Drought monitoring with Earth Observation Data and Machine Learning methods

Prof. Dr. Elif Sertel

Geomatics Engineering Department

Istanbul Technical University

sertele@itu.edu.tr

Introduction

- Drought is a natural disaster that slowly occurs and has adverse hydrologic, environmental, agricultural, economic, and health-related impacts.
  - Precipitation deficiency combined with high temperatures
  - Increased evapotranspiration rate
- Drought is an important natural hazard causing adverse effects on the economy, agriculture, ecology, and human life.
  - Devastating ecological effects, such as vegetation stress, tree mortality, food security,
  - Forest fires
- Climate change has a solid potential to increase the frequency and intensity of dry conditions.

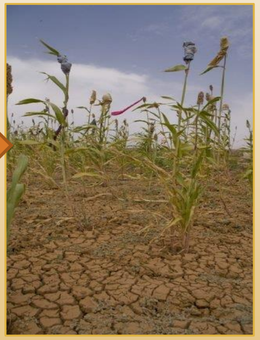
Meteorological Drought

- ➢ Lack of Precipitation
- ➢ High temperatures and winds
- ➢ Low relative humidity
- ➢ Evaporation and transpiration increase

- ❖ Precipitation departure from normal over time
- ❖ Region specific, high spatial variability

➢ Prolonged dry period??

Agricultural Drought



- ➢ Soil water decrease
- ➢ Difference between AET and PET
- ❖ Plant water stress
- ❖ Reduced biomass and crop yields

➢ Low soil moisture levels??

Hydrological Drought

- ➢ Decrease in streamflow, groundwater and inflows to lakes, reservoirs
- ❖ Reduced in surface and subsurface water supplies

➢ Low river and lake levels??

Socioeconomic Drought

- ➢ Water supply is not enough for community and economy
- ➢ Economic, social and environmental impacts
- ❖ Physical water shortage starts to affect people, individually and collectively

➢ Restrictions to main water supplies, food??

Why DROUGHT monitoring is important ?

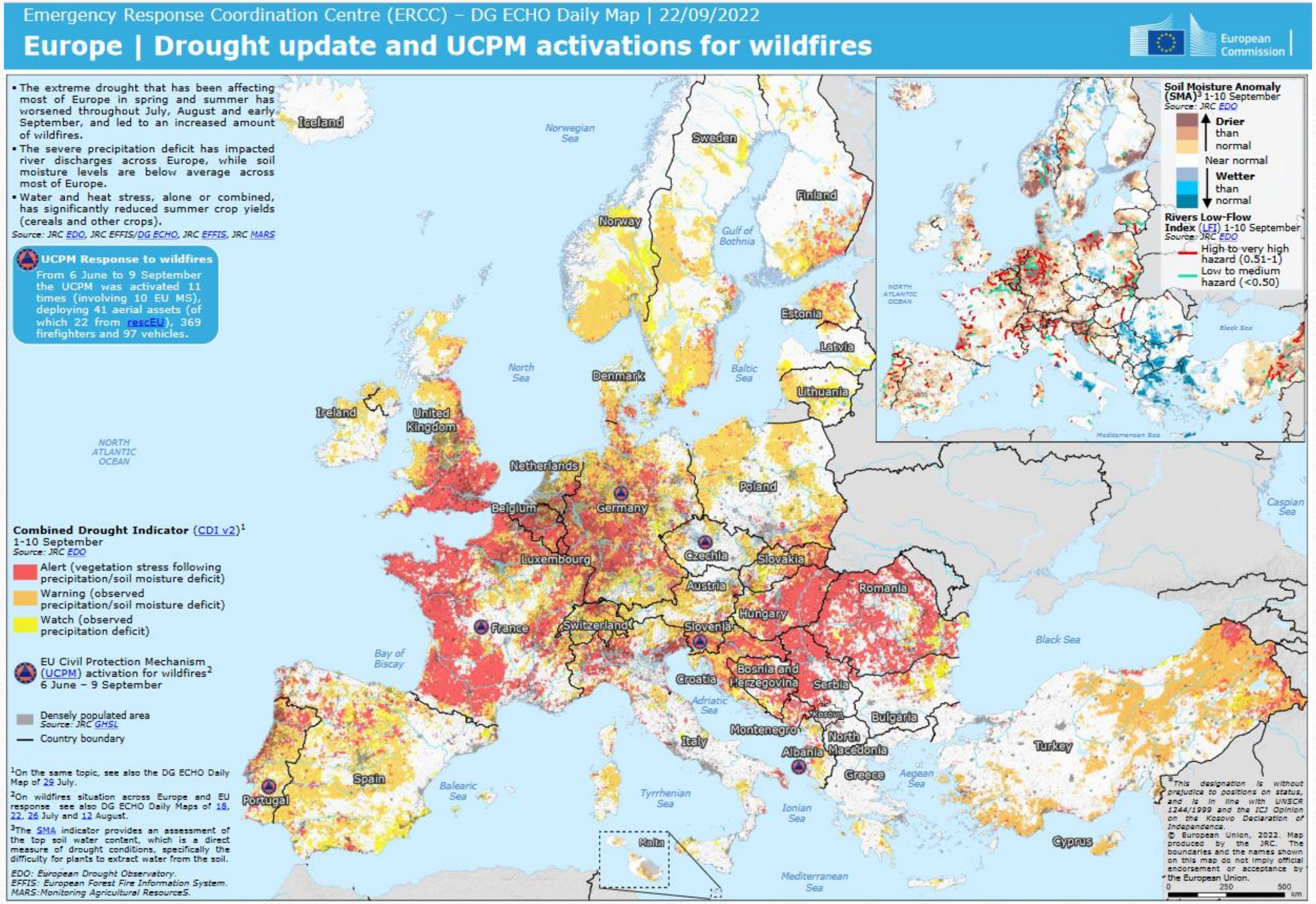
Quantifying and analyzing droughts is challenging due to their slow development nature, prolonged impacts, and spatio-temporally heterogeneous distribution.

Drought monitoring using both in-situ and Earth Observation data is an important topic to quantify drought conditions.

Heat waves, drought and wildfires frequently co-occur

Detecting, monitoring and preventing the drought is a crucial process.

- 2022 has been a drought year specifically for Europe and neighborhood countries exacerbated by heat waves.
- JRC Global Drought Observatory (GDO) published several reports in 2022 showing severe-to-extreme drought conditions in the Netherlands, United Kingdom, Slovakia, Hungary, Romania, Moldova, and most parts of western Europe.



Published :22 Sep 2022

Sources: JRC EDO, JRC EFFIS, JRC MARS, DG ECHO, JRC GHSL

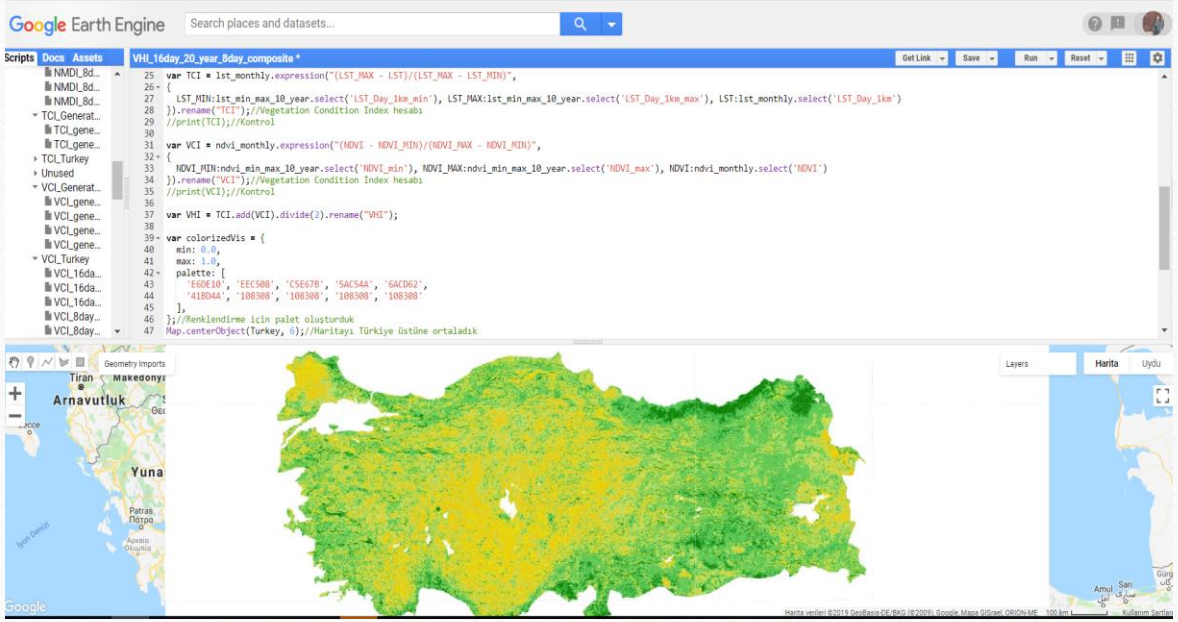
https://erccportal.jrc.ec.europa.eu/ECHO-Products/

Widely used satellites

- Landsat: 07/1972 – present
- Tropical Rainfall Measuring Mission (TRMM): 11/1997 – 04/2015
- Global Precipitation Measurements (GPM): 02/2014 – present
- Terra: 12/1999 – present
- Aqua: 05/2002 – present
- Soil Moisture Active Passive (SMAP): 01/2015 – present
- Gravity Recovery and Climate Experiment (GRACE): 03/2002 – present

Google Earth Engine

- GEE geospatial analysis platform that has been empowered by Google's computational cloud infrastructure allows geospatial analysis even in planetary scale without a need for technical capacity.
- It stores huge amount of satellite images and products as well as built-in geospatial capabilities.
- Thanks to ready-use dataset of GEE, it is easier to analysis of spatio-temporal datasets. (https://earthengine.google.com)
- One of the benefits of the GEE platform for drought monitoring is that it is very useful for storing and processing big geospatial datasets.



Earth Engine Data Catalog

Search

Home | View all datasets | Browse by tags | Landsat | MODIS | Sentinel | API Docs

MOD09A1.061 Terra Surface Reflectance 8-Day Global 500m

Dataset Availability

2000-02-18T00:00:00Z–2022-11-01T00:00:00

Dataset Provider

NASA LP DAAC at the USGS EROS Center

Earth Engine Snippet

```
ee.ImageCollection("MODIS/061/MOD09A1")
```

Tags

8-day global mod09a1 modis nasa sr surface-reflectance terra usgs

Description | Bands | Terms of Use | Citations | DOIs

The MOD09A1 V6.1 product provides an estimate of the surface spectral reflectance of Terra MODIS bands 1-7 at 500m resolution and corrected for atmospheric conditions such as gasses, aerosols, and Rayleigh scattering. Along with the seven reflectance bands is a quality layer and four observation bands. For each pixel, a value is selected from composite on the basis of high observation coverage, low view angle, the absence of clouds or cloud shadow, and aerosol loading.

Documentation:

- User's Guide
- Algorithm Theoretical Basis Document (ATBD)
- General Documentation

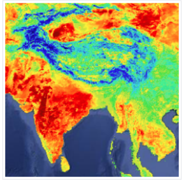
Earth Engine Data Catalog

lst 1/3

Home | View all datasets | Browse by tags | Landsat | MODIS | Sentinel | API Docs

MOD11A1.006 Terra Land Surface Temperature and Emissivity Daily Global 1km [deprecated]

Caution: This dataset has been superseded by MODIS/061/MOD11A1.



