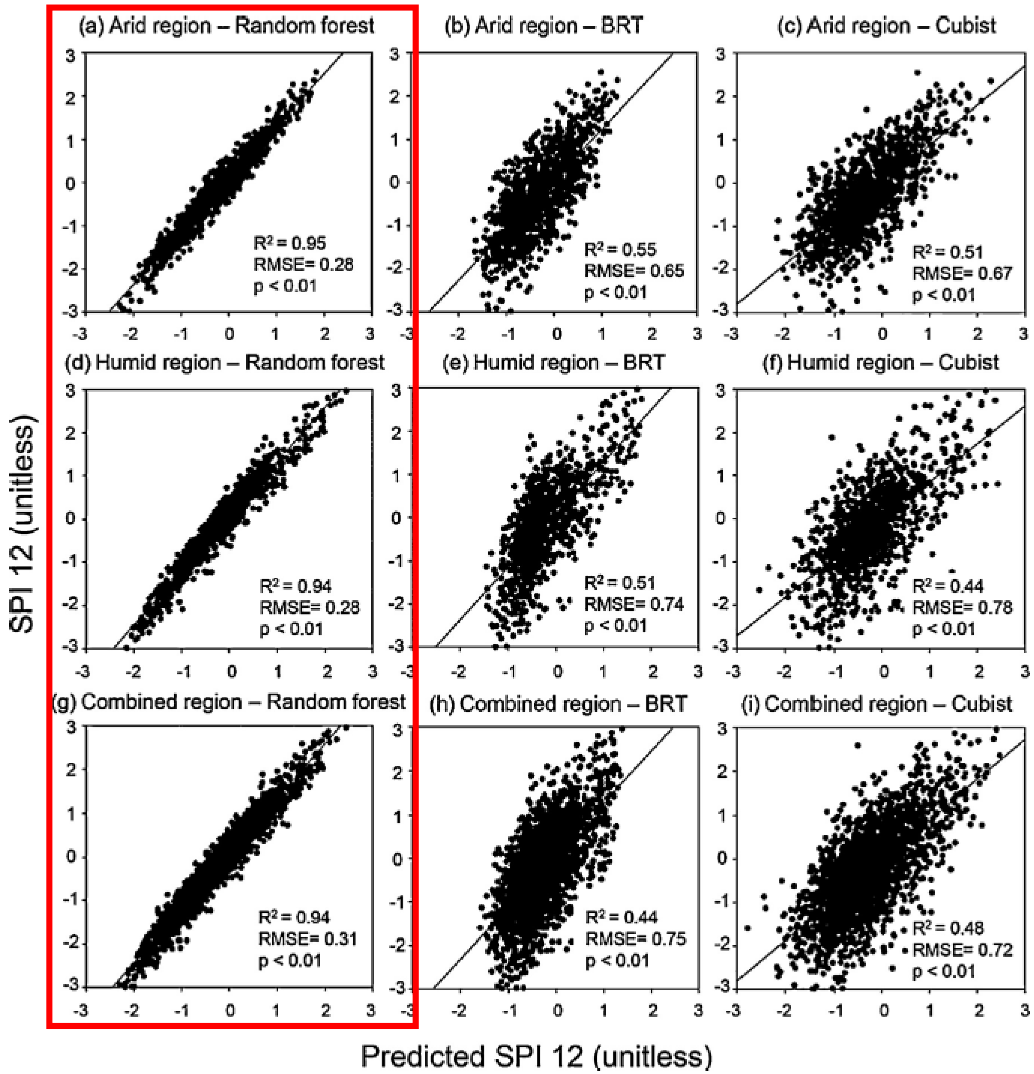
Scaled TRMM $(\text{TRMM} - \text{TRMM}_{\text{min}})/(\text{TRMM}_{\text{max}} - \text{TRMM}_{\text{min}})$



the driest condition, while values of 1 represent the wettest

Modeling performance

Scatter plots between predicted 12-month SPI based on random forest (RF), boosted regression trees (BRT), and Cubist



Relative variable importance for drought duration

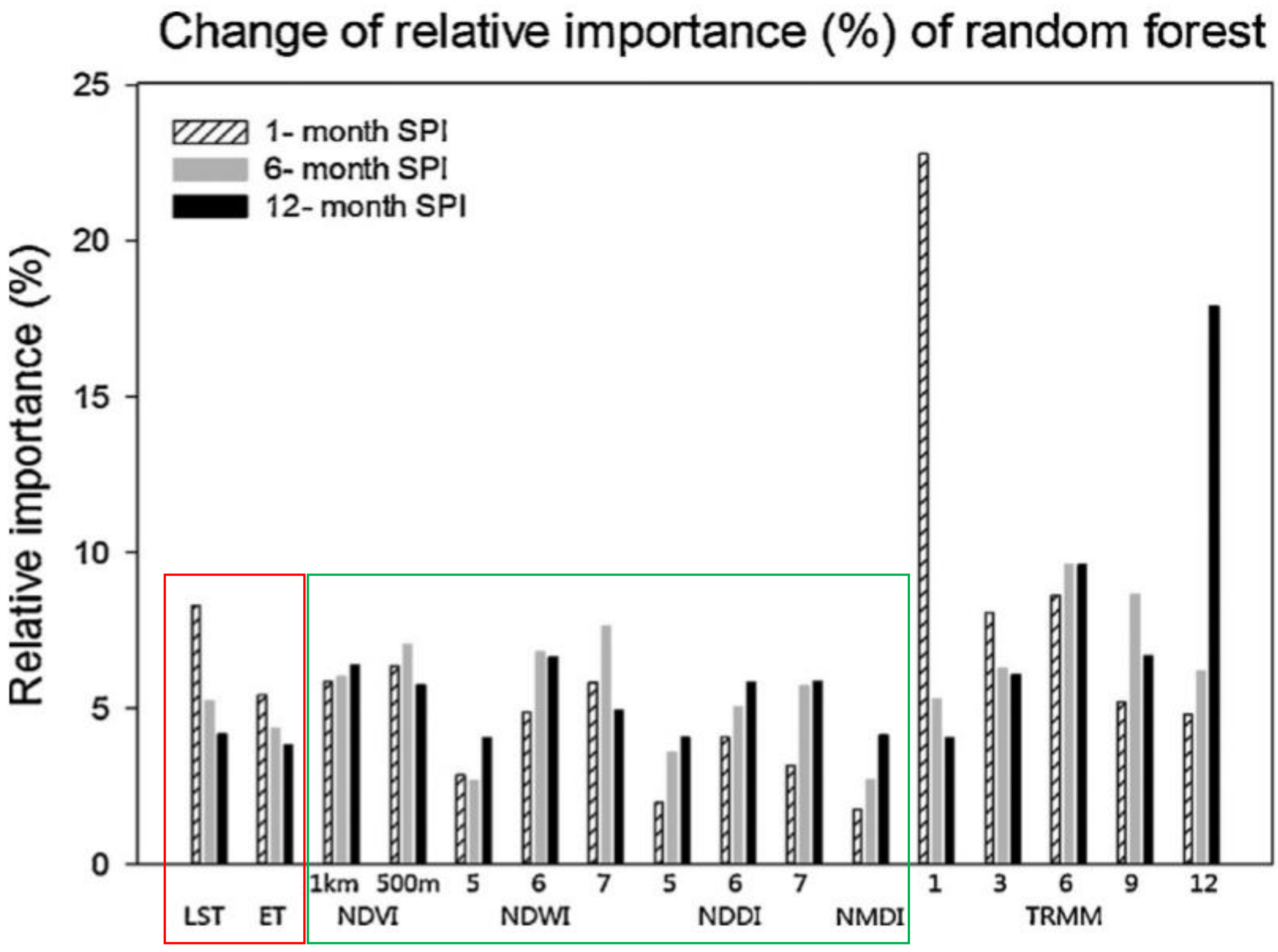


Fig. 5. The relative importance (%) of the sixteen drought factors using random forest for 1-, 6-, and 12-month SPI.

Select six variables

Table 3
The Relative importance (%) of the most important five drought factors among the sixteen variables for meteorological drought (SPI) using random forest (RF) and boosted regression trees (BRT) in the arid, humid and combined regions for 1-, 3-, 6-, 9-, and 12-month SPI.