Dataset Availability

2000-02-24T00:00:00Z–2022-11-09T00:00:00

Dataset Provider

NASA LP DAAC at the USGS EROS Center

Earth Engine Snippet

```
ee.ImageCollection("MODIS/006/MOD11A1")
```

Tags

daily emissivity global lst mod11a1 modis nasa surface-temperature terra usgs

Description | Bands | Terms of Use | Citations | DOIs

The MOD11A1 V6 product provides daily land surface temperature (LST) and emissivity values in a 1200 x 1200 kilometer grid. The temperature value is derived from the MOD11_L2 swath product. Above 30 degrees latitude, some pixels may have multiple observations where the criteria for clear-sky are met. When this occurs, the pixel value is the average of all qualifying observations. Provided along with both the day-time and night-time surface temperature bands and their quality indicator layers are MODIS bands 31 and 32 and six observation layers.

Documentation:

- User's Guide
- Algorithm Theoretical Basis Document (ATBD)
- General Documentation

Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling

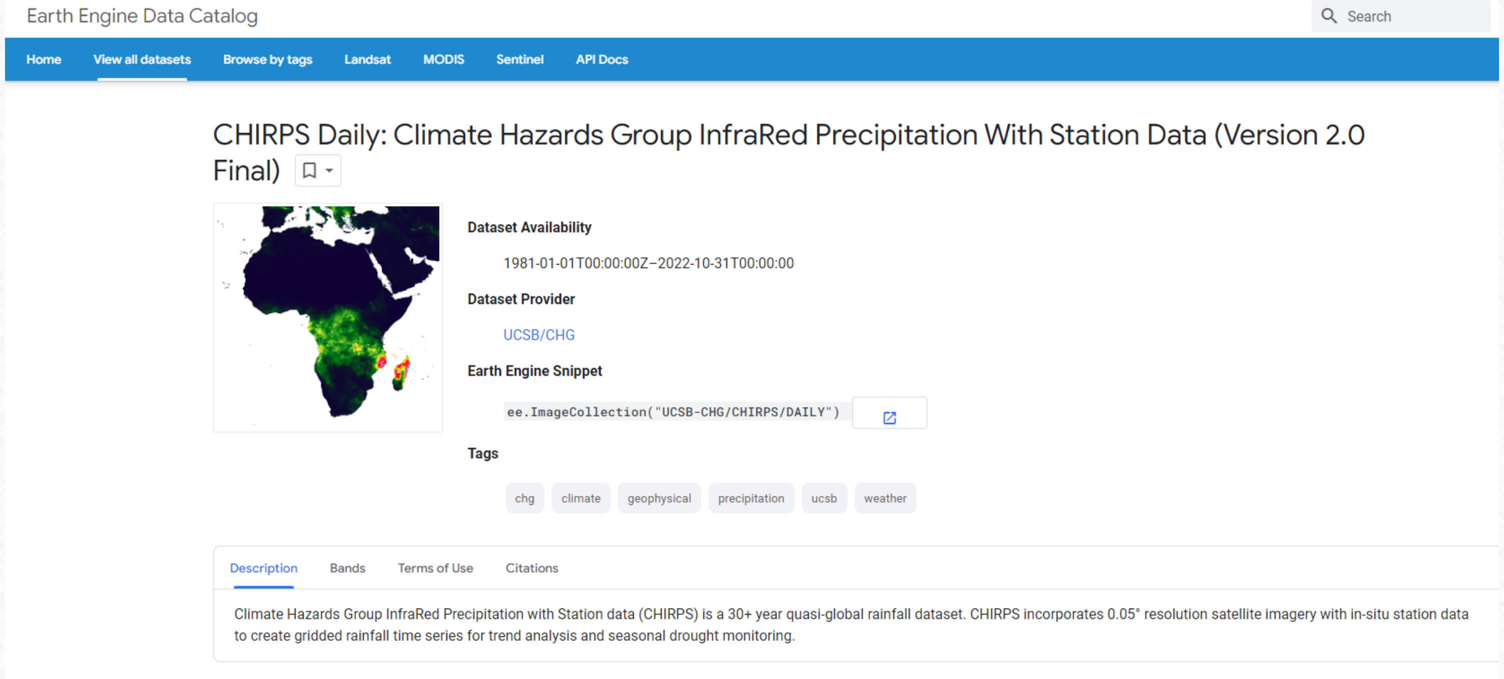
Table 1. Overview of the 22 (quasi-)global (sub-)daily gridded *P* datasets evaluated in this study. Abbreviations in the data source(s) column defined as follows: G, gauge; S, satellite; and R, reanalysis. The acronym NRT in the temporal coverage column stands for near real time. In the spatial coverage column, "global" indicates fully global coverage including ocean areas, while "land" indicates that the coverage is limited to the terrestrial surface.

Short name	Full name and details	Data source(s)	Spatial resolution	Spatial coverage	Temporal resolution	Temporal coverage	Reference
Non-gauge-corrected datasets							
CHIRP V2.0	Climate Hazards group Infrared Precipitation (CHIRP) V2.0 (http://chg.ucsb.edu/data/chirps/)	S, R	0.05°	Land, < 50°	Daily	1981–NRT[2]	Funk et al. (2015a)
CMORPH V1.0	CPC MORPHing technique (CMORPH) V1 (www.cpc.ncep.noaa.gov)	S	0.07°	< 60°	30 min	1998–NRT[1]	Joyce et al. (2004)
ERA-Interim	European Centre for Medium-range Weather Forecasts ReAnalysis Interim (ERA-Interim; https://www.ecmwf.int/en/research/climate-reanalysis/era-interim)	R	~0.75°	Global	3-hourly	1979–2017[3]	Dee et al. (2011)
GSMaP V5/6	Global Satellite Mapping of Precipitation (GSMaP) Moving Vector with Kalman (MVK) standard V5 and V6 (http://sharaku.eorc.jaxa.jp/GSMaP/)	S	0.1°	< 60°	Hourly	2000–NRT[1]	Ushio et al. (2009)
GridSat V1.0	*P* derived from the Gridded Satellite (GridSat) B1 thermal infrared archive v02r01 (Knapp et al., 2011; https://www.ncdc.noaa.gov/gridsat/)	S	0.1°	< 50°	3-hourly	1983–2016	Beck (2017)
JRA-55	Japanese 55-year ReAnalysis (JRA-55; jra.kishou.go.jp/JRA-55)	R	~0.56°	Global	3-hourly	1959–NRT[2]	Kobayashi et al. (2015)
MSWEP-ng V1.2	Multi-Source Weighted-Ensemble Precipitation (MSWEP) no-gauge (ng) V1.2 (www.gloh2o.org)	S, R	0.25°	Global	3-hourly	1979–2015	Beck et al. (2017b)
MSWEP-ng V2.0	Multi-Source Weighted-Ensemble Precipitation (MSWEP) no-gauge (ng) V2.0 (www.gloh2o.org)	S, R	0.1°	Global	3-hourly	1979–NRT[1]	Beck (2017)
NCEP-CFSR	National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR; http://cfs.ncep.noaa.gov/cfsr/)	R	~0.31°	Global	Hourly	1979–2010	Saha et al. (2010)
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN; http://chrs.web.uci.edu)	S	0.25°	< 60°	Hourly	2000–NRT[1]	Sorooshian et al. (2000)
PERSIANN-CCS	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) Cloud Classification System (CCS; http://chrs.web.uci.edu)	S	0.04°	< 60°	Hourly	2003–NRT[1]	Hong et al. (2004)
SM2RAIN-ASCAT	*P* inferred from Advanced Scatterometer (ASCAT) satellite near-surface soil moisture (http://hydrology.irpi.cnr.it)	S	0.5°	Land	Daily	2007–2015	Brocca et al. (2014)
TMPA 3B42RT V7	TRMM Multi-satellite Precipitation Analysis (TMPA) 3B42RT V7 (https://mirador.gsfc.nasa.gov)	S	0.25°	< 50°	3-hourly	2000–NRT[1]	Huffman et al. (2007)
Gauge-corrected datasets							
CHIRPS V2.0	Climate Hazards group Infrared Precipitation with Stations (CHIRPS) V2.0 (http://chg.ucsb.edu/data/chirps/)	G, S, R	0.05°	Land, < 50°	Daily	1981–NRT[2]	Funk et al. (2015a)
CMORPH-CRT V1.0	CPC MORPHing technique (CMORPH) bias corrected (CRT) V1.0 (www.cpc.ncep.noaa.gov)	G, S	0.07°	< 60°	30 min	1998–2015	Not available
CPC Unified	Climate Prediction Center (CPC) Unified V1.0 and RT (https://www.esrl.noaa.gov/psd/data/gridded/)	G	0.5°	Land	Daily	1979–NRT[2]	Chen et al. (2008)
GPCP-1DD V1.2	Global Precipitation Climatology Project (GPCP) 1-Degree Daily (1DD) Combination V1.2 (https://precip.gsfc.nasa.gov)	G, S	1°	Global	Daily	1996–2015	Huffman et al. (2001)
MSWEP V1.2	Multi-Source Weighted-Ensemble Precipitation (MSWEP) V1.2 (www.gloh2o.org)	G, S, R	0.25°	Global	3-hourly	1979–2015	Beck et al. (2017b)
MSWEP V2.0	Multi-Source Weighted-Ensemble Precipitation (MSWEP) V2.0 (www.gloh2o.org)	G, S, R	0.1°	Global	3-hourly	1979–NRT[1]	Beck (2017)
PERSIANN-CDR V1R1	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) Climate Data Record (CDR) V1R1 (http://chrs.web.uci.edu)	G, S	0.25°	< 60°	6-hourly	1983–2016	Ashouri et al. (2015)
TMPA 3B42 V7	TRMM Multi-satellite Precipitation Analysis (TMPA)3B42 V7 (https://mirador.gsfc.nasa.gov/)	G, S	0.25°	< 50°	3-hourly	2000–2017[3]	Huffman et al. (2007)
WFDEI-CRU	WATCH Forcing Data ERA-Interim (WFDEI; www.eu-watch.org)	G, R	0.5°	Global	3-hourly	1979–2015	Weedon et al. (2014)

[1] Available until the present with a delay of several hours.
[2] Available until the present with a delay of several days.
[3] Available until the present with a delay of several months.

Hydrol. Earth Syst. Sci., 21, 6201–6217, 2017 https://doi.org/10.5194/hess-21-6201-2017

Climate Hazards group Infrared Precipitation with Stations (CHIRPS)

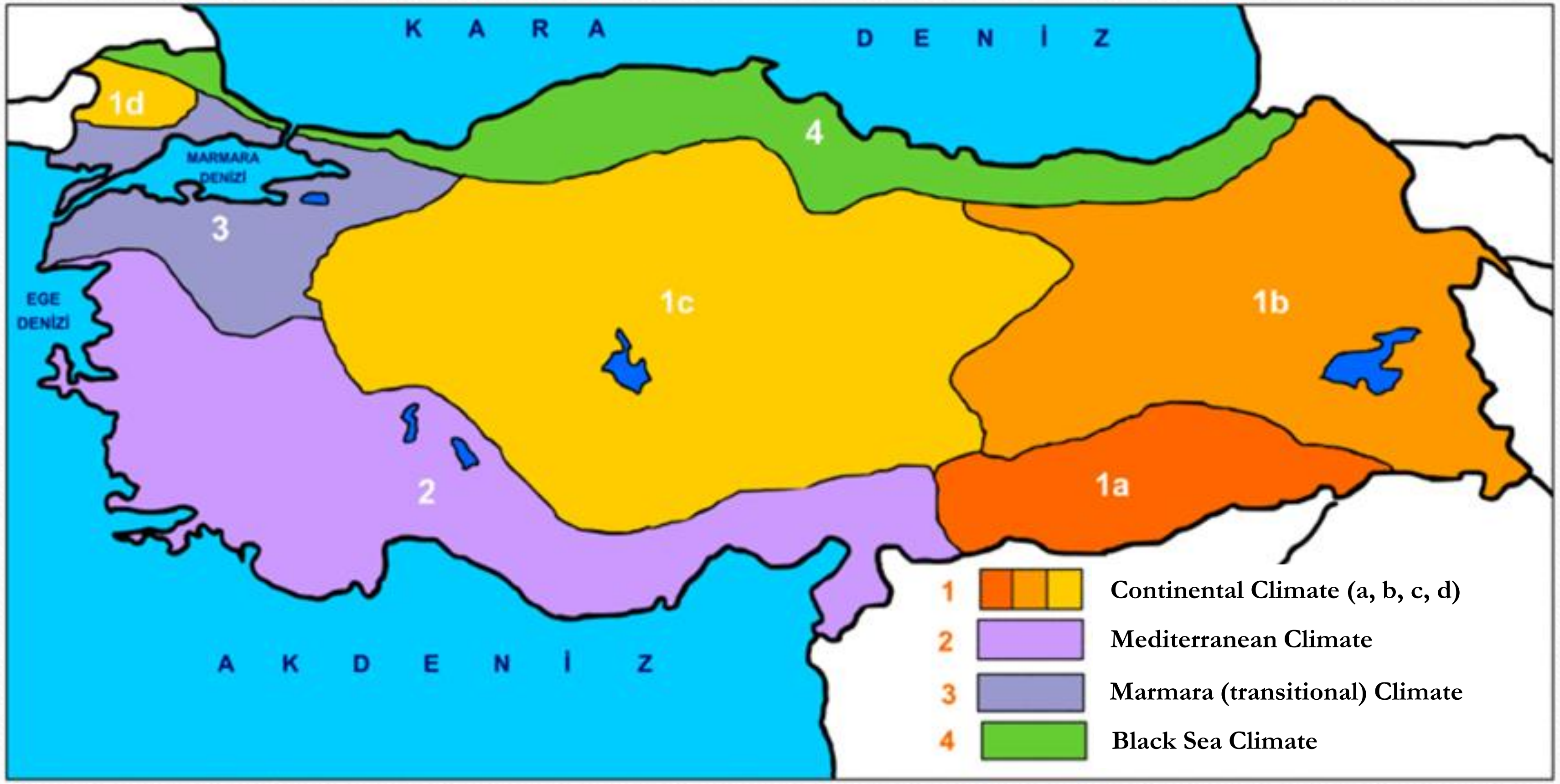


- quasi-global (50°S-50°N),
- high resolution (0.05°),
- daily, pentadal, and monthly precipitation dataset.
- 0.05° resolution satellite imagery, and in-situ station data to create gridded rainfall time series.

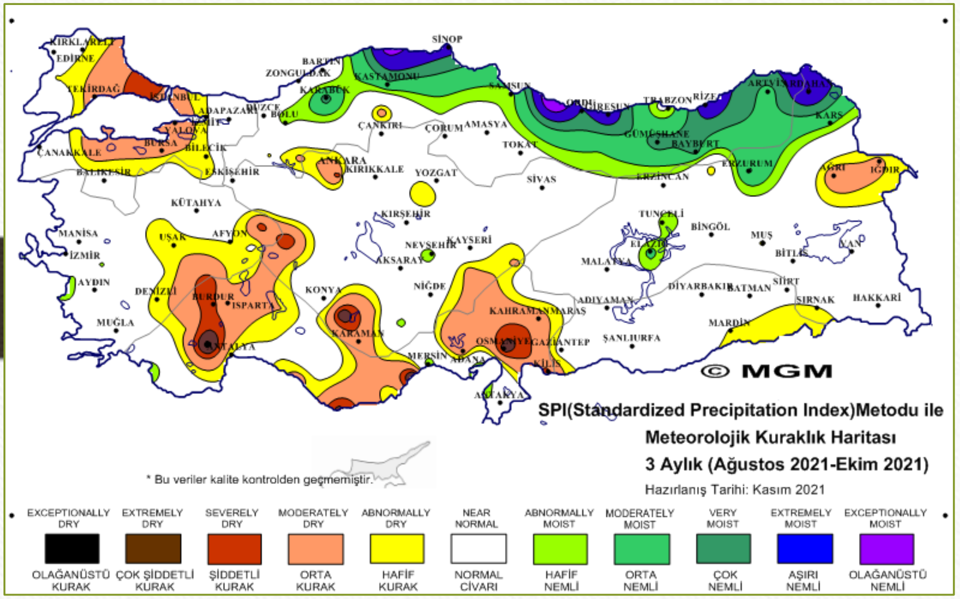
CHIRPS vs PERSIAN-CSS
3 month period

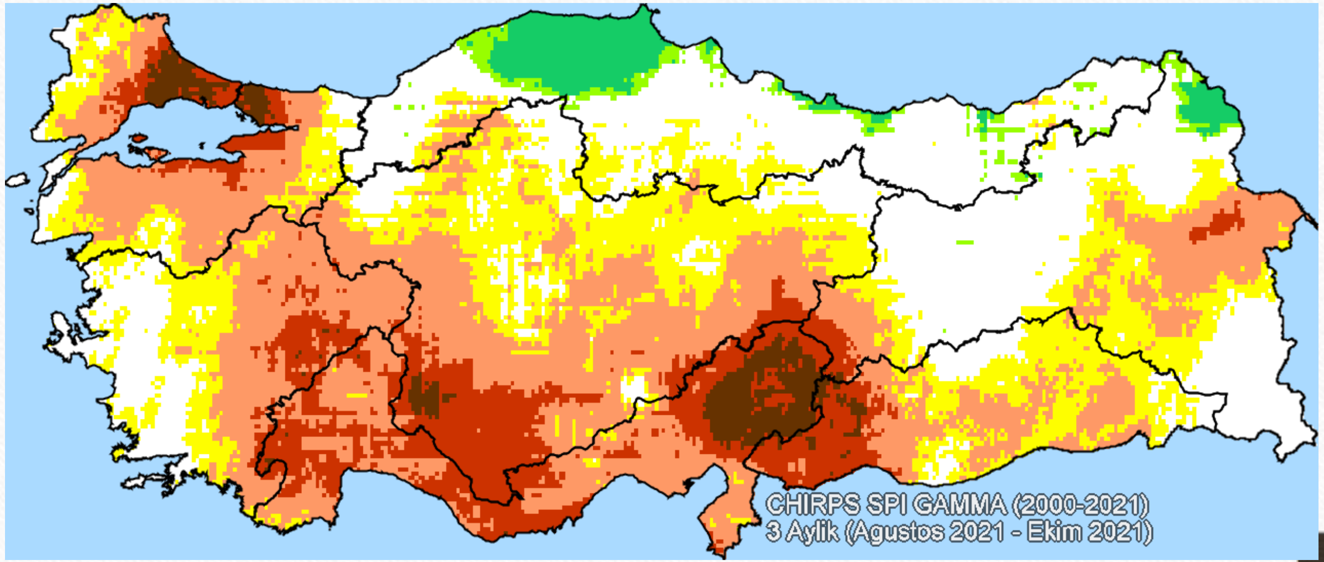
Turkey covers an area of 785,816 km2 and constitute different climatic regions in different parts of the country namely;

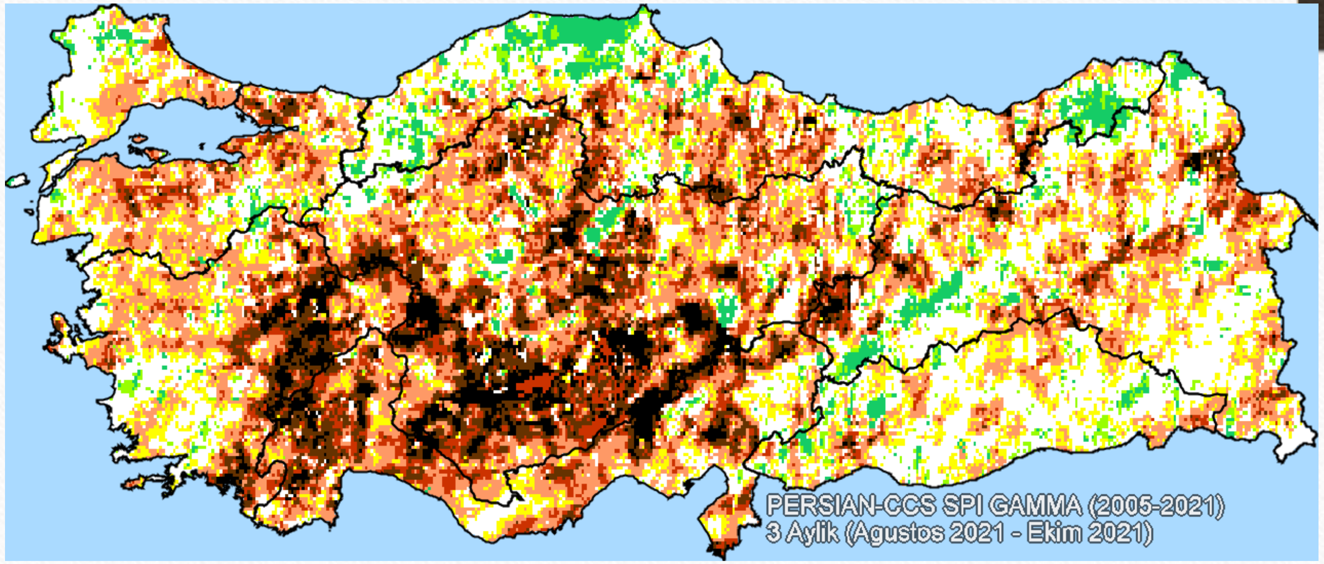
1. Continental Climate
2. Mediterranean Climate
3. Marmara (transitional) Climate
4. Black Sea Climate