Rank	Relative importance % (random forest and boosted regression trees)									
	SPI1		SPI3		SPI6		SPI9		SPI12	
(a) Arid region										
1	TRMM1 (21.3)	TRMM1 (38.0)	TRMM6 (12.3)	TRMM6 (19.8)	TRMM6 (17.8)	TRMM1 (21.3)	TRMM1 (38.0)	TRMM6 (12.3)	TRMM6 (19.8)	TRMM6 (17.8)
2	TRMM6 (10.3)	TRMM3 (12.0)	TRMM3 (9.8)	NDWI6 (13.0	NDWI6 (9.6)	TRMM6 (10.3)	TRMM3 (12.0)	TRMM3 (9.8)	NDWI6 (13.0	NDWI6 (9.6)
3	TRMM3 (9.6)	TRMM6 (11.6)	NDWI6 (8.1)	TRMM3 (12.6)	NDWI7 (9.3)	TRMM3 (9.6)	TRMM6 (11.6)	NDWI6 (8.1)	TRMM3 (12.6)	NDWI7 (9.3)
4	ET (8.7)	LST (8.5)	NDWI7 (7.2)	ET (9.0)	NDDI6 (9.1)	ET (8.7)	LST (8.5)	NDWI7 (7.2)	ET (9.0)	NDDI6 (9.1)
5	LST (6.4)	ET (6.3)	NDDI6 (7.1)	NDVI (8.7)	NDVI (7.8)	LST (6.4)	ET (6.3)	NDDI6 (7.1)	NDVI (8.7)	NDVI (7.8)
(b) Humid region										
1	TRMM1 (25.4)	TRMM1 (50.0)	TRMM3 (13.2)	TRMM3 (27.2)	TRMM6 (15.0)	TRMM6 (40.7)	TRMM9 (15.2)	TRMM9 (47.8)	TRMM12 (21.3)	TRMM12 (55.4)
2	LST (10.1)	LST (14.1)	TRMM1 (11.5)	TRMM1 (16.9)	TRMM9 (10.6)	TRMM9 (11.9)	TRMM12 (11.9)	TRMM12 (10.8)	TRMM9 (8.6)	TRMM1 (7.8)
3	TRMM3 (7.4)	TRMM6 (4.8)	TRMM6 (9.4)	LST (11.0)	TRMM3 (8.4)	TRMM1 (9.8)	TRMM6 (9.6)	TRMM1 (9.3)	TRMM6 (7.1)	LST (5.7)
4	TRMM6 (7.0)	NDVI500 (4.0)	TRMM9 (8.8)	TRMM9 (9.1)	TRMM12 (8.1)	LST (8.8)	TRMM1 (8.2)	LST (5.9)	NDDI6 (6.8)	NDVI (4.3)
5	TRMM9 (6.4)	TRMM3 (2.9)	TRMM12 (8.4)	NDWI7 (5.3)	TRMM1 (8.0)	NDVI (3.8)	TRMM3 (6.7)	NDVI (3.8)	TRMM1 (6.8)	NMDI (3.9)
(c) Combined region										
1	TRMM1 (13.2)	TRMM1 (52.7)	TRMM6 (14.1)	TRMM3 (28.2)	TRMM6 (12.2)	TRMM6 (45.9)	TRMM9 (15.2)	TRMM9 (47.1)	TRMM12 (13.2)	TRMM12 (54.3)
2	TRMM3 (12.3)	LST (13.1)	TRMM3 (10.3)	TRMM6 (14.8)	TRMM9 (10.0)	TRMM9 (9.7)	TRMM12 (11.9)	TRMM12 (9.1)	ET (12.1)	TRMM6 (7.4)
3	TRMM6 (9.5)	TRMM3 (7.9)	NDWI7 (8.1)	NDWI6 (9.4)	TRMM12 (7.6)	LST (7.0)	TRMM6 (9.6)	TRMM6 (8.1)	TRMM6 (7.6)	NDWI7 (5.8)
4	LST (8.5)	TRMM6 (5.4)	NDWI6 (7.4)	TRMM1 (9.3)	NDWI7 (7.4)	NDWI7 (6.4)	TRMM1 (8.2)	NDWI6 (4.7)	NDVI (6.6)	NDVI (5.7)
5	ET (6.9)	ET (2.8)	ET (6.9)	LST (9.3)	ET (6.9)	NDWI6 (5.4)	NDDI7 (5.5)	NDVI (4.7)	NDWI6 (6.4)	LST (4.2)

teen variables for meteorological drought (SPI) using

	SPI12		
1	TRMM9 (100)	TRMM12 (100)	TRMM12 (100)
2	NDVI500 (93)	TRMM6 (19)	TRMM6 (100)
3	TRMM6 (88)		NDWI6 (100)
4	NDWI6 (100)		NDDI6 (100)
5	TRMM3 (100)		NDVI500 (86)
1	TRMM9 (100)	TRMM12 (100)	TRMM12 (100)
2	TRMM1 (100)	TRMM1 (53)	TRMM1 (53)
3	NDDI6 (95)		NDDI5 (100)
4	TRMM6 (93)		NDVI500 (100)
5	NDDI7 (93)		NMDI (100)

1								TRMM9 (98)	TRMM12 (73)	TRMM12 (97)
2	TRMM3 (54)	TRMM3 (100)	NDWI6 (88)	NDWI6 (100)	NDWI7 (69)	NDWI7 (100)	NDWI6 (83)	NDWI6 (83)	NDWI6 (87)	NDWI6 (69)
3		LST (100)	TRMM1 (69)	TRMM1 (59)	TRMM1 (66)	TRMM1 (54)	TRMM3 (74)	TRMM3 (83)	TRMM9 (41)	TRMM9 (100)
4		NDVI500 (100)		NDVI500 (100)	LST (19)	LST (88)		NDDI6 (100)	NDDI6 (74)	NDDI6 (49)
5		NDWI7 (100)		TRMM6 (100)		NDVI500 (96)		NDWI7 (98)	LST (17)	LST (74)

Development of Drought Index based on variable importance

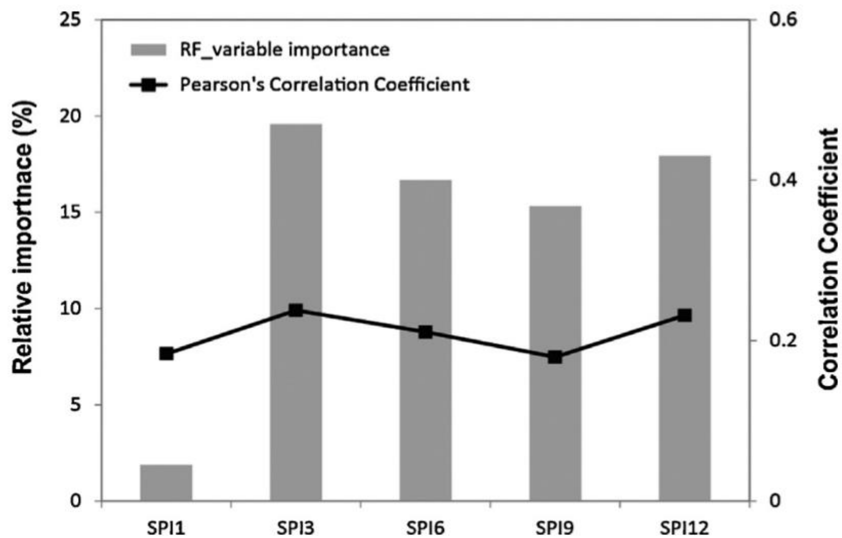
- The scaled relative importance of the selected six variables for 1- to 12-SPI

Drought factors	Target feature														
	SPI1			SPI3			SPI6			SPI9			SPI12		
	C	A	H	C	A	H	C	A	H	C	A	H	C	A	H
LST	0.17	0.13	0.21	0.14	0.14	0.16	0.12	0.12	0.14	0.10	0.12	0.12	0.08	0.06	0.08
NDVI	0.12	0.14	0.06	0.16	0.16	0.10	0.11	0.13	0.04	0.12	0.15	0.07	0.13	0.13	0.10
NDWI	0.12	0.11	0.07	0.17	0.21	0.10	0.13	0.17	0.08	0.11	0.17	0.06	0.11	0.17	0.06
NMDI	0.04	0.04	0.02	0.05	0.08	0.07	0.06	0.09	0.04	0.06	0.10	0.06	0.07	0.12	0.06
ET	0.08	0.19	0.07	0.04	0.13	0.04	0.09	0.11	0.06	0.07	0.10	0.07	0.07	0.10	0.05
TRMM	0.47	0.39	0.57	0.44	0.28	0.53	0.49	0.38	0.65	0.54	0.36	0.62	0.54	0.42	0.65
R^2	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.92
RMSE	0.37	0.37	0.36	0.37	0.36	0.38	0.36	0.36	0.35	0.36	0.35	0.35	0.36	0.34	0.37