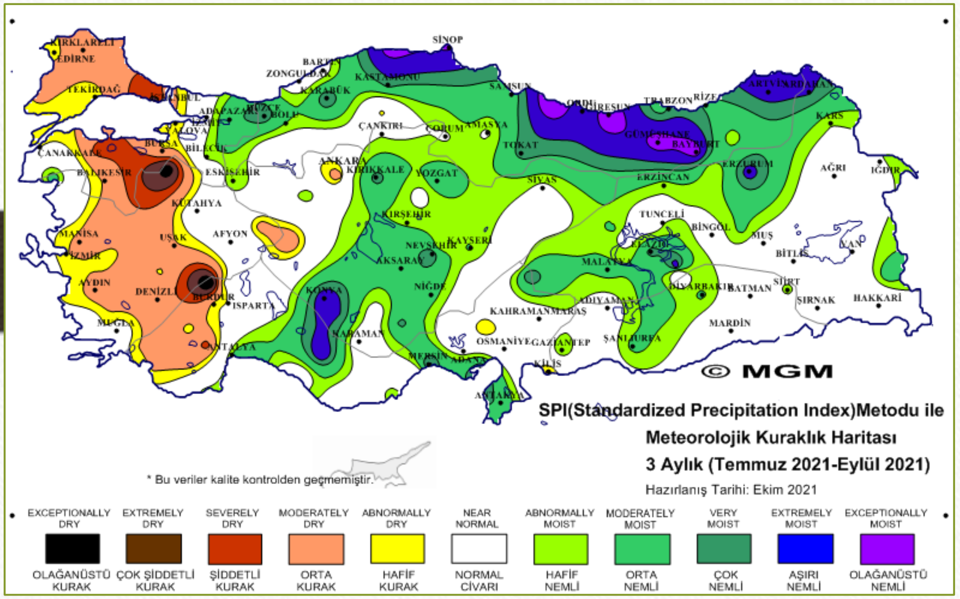
3 month SPI (August-October) 2021

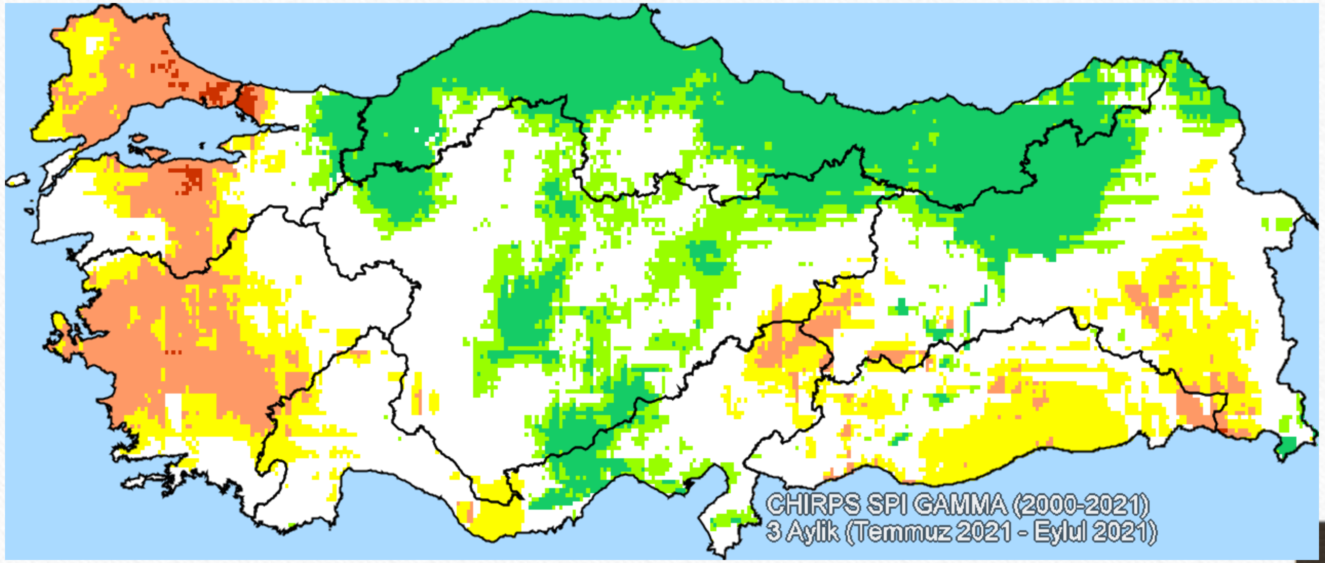


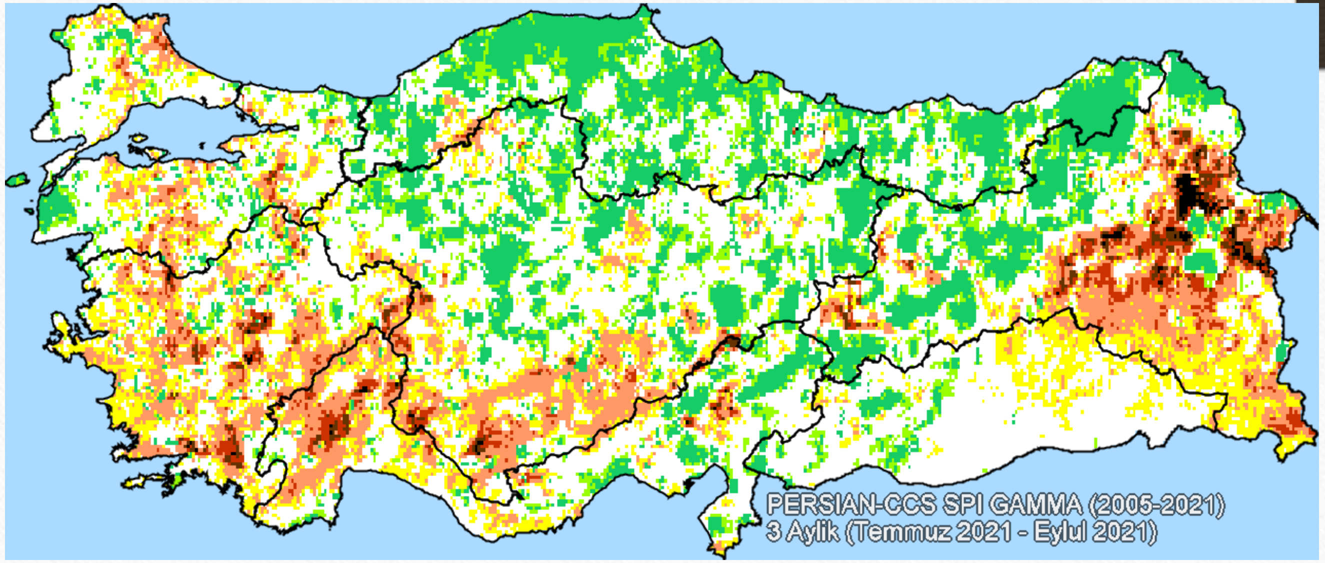




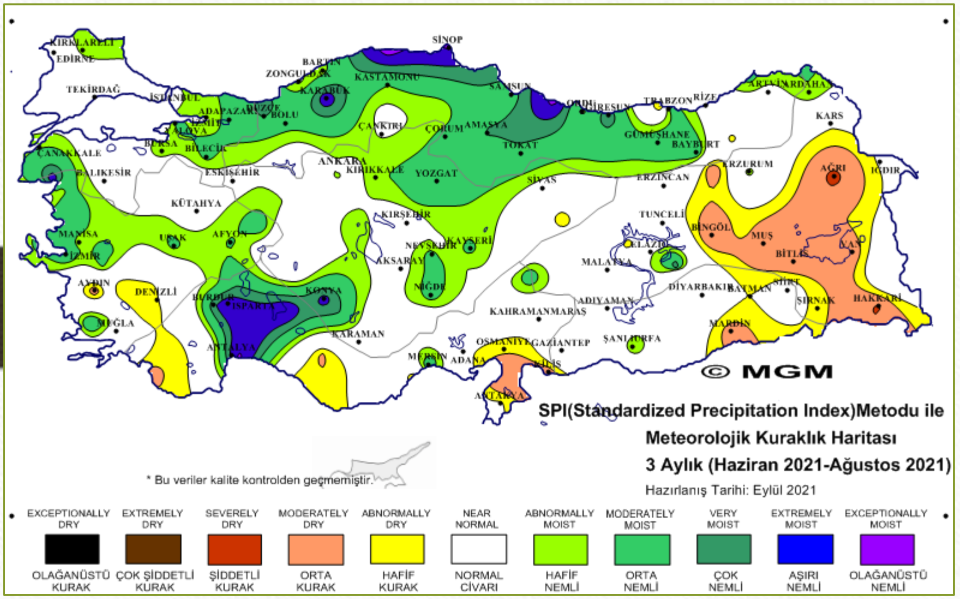
3 month SPI (July-September) 2021

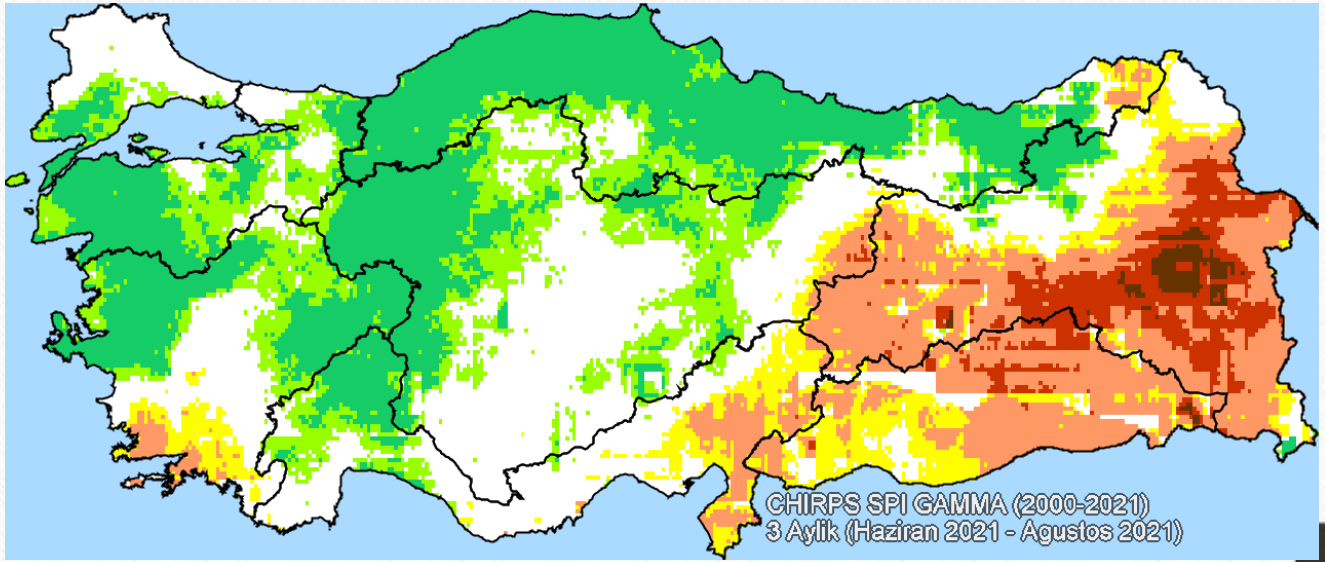


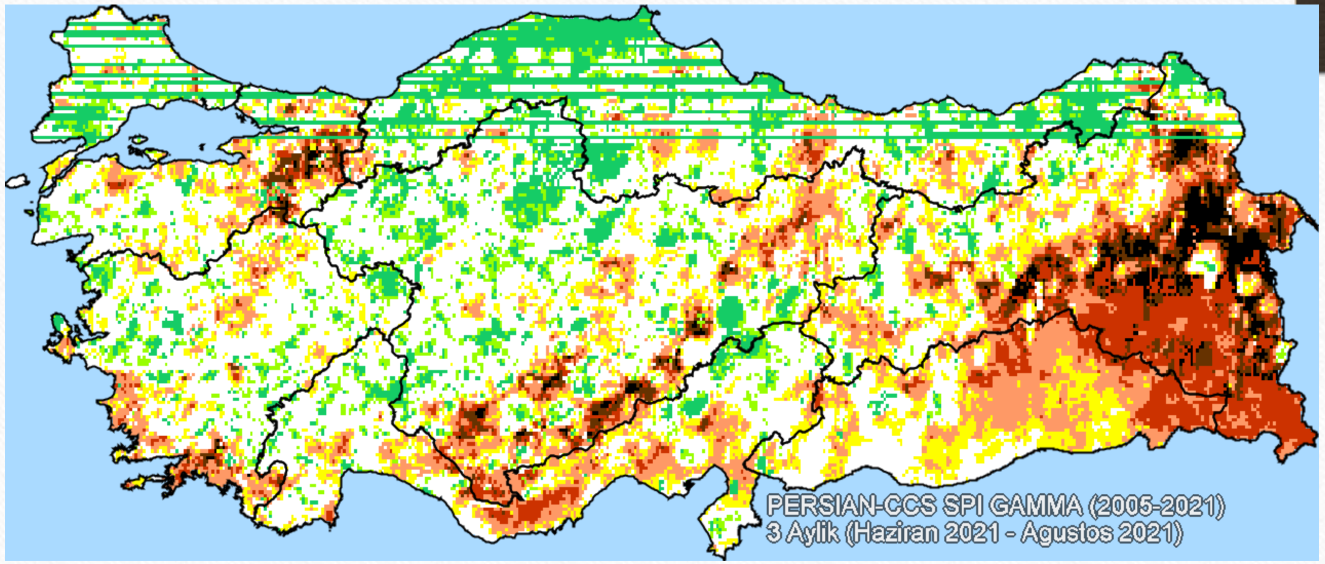




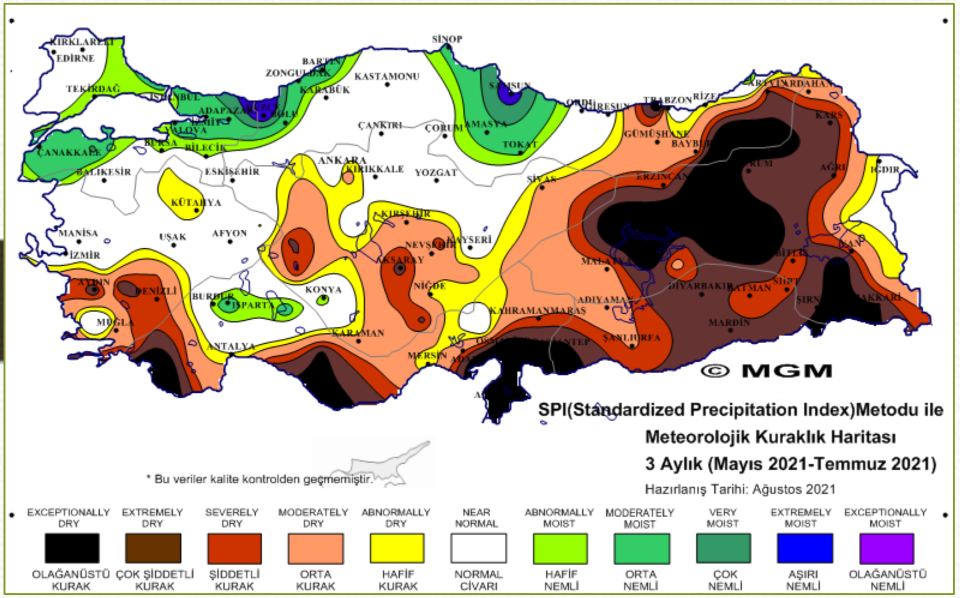
3 month SPI (June-August) 2021

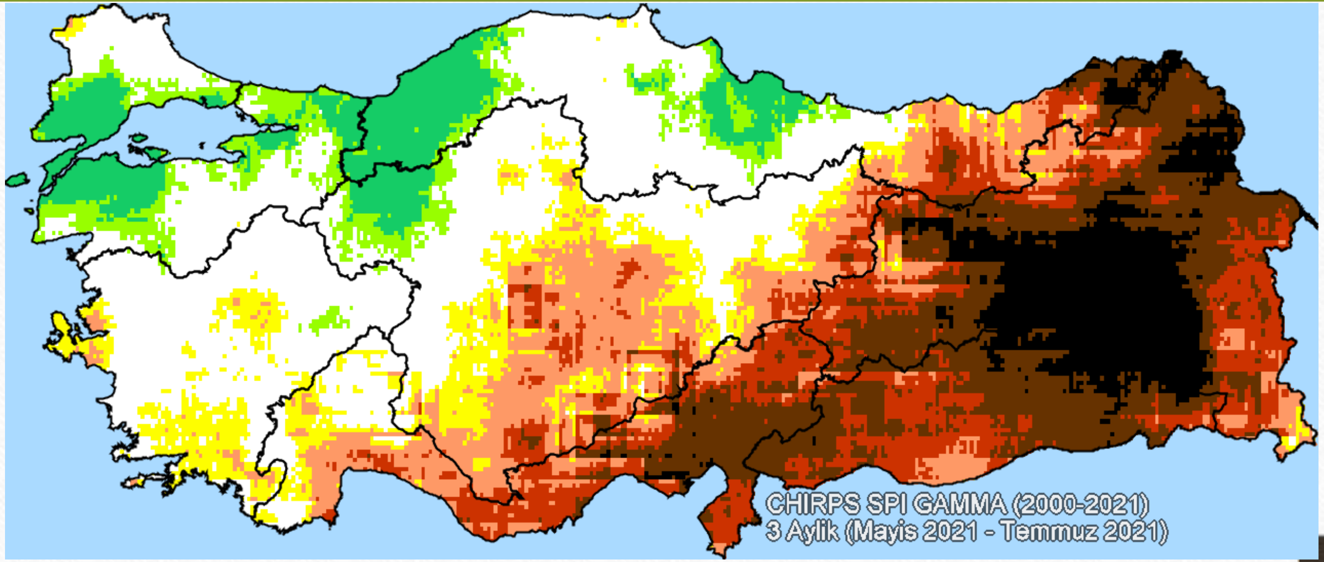


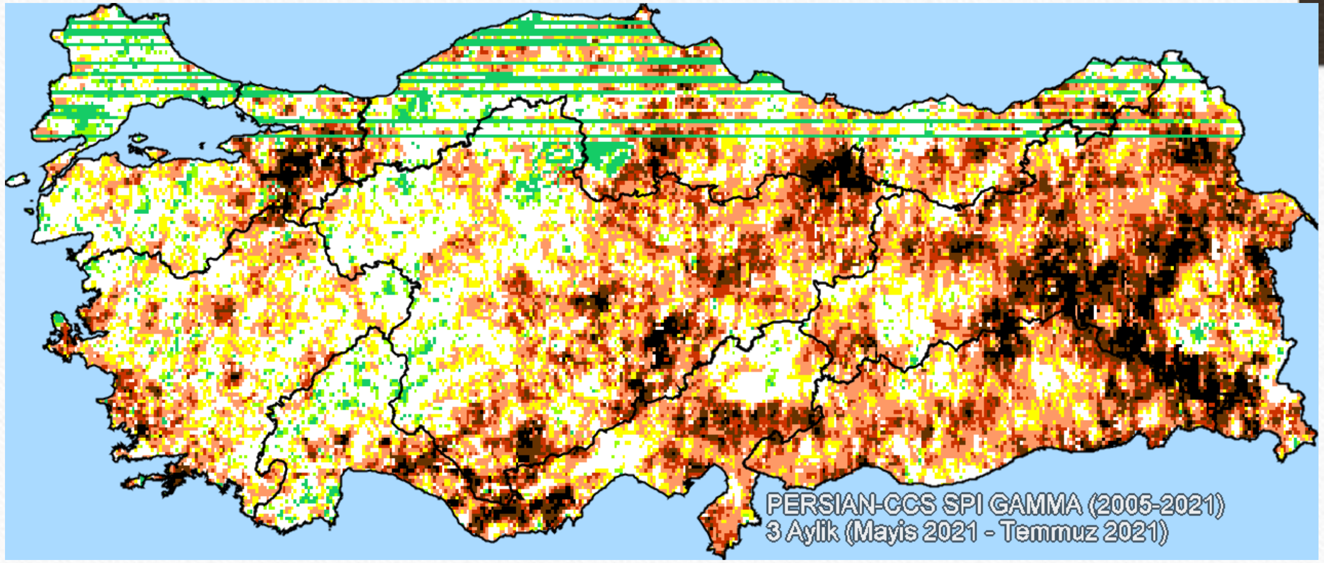




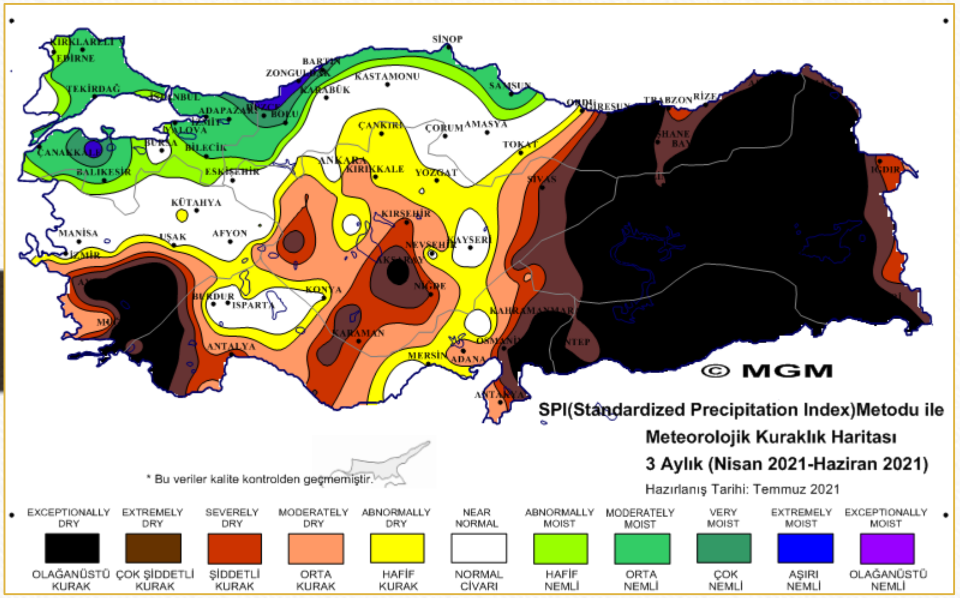
3 month SPI (May-July) 2021

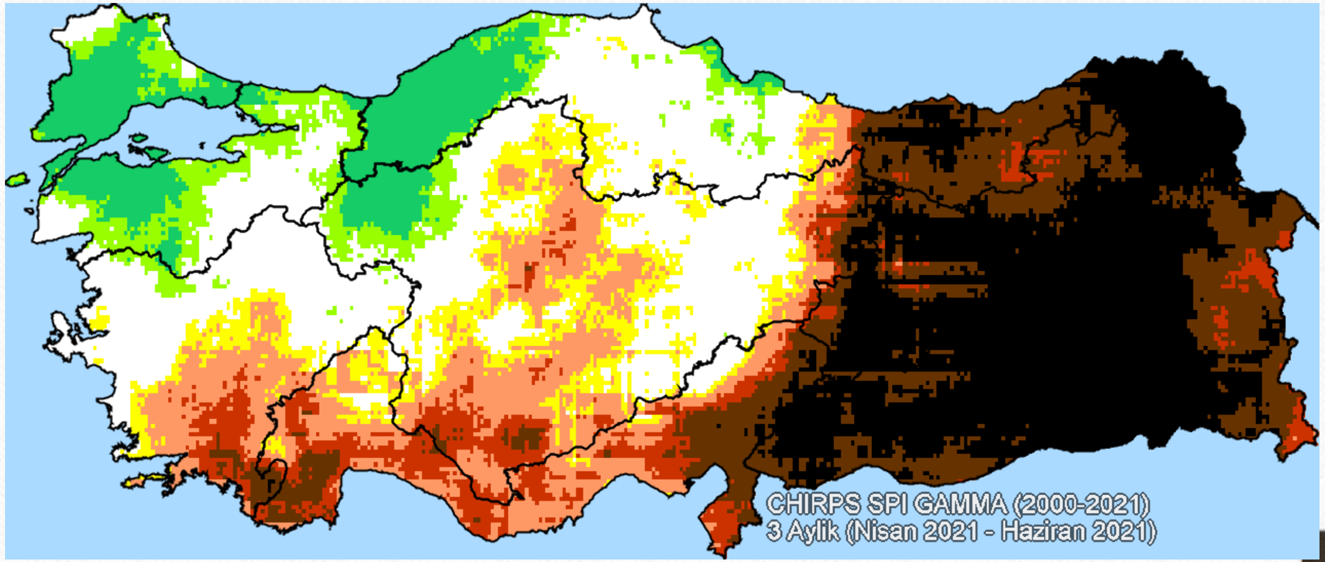


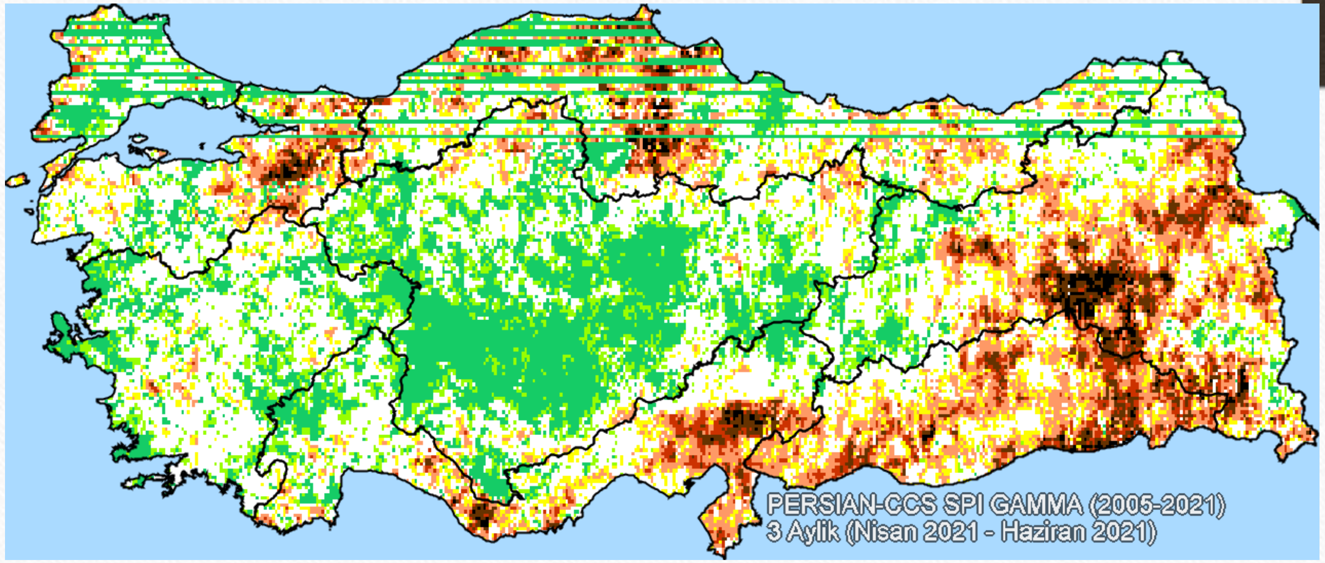




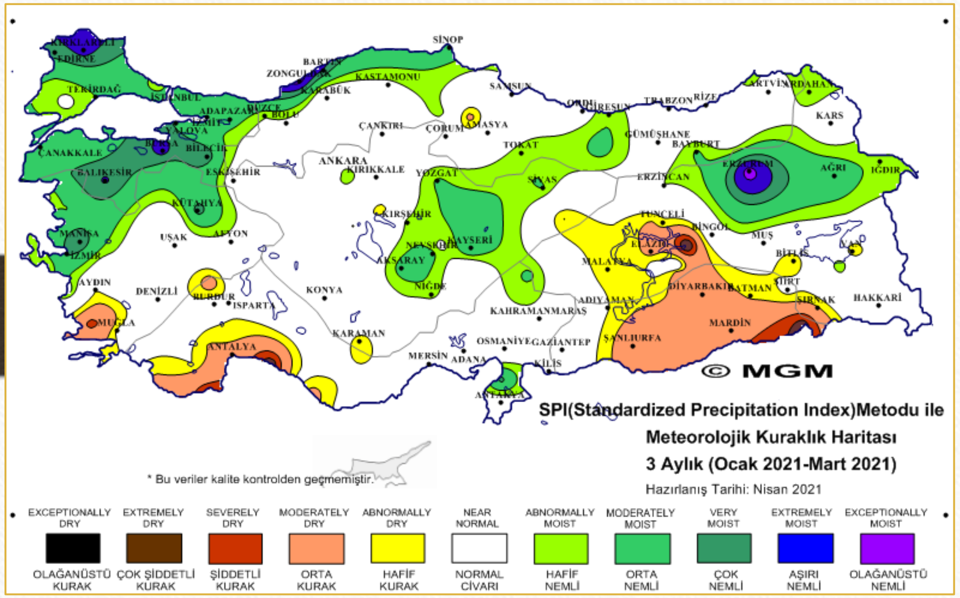