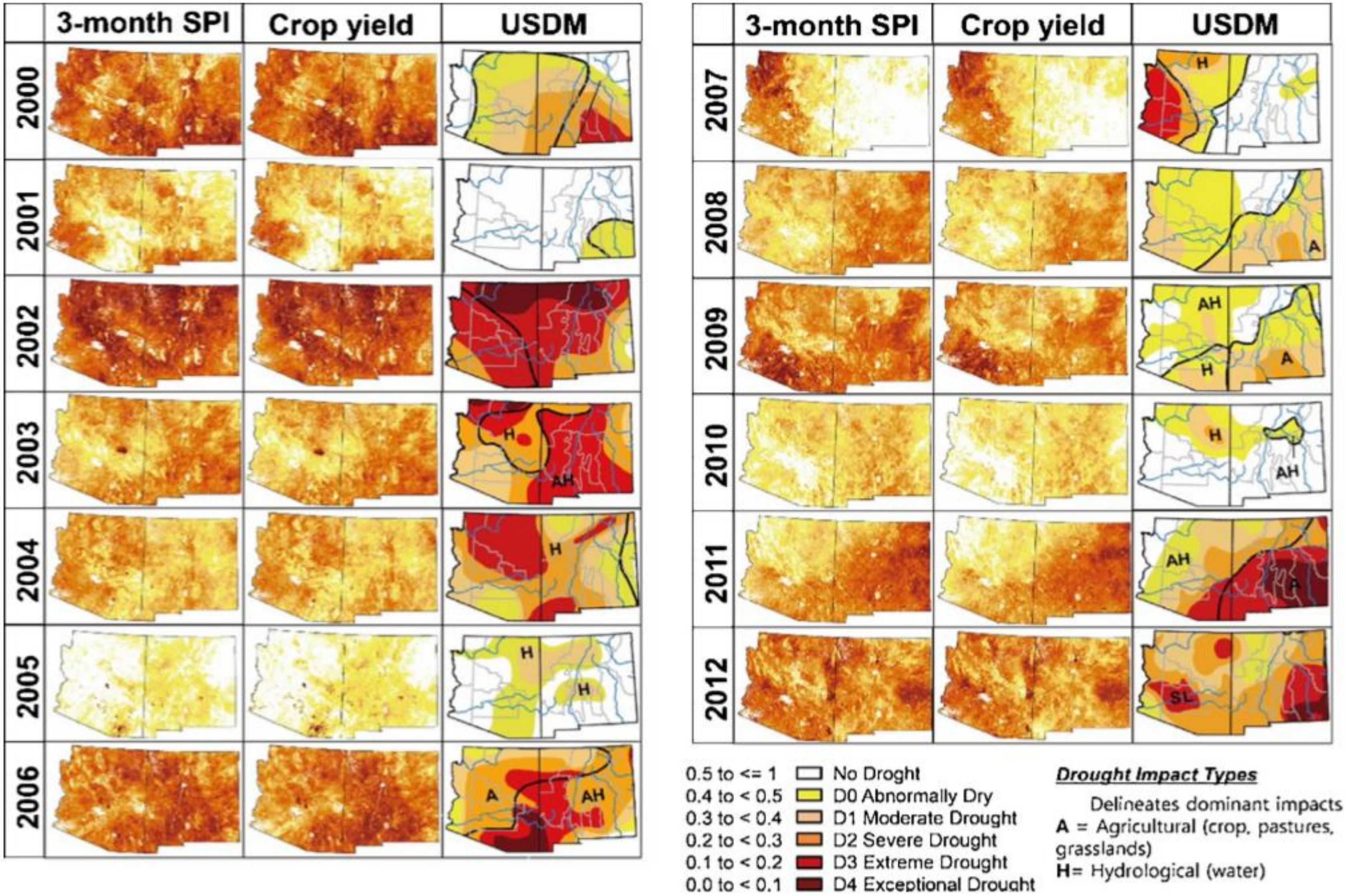
- The scaled relative importance of the selected six variables for Crop yield

Drought factors	Target feature		
	Arid (Irrigated)	Humid (Non-irrigated)	
	Corn	Corn	Soybean
LST	0.15	0.29	0.29
NDVI	0.22	0.07	0.13
NDWI	0.05	0.11	0.07
NMDI	0.22	0.29	0.16
ET	0.20	0.11	0.15
TRMM3	0.16	0.13	0.20
R^2	0.94	0.94	0.94
RMSE	9.87	14.95	3.04
rRMSE	0.05	0.18	0.12

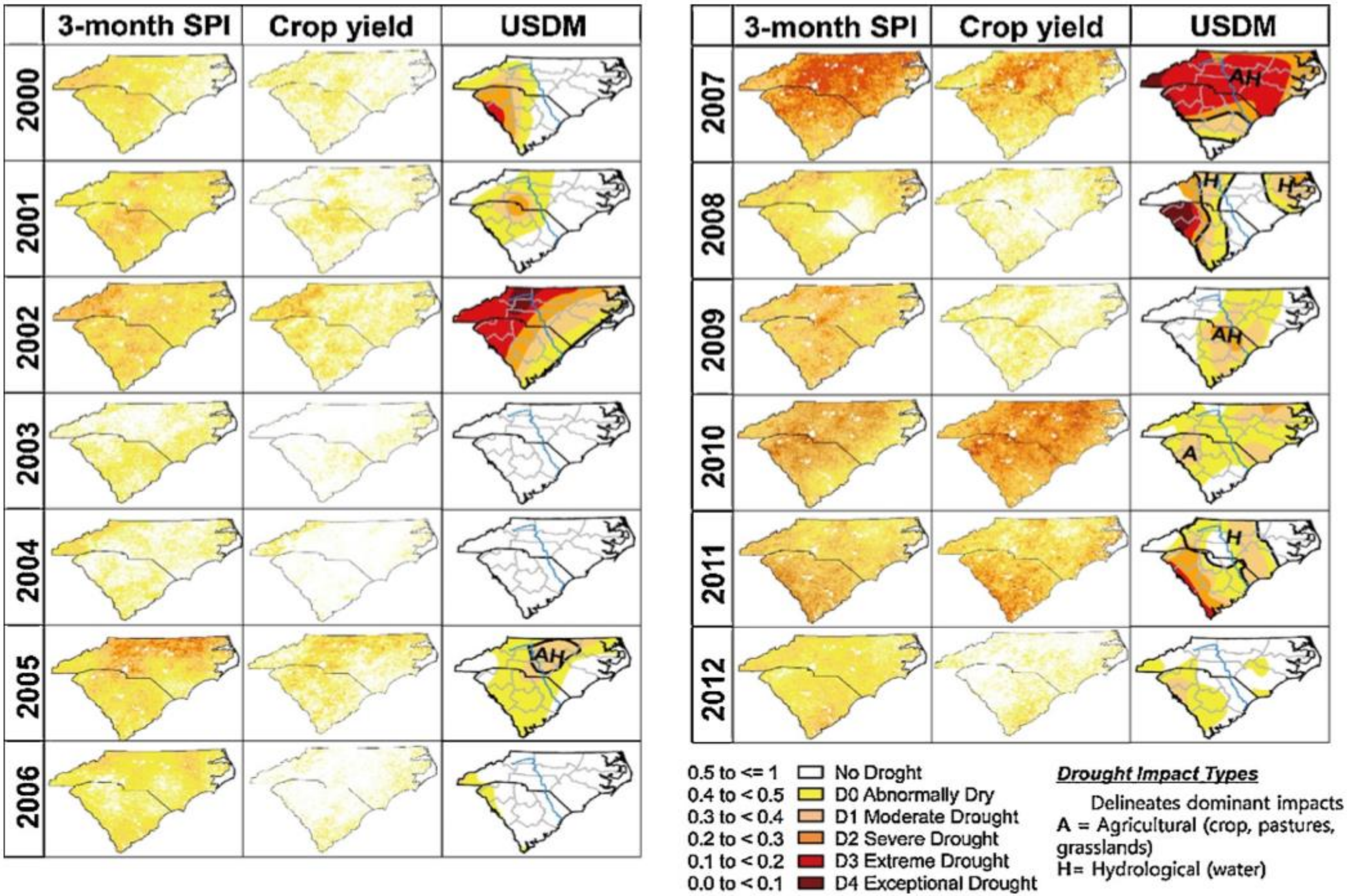
- The relationship between SPI and crop yield



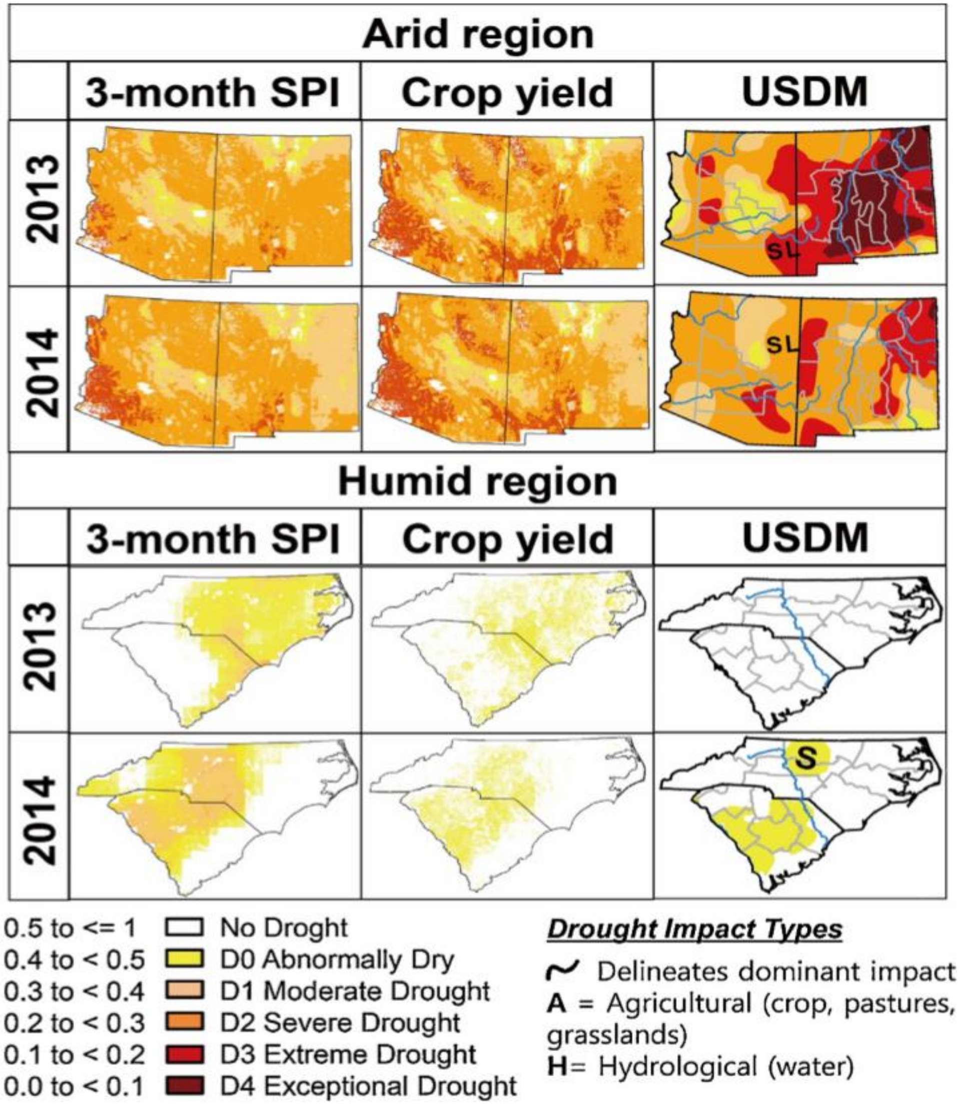
Comparison of spatial distribution of drought with USDM (arid region)



Comparison of spatial distribution of drought with USDM (humid region)



Comparison of spatial distribution of drought with USDM



Conclusion

- **The characteristics of drought factors** were analyzed using three machine learning approaches targeting a meteorological drought index (SPI) and an agricultural drought index (crop yield).
- The characteristics of drought factors for meteorological and agricultural drought were examined using **relative importance of variables**.
- RF outperformed the other approaches and was used to select the most important six variables (LST, NDVI, NDWI, NMDI, ET, and TRMM).
- The approach proposed in this study can be applied to any vegetated region where remote sensing data are available even with limited *in situ* data availability.

There are some limitations:

- Crop yield samples were limited due to the study area selection.
- As the current thresholds (e.g., 0.5 for normal condition) to determine drought conditions are arbitrary, specific standards and guidelines on thresholds should follow.

Future research direction:

- The incorporation of soil moisture into development of drought indicators
- The development of remote sensing-based optimized approaches to different types of drought (i.e., hydrological drought).

2. Very short-term prediction of drought using remote sensing data and MJO index through Random forest over East Asia

remote sensing

MDPI

Article

Prediction of Drought on Pentad Scale Using Remote Sensing Data and MJO Index through Random Forest over East Asia

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Abstract: Rapidly developing droughts, including flash droughts, have frequently occurred throughout East Asia in recent years, causing significant damage to agricultural ecosystems. Although many drought monitoring and warning systems have been developed in recent decades, the short-term prediction of droughts (within 10 days) is still challenging. This study has developed drought prediction models for a short-period of time (one pentad) using remote-sensing data and climate variability indices over East Asia (20°–50°N, 90°–150°E) through random forest machine learning. Satellite-based drought indices were calculated using the European Space Agency (ESA) Climate Change Initiative (CCI) soil moisture, Tropical Rainfall Measuring Mission (TRMM) precipitation, Moderate Resolution Imaging Spectroradiometer (MODIS) land surface temperature (LST), and normalized difference vegetation index (NDVI). The real-time multivariate (RMM) Madden–Julian oscillation (MJO) indices were used because the MJO is a short timescale climate variability and has important implications for droughts in East Asia. The validation results show that those drought prediction models with the MJO variables (r ~ 0.7 on average) outperformed the original models without the MJO variables (r ~ 0.4 on average). The predicted drought index maps showed similar spatial distribution to actual drought index maps. In particular, the MJO-based models captured sudden changes in drought conditions well, from normal/wet to dry or dry to normal/wet. Since the developed models can produce drought prediction maps at high resolution (5 km) for a very short timescale (one pentad), they are expected to provide decision makers with more accurate information on rapidly changing drought conditions.

Keywords: drought prediction; MJO; random forest; East Asia

Research 2

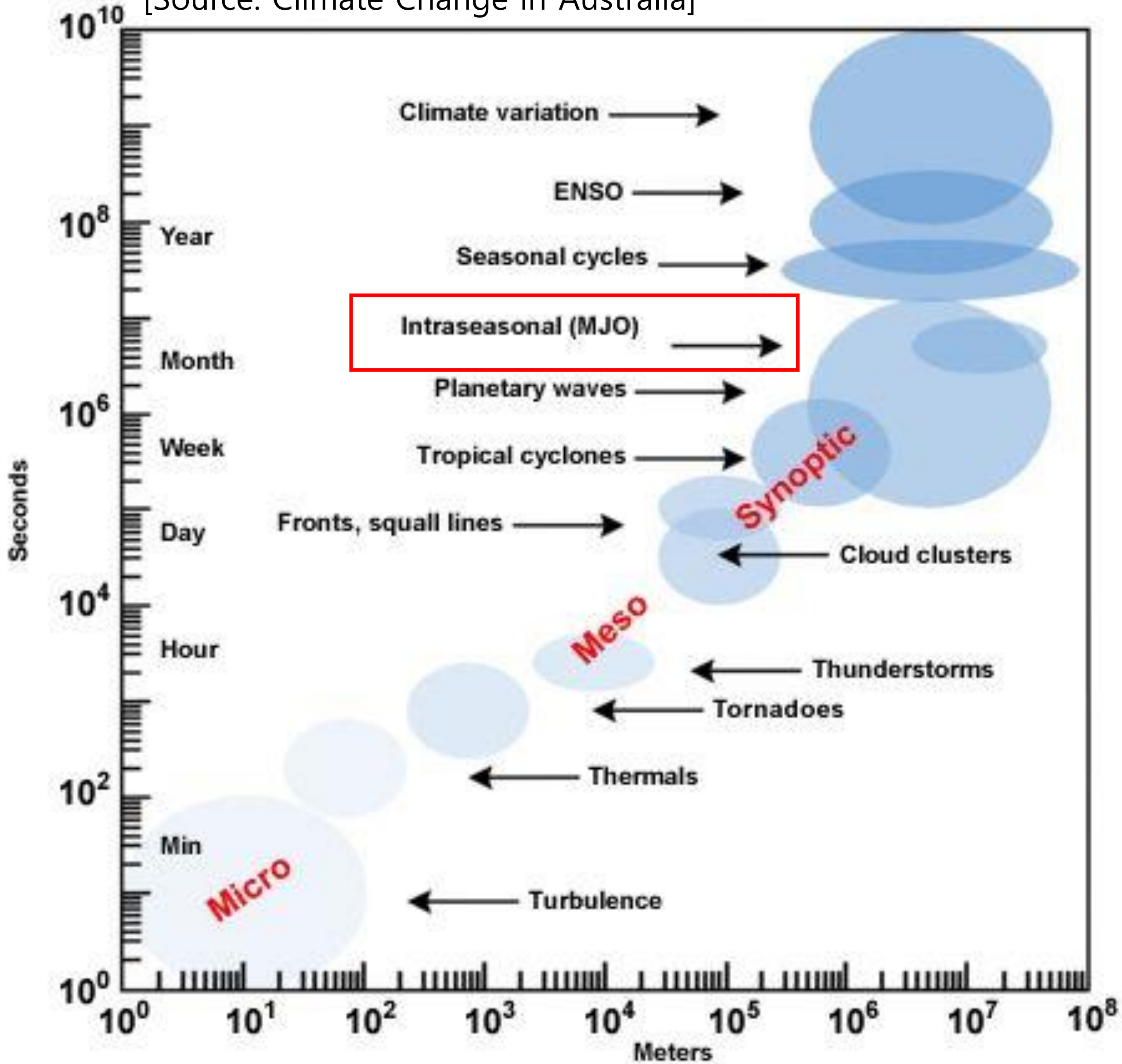
Very short-term prediction of drought using remote sensing data and MJO index through Random forest over East Asia

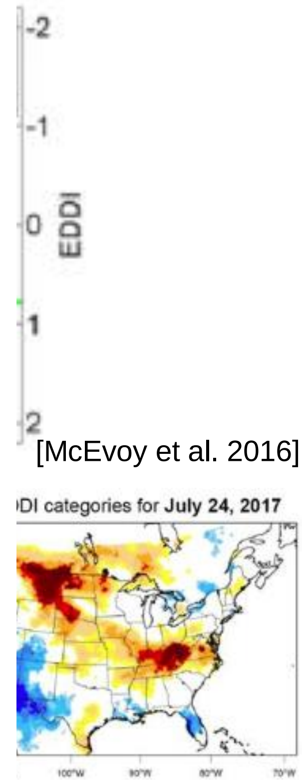
<Research highlight>

- Drought short-term prediction model was developed using Random forest.
- Very short-term Drought Index (VSDI) was proposed.
- Climate variability, **Madden-Julian Oscillation (MJO) improved** the performance of prediction model.