3 month SPI (April-June) 2021

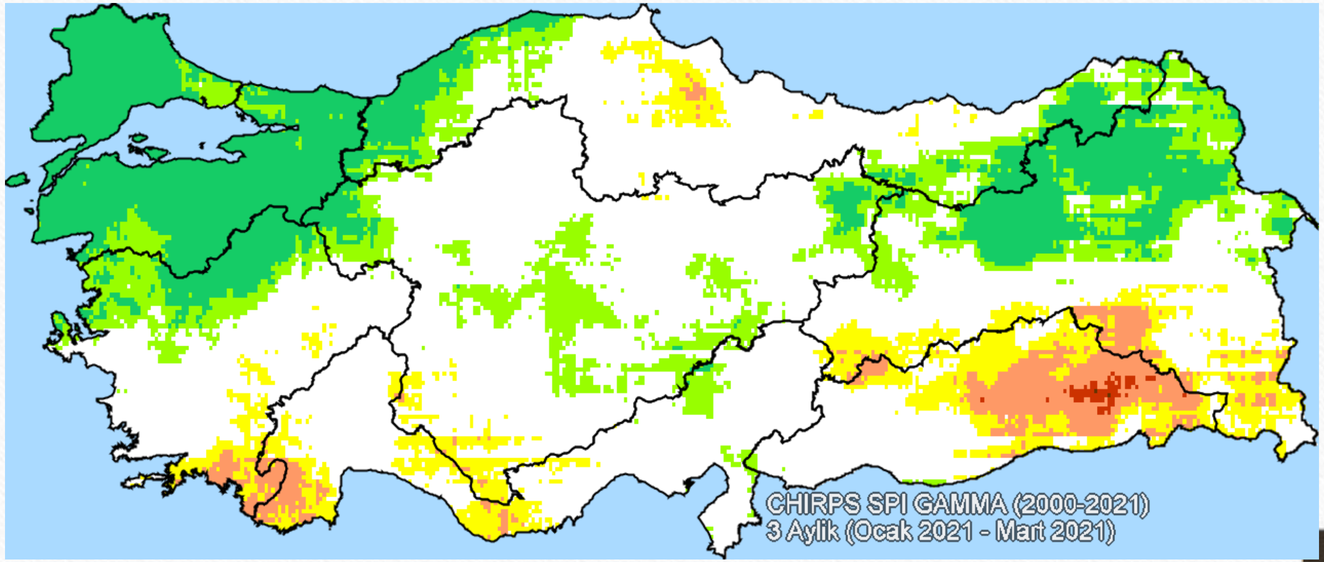


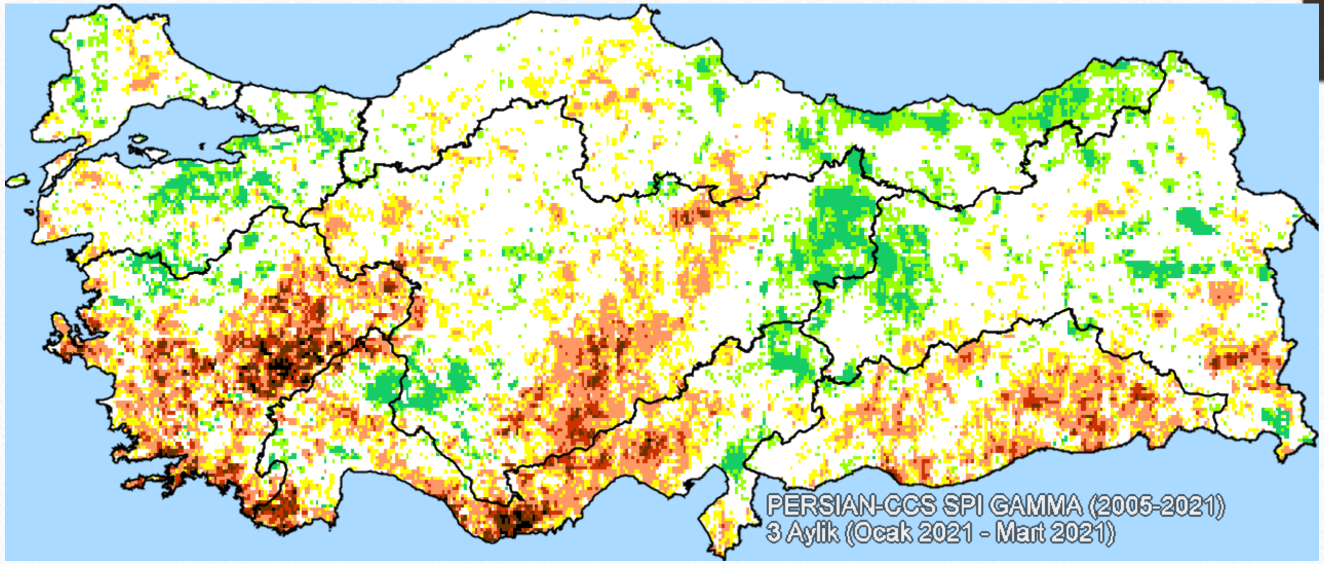




3 month SPI (January-March) 2021

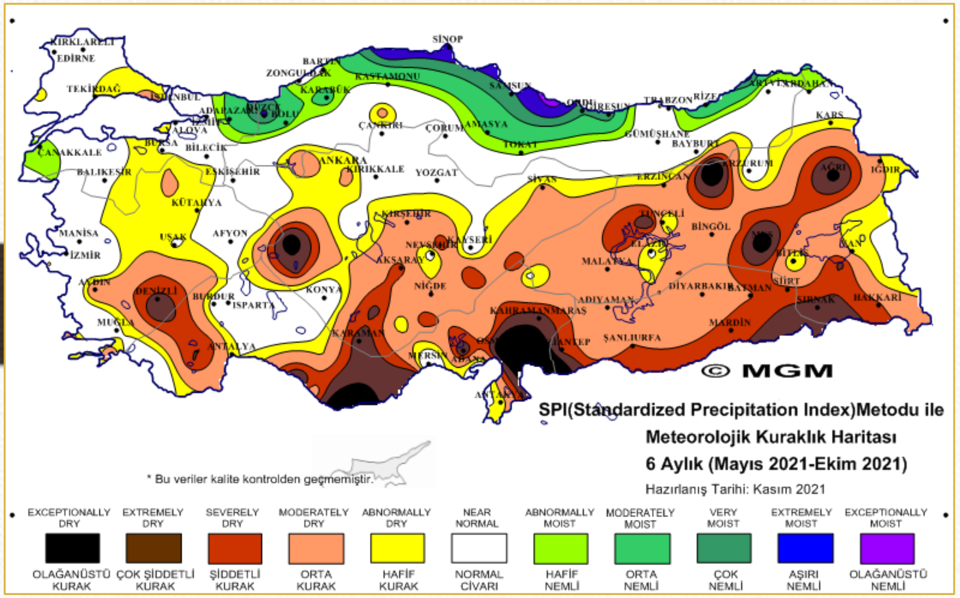


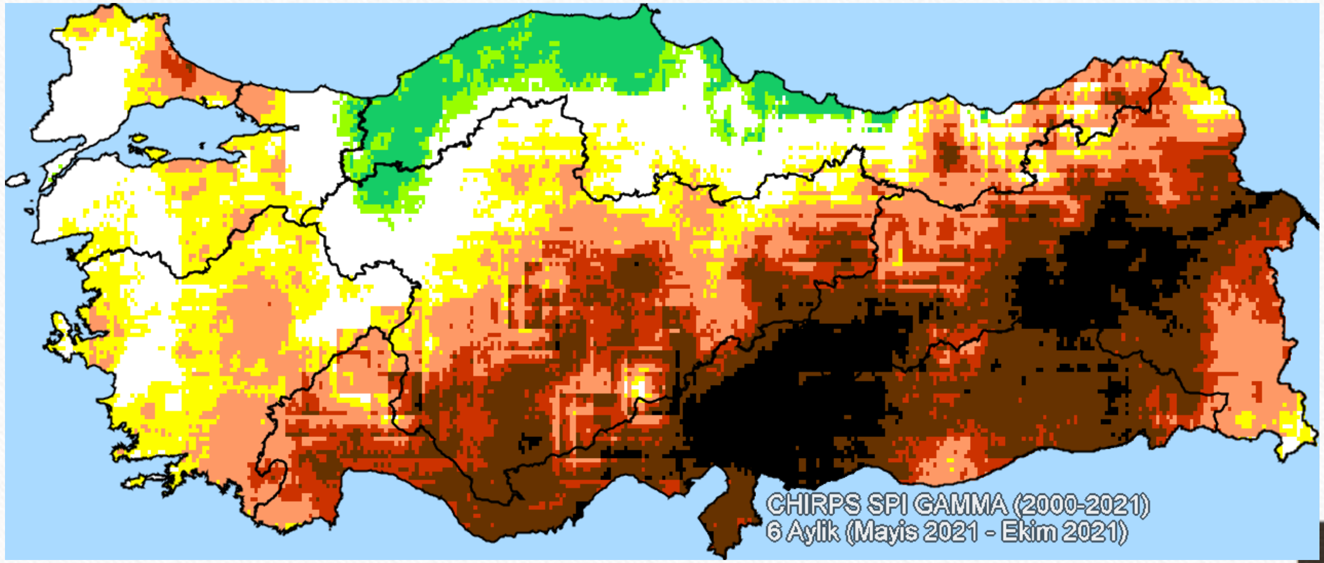


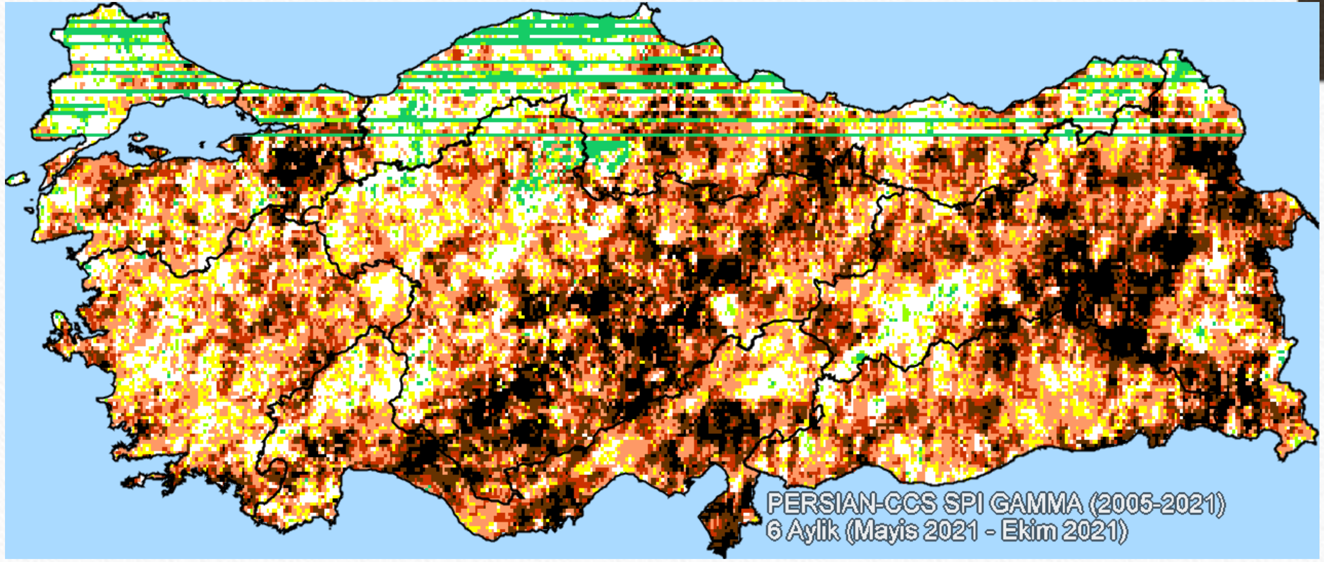


CHIRPS vs PERSIAN-CSS
6 month period