Introduction

[Source: Climate Change in Australia]



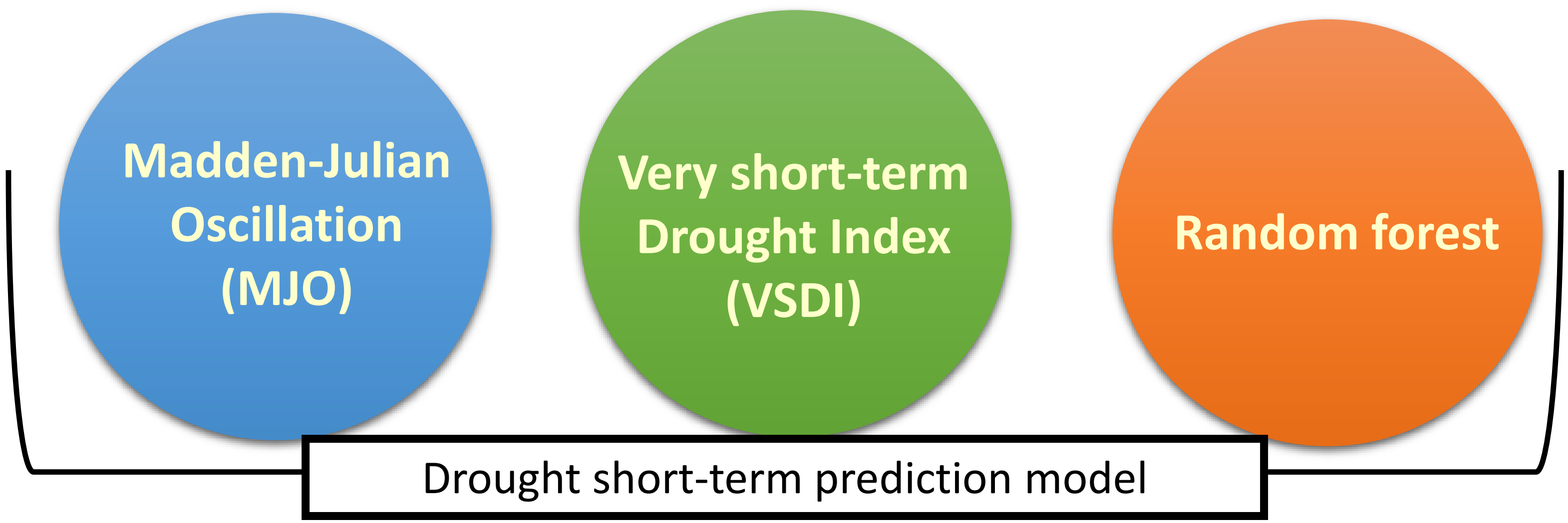


[McEvoy et al. 2016]

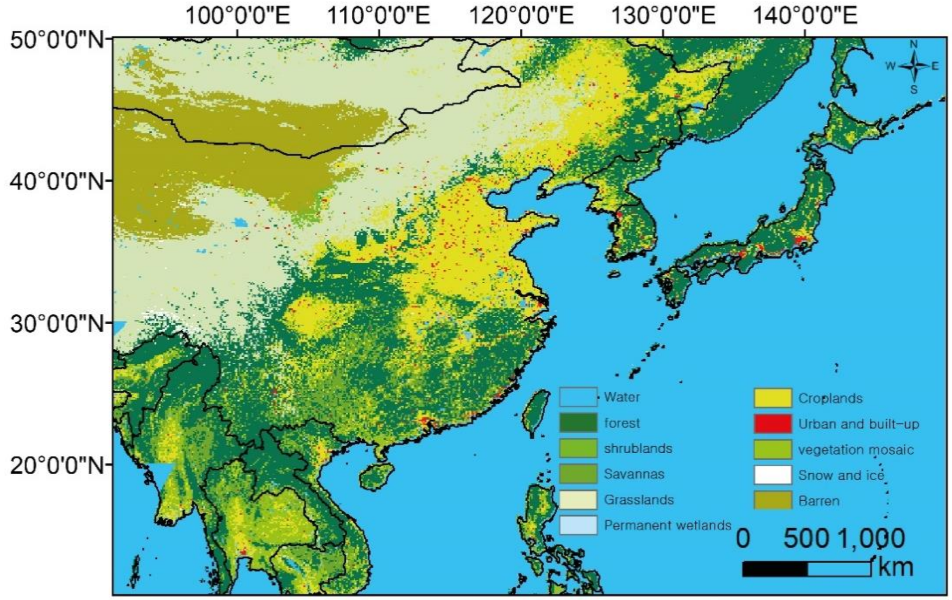
Purpose

Purpose

- ✓Developing Short-term drought index by modifying SDCI and MIDI
- ✓Developing drought short-term prediction model using MJO index
- ✓Evaluating the effect of MJO in drought prediction



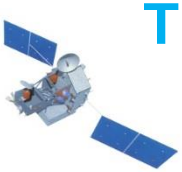
Study area and data



✓ **Study period** : 2000 – 2016 (April-May)

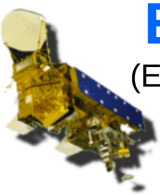
MODIS

MODIS Product	Resolution
MOD11C1 (LST)	0.05°, daily
MOD09CMG (reflectance)	0.05°, daily



TRMM (Tropical Rainfall Measuring Mission)

- Rainfall data (3B42)
- 0.25°, Daily



ESA-CCI Soil Moisture

(European Space Agency - Climate Change Initiative)

- Soil moisture data (v3.3)
- 0.25°, Daily

Drought indices

SDCI = 0.5*PCI + 0.25*TCI + 0.25*VCI

MIDI = 0.5*PCI + 0.3*SMCI + 0.2*TCI

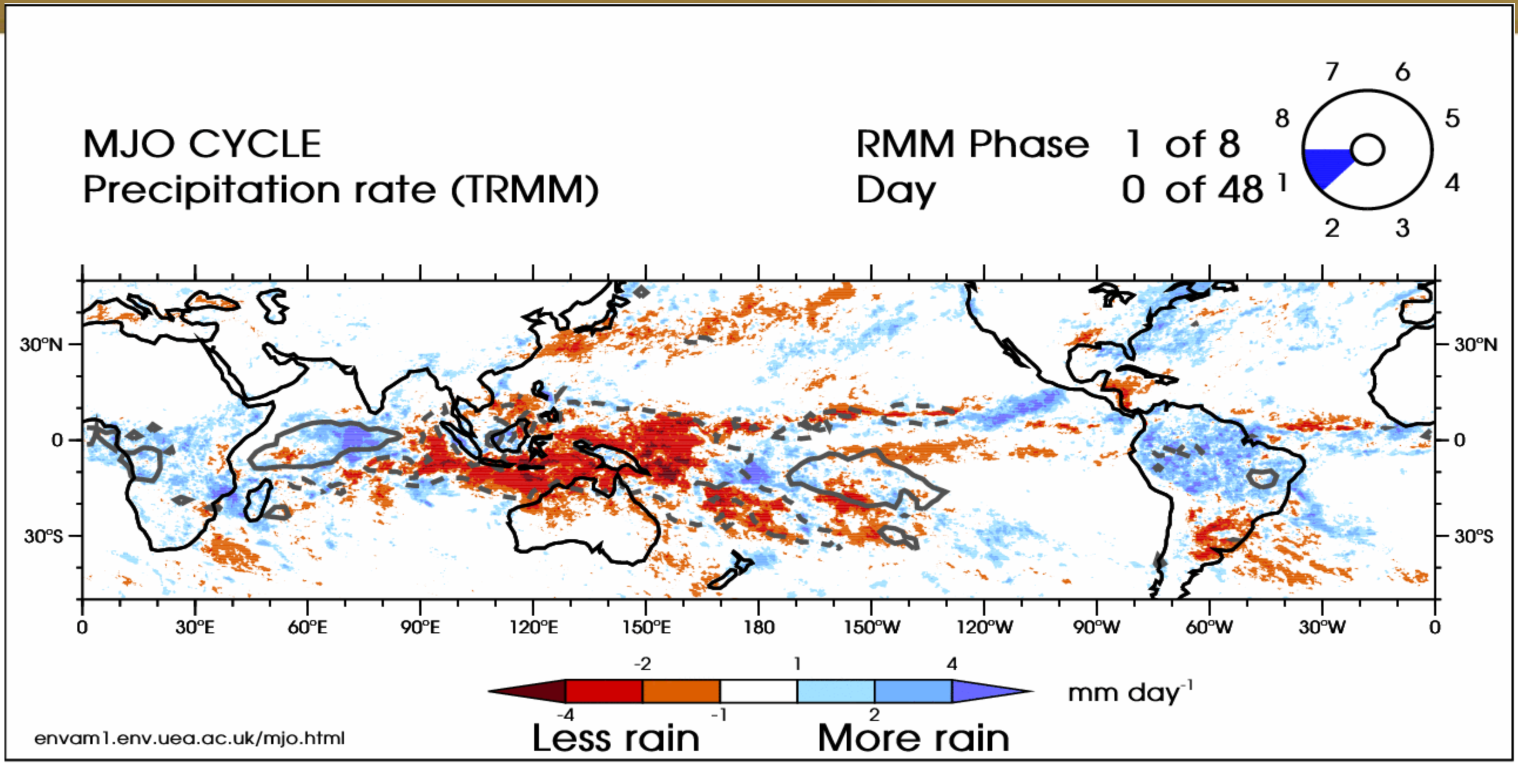
VSDI = 0.5*SMCI + 0.25*TCI + 0.25*VCI

SDCI: Scaled Drought Condition Index
MIDI: Microwave Integrated Drought Index
VSDI: Very short-term Drought Index
PCI: Precipitation Condition Index; **TCI**: Temperature Condition Index;
VCI: Vegetation Condition Index; **SMCI**: Soil Moisture Condition Index

RMM MJO indices

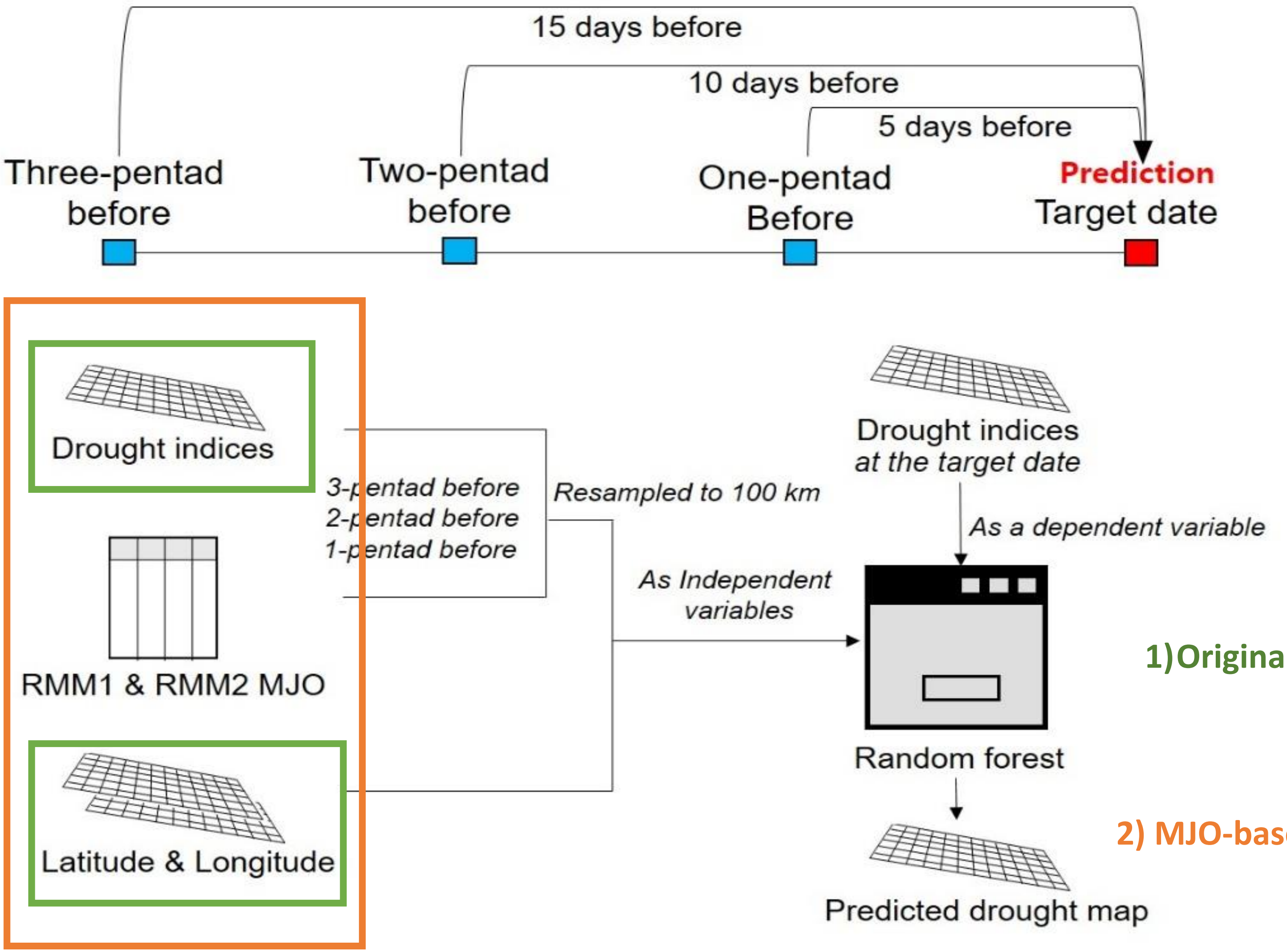
(Madden-Julian Oscillation)

Madden-Julian Oscillation (MJO)



- MJO phases based on a pair of empirical orthogonal functions (EOFs) of the combined fields of 850-hPa, 200-hPa zonal wind anomalies and outgoing longwave radiation (OLR) (Wheeler and Hendon 2004).
- Two leading principal components (PC1 and PC2) of the EOFs are Real-time Multivariate MJO series 1 (RMM1) and 2 (RMM2)
- $MJO_{intensity} = \sqrt{RMM1^2 + RMM2^2}$
- This study used Real-time Multivariate MJO series 1 (RMM1) and 2 (RMM2)

Methodology



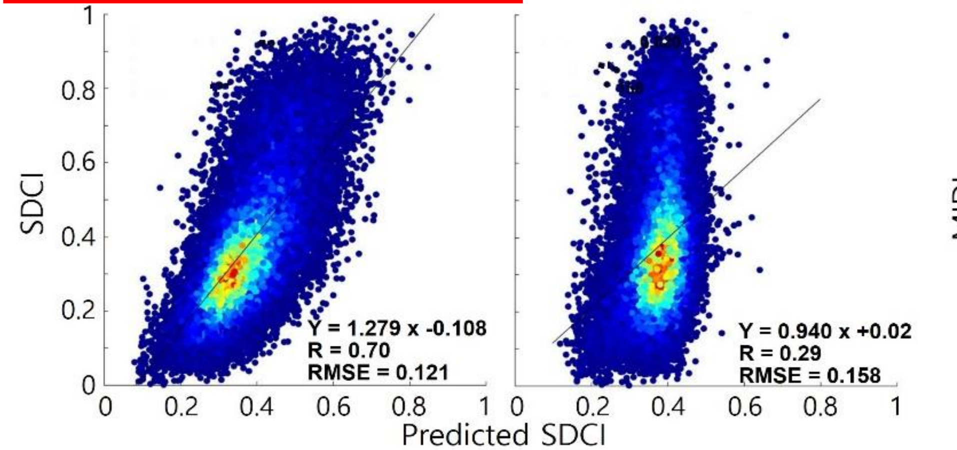
1)Original prediction model

VS.

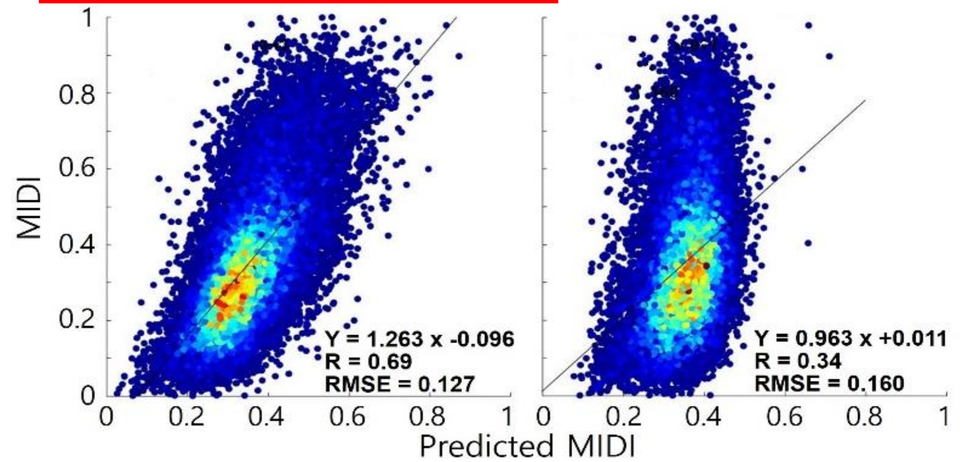
2) MJO-based prediction model

Comparison of model performances

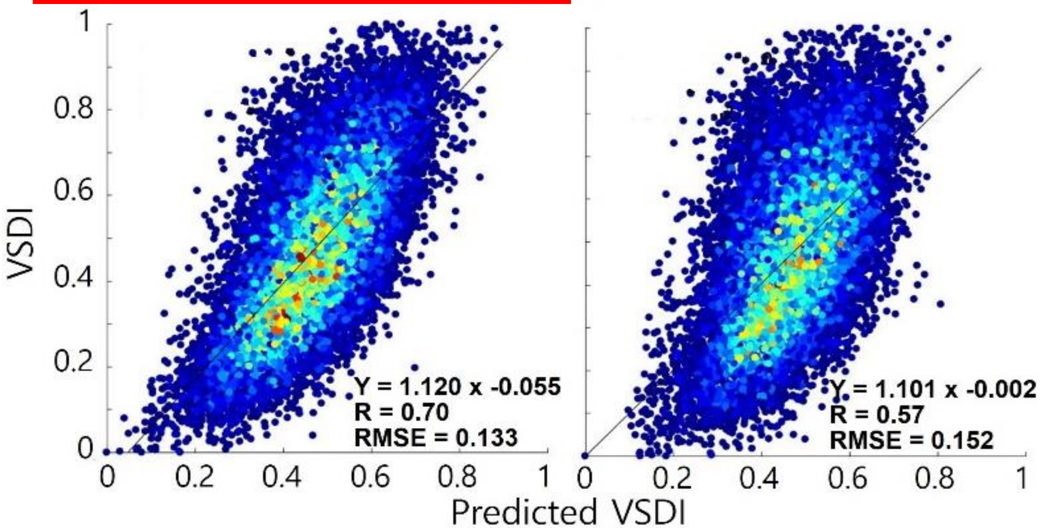
MJO-based prediction model | Original prediction model