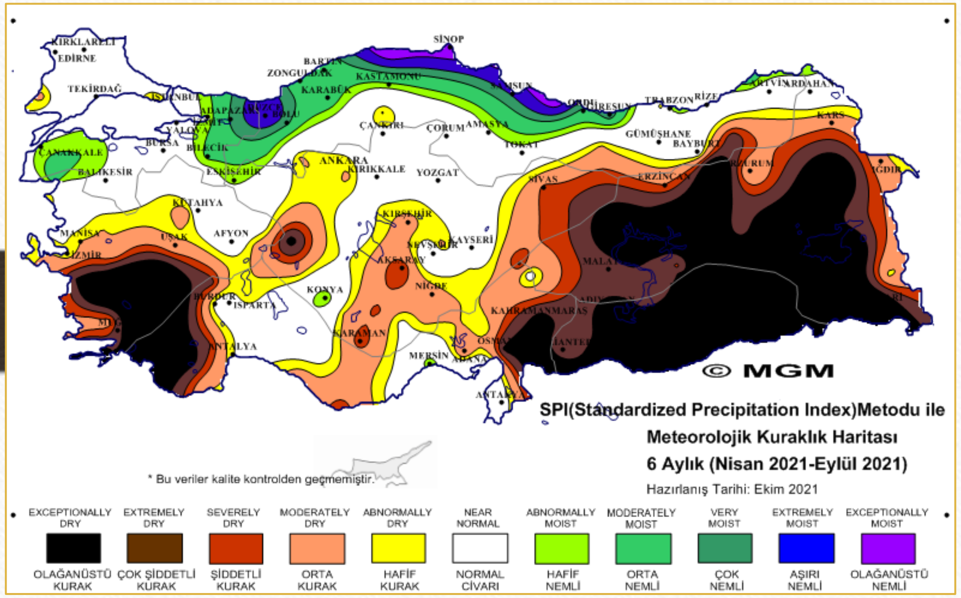
6 month SPI (May-October) 2021

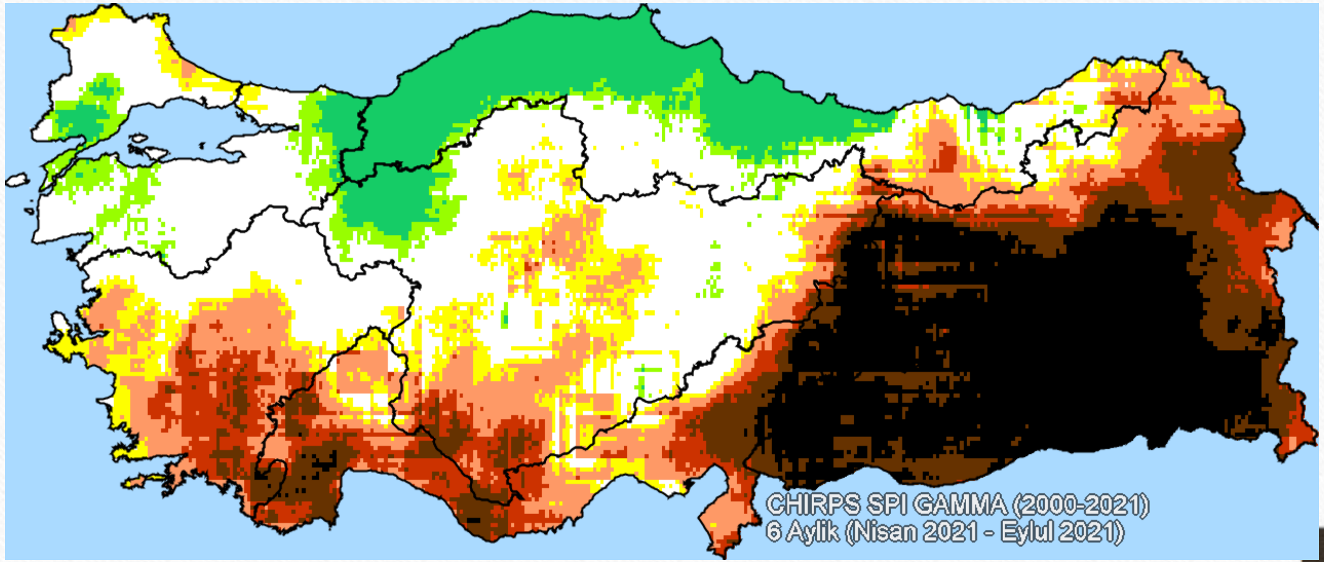


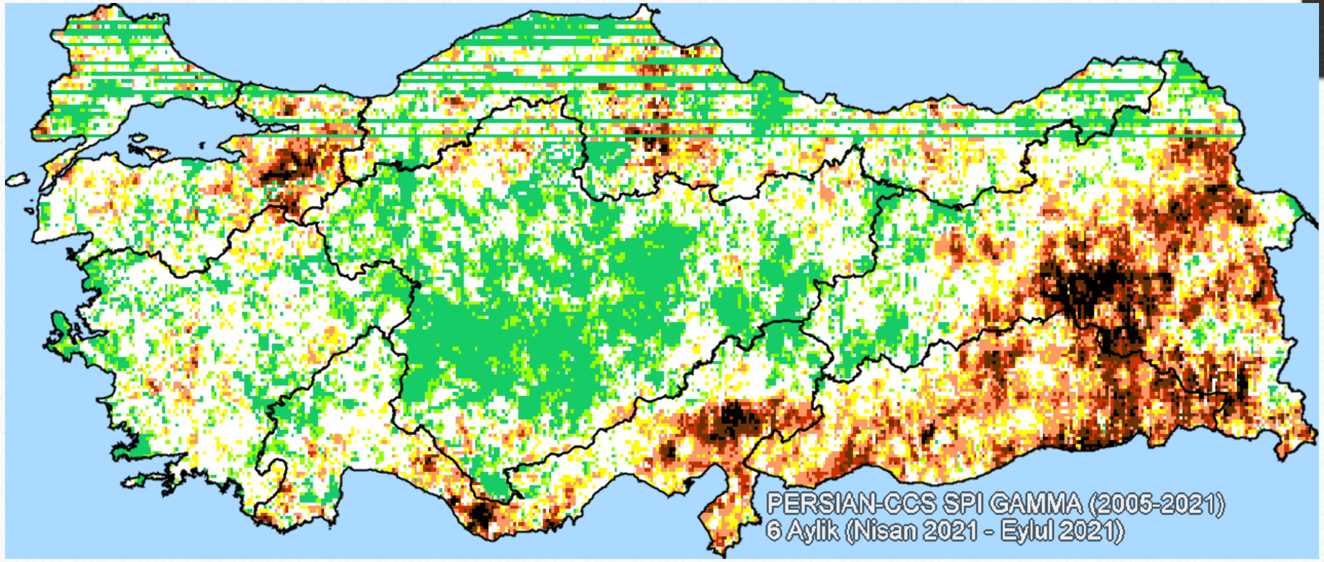




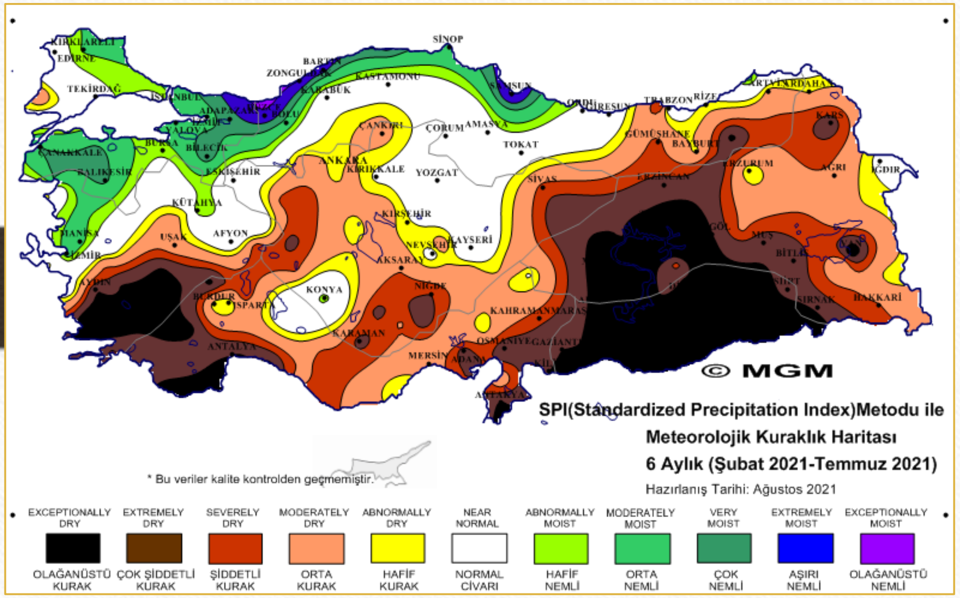
6 month SPI (April-September) 2021

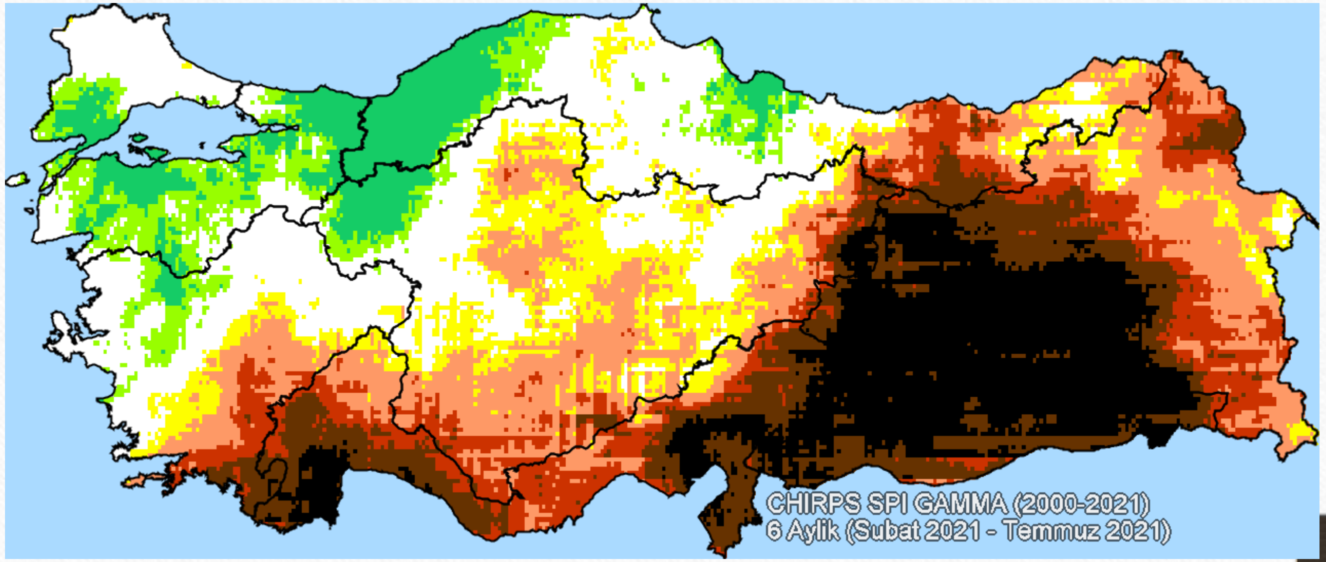


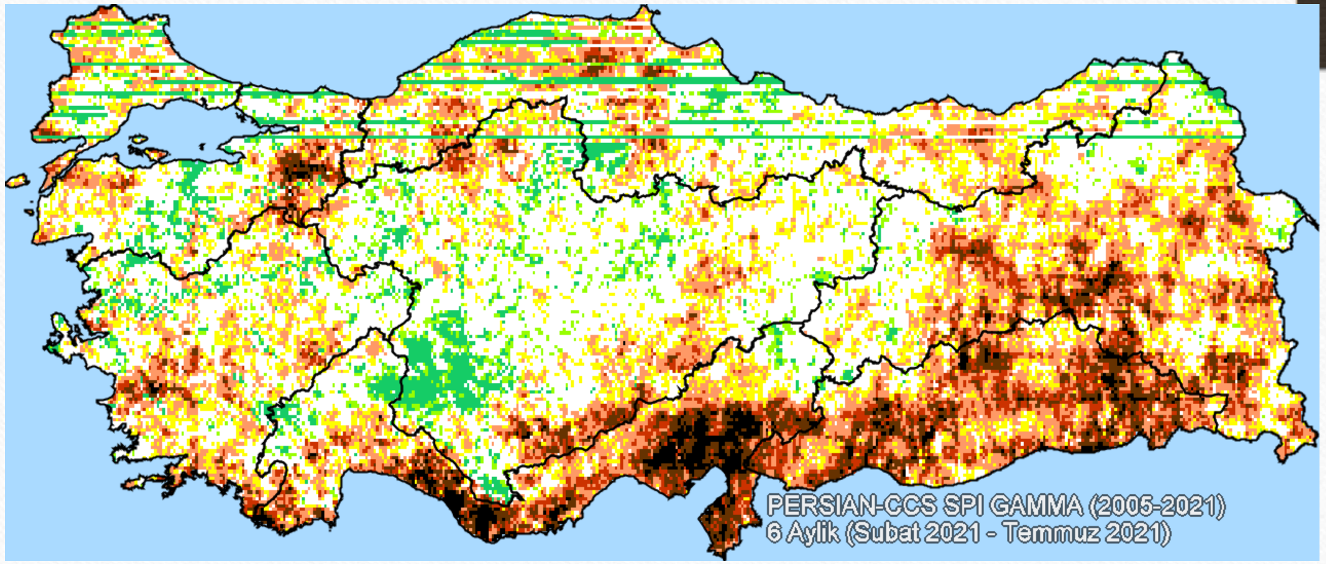


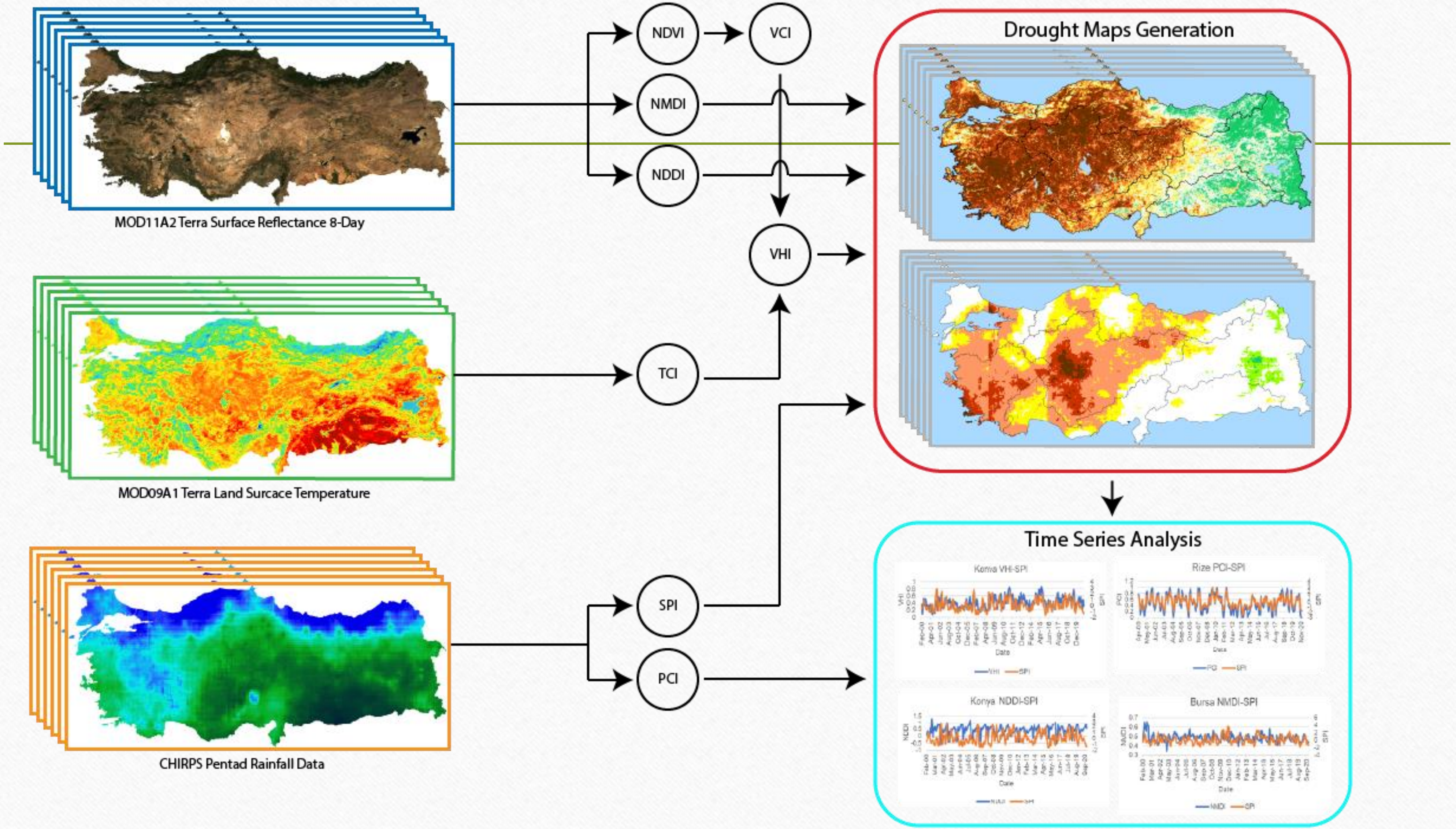


6 month SPI (February-July) 2021









NDVI
VCI
NMDI
NDDI
VHI
TCI
SPI
PCI
MOD11A2 Terra Surface Reflectance 8-Day
MOD09A1 Terra Land Surcace Temperature
CHIRPS Pentad Rainfall Data
Drought Maps Generation
Time Series Analysis
Konya VHI-SPI
Rize PCI-SPI
Konya NDDI-SPI
Bursa NMDI-SPI

Remote Sensing Indices

- Normalized