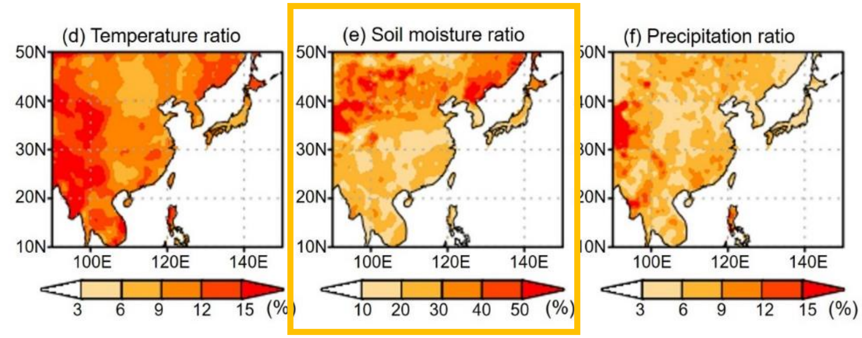


MJO-based prediction model | Original prediction model



MJO-based prediction model | Original prediction model





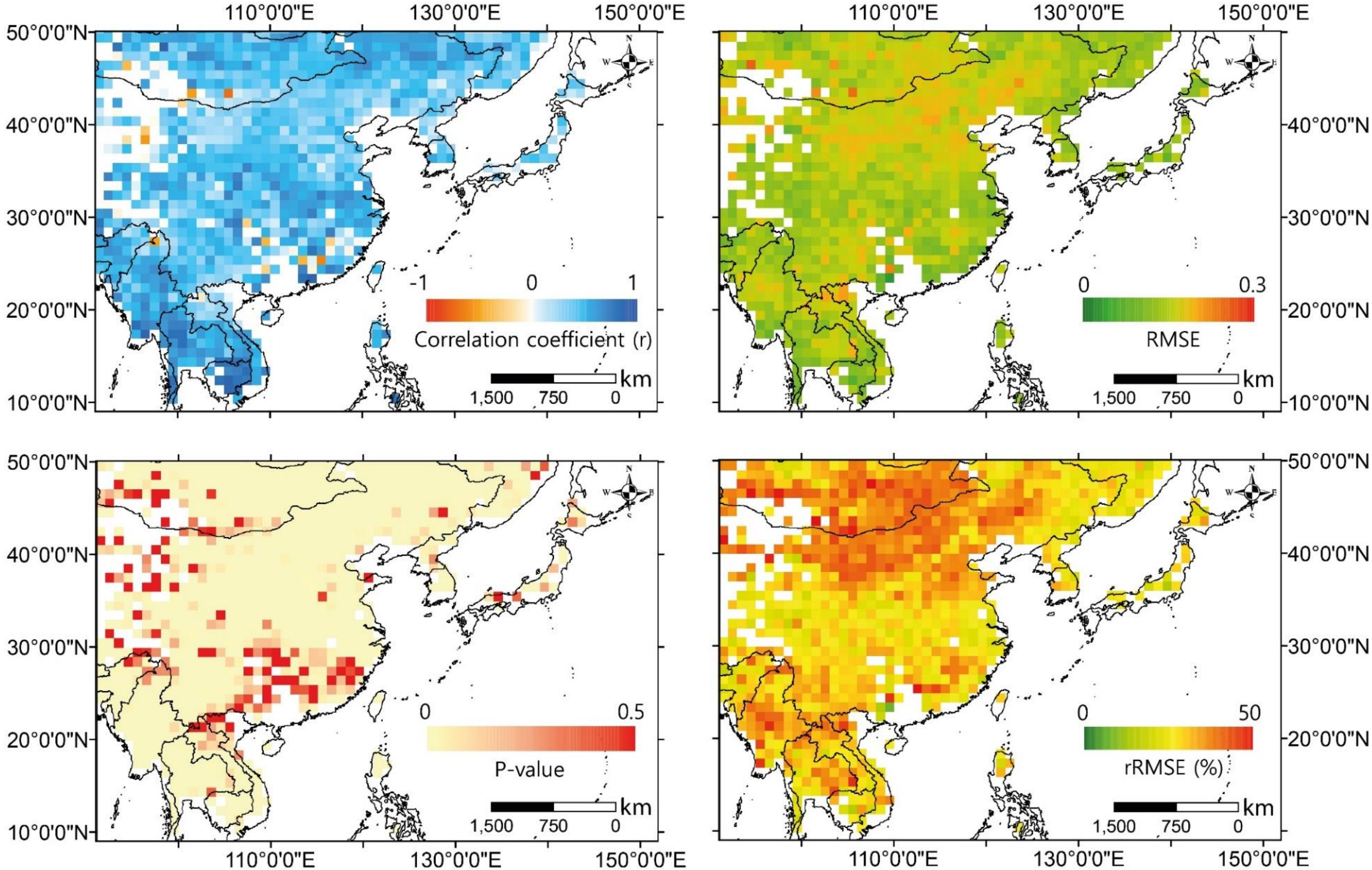
The ratios to total variance of (d) air temperature, (e) top-level soil moisture, and (f) precipitation bandpass filtered for 30-90 days during 22 springs between 1991–2012

Variable importance

Variable importance of two drought prediction models (with MJO and without MJO) for three drought indices.

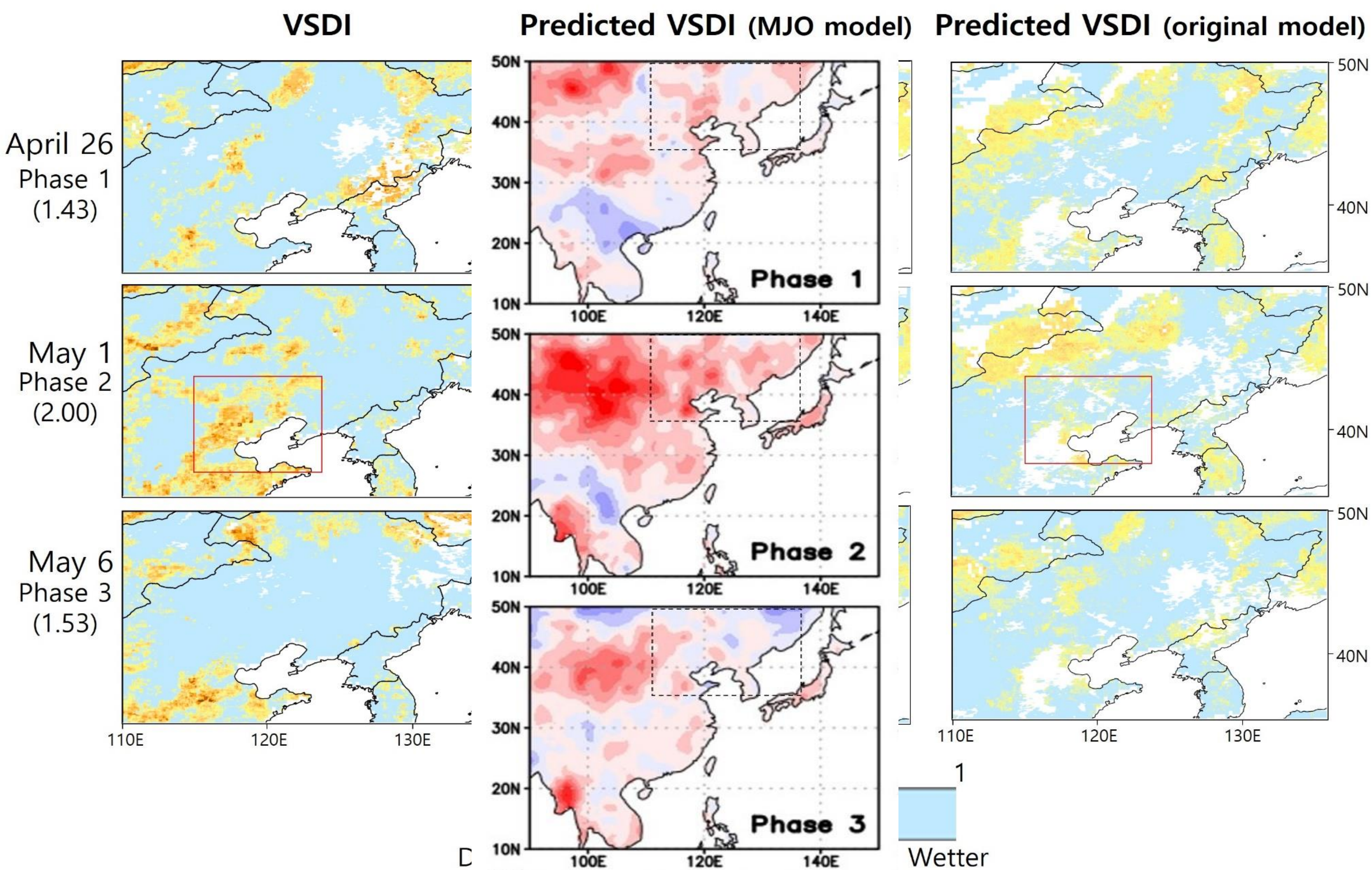
	SDCI		MIDI		VSDI	
Variables	MJO-based model	Original model	MJO-based model	Original model	MJO-based model	Original model
1-P before drought index	189.21	126.74	208.45	151.64	267.95	227.17
2-P before drought index	144.38	66.42	146.00	81.43	128.91	107.89
3-P before drought index	146.22	64.62	141.75	73.25	127.34	111.08
Latitude	205.26	117.25	150.36	85.28	92.67	79.32
Longitude	215.02	76.10	177.90	67.37	106.38	74.55
1-P before RMM1	144.23		133.19		130.05	
1-P before RMM2	139.66		117.60		88.32	
2-P before RMM1	110.21		110.71		127.19	
2-P before RMM2	106.79		107.22		81.07	
3-P before RMM1	113.44		114.50		103.56	
3-P before RMM2	97.37		97.84		82.79	

17-fold cross validation of VSDI prediction model

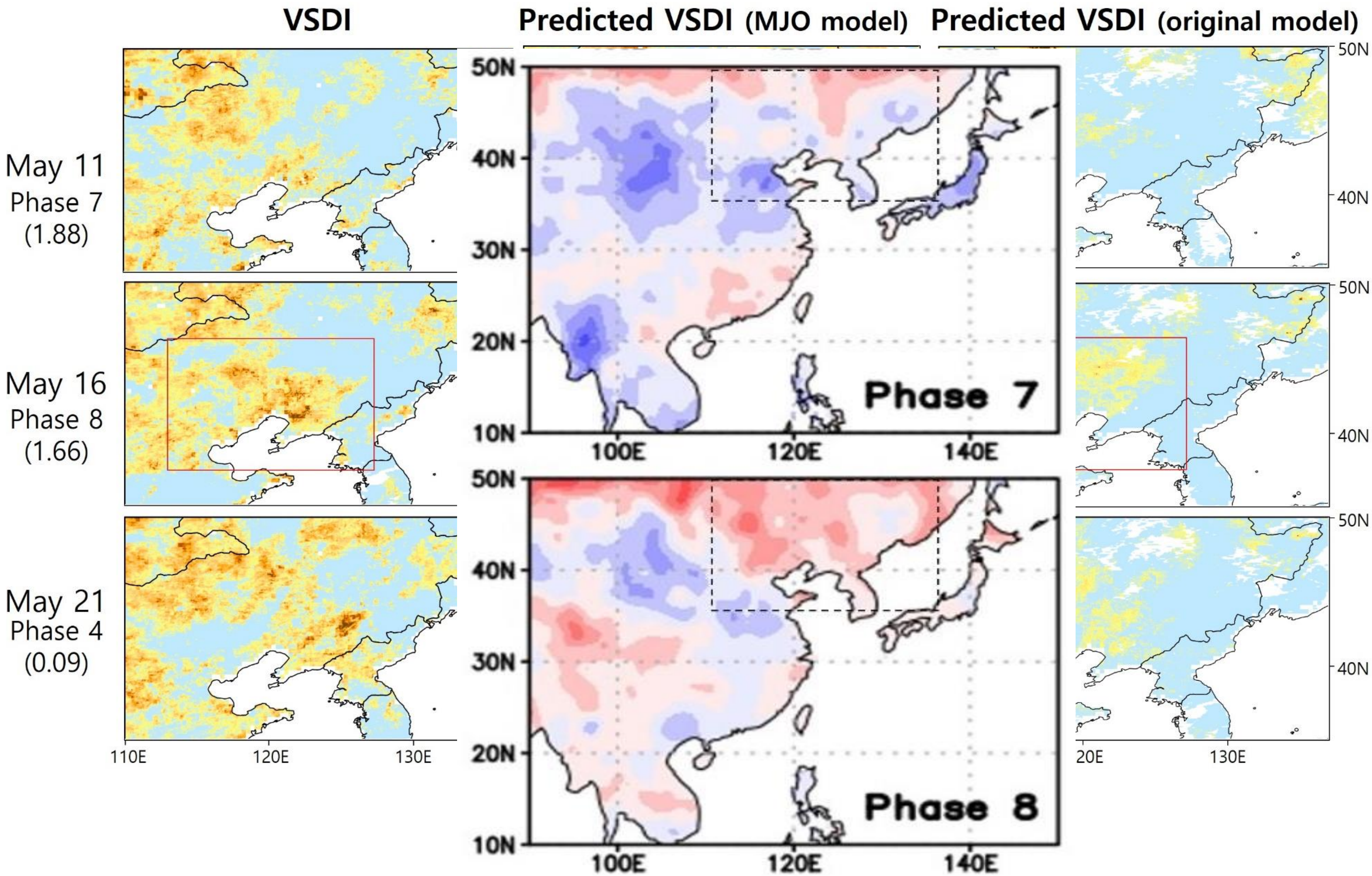


Leave one year out cross validation for 17 years

Comparison of change of drought conditions in 2010



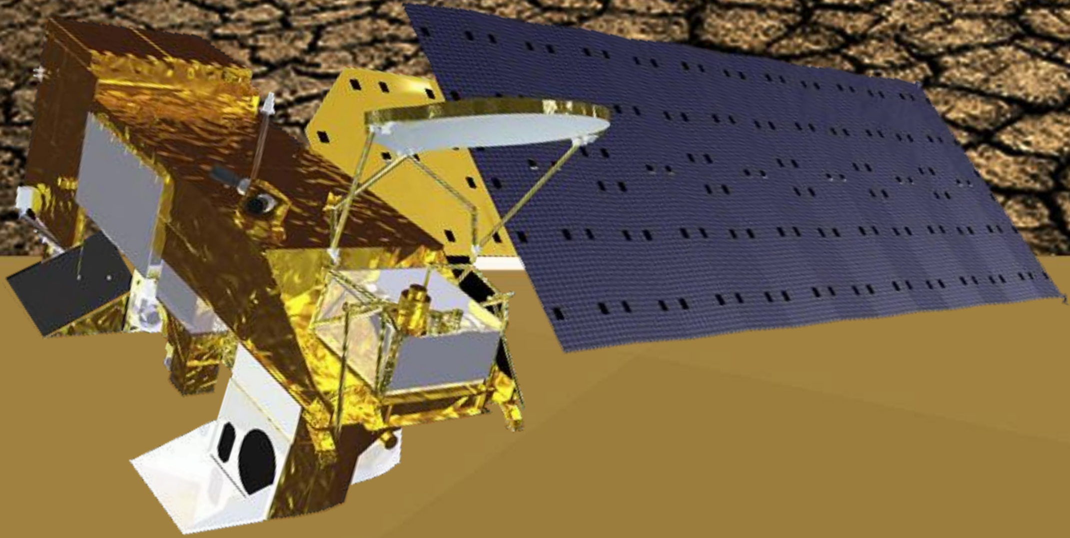
Comparison of change of drought conditions in 2011

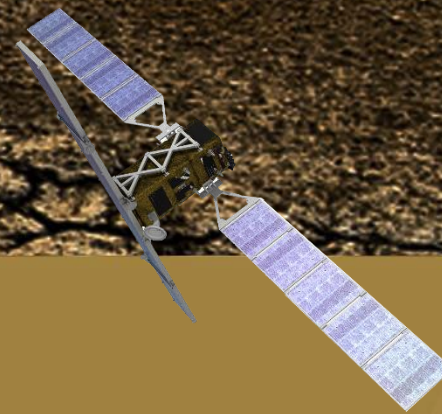


Conclusion

- Drought short-term prediction model considering climate variability was developed using random forest.
- Three satellite-based drought indices—SDCI, MIDI, and VSDI—were predicted with very short time scale (one pentad), and RMM MJO indices were used to improve drought predictability.
- The performance of drought prediction model including RMM MJO indices was improved in all drought indices.
- The performance of MJO-based drought prediction model was improved the most in SDCI and the least in VSDI.
- VSDI which modified SDCI and MIDI was regarded as the most acceptable drought index to predict and monitor drought for the short-period of time.
- Although RMM MJO indices contributed to enhancement of drought prediction, there is still a limitation. The performances of drought prediction models were saturated to 0.7 in correlation in three drought indices.
- Therefore, in further study, other factors including interannual climate variability (e.g., ENSO) and local characteristics including topography and land use will be investigated to develop more accurate prediction model.

AI-based satellite applications for Earth environment monitoring and prediction





Thank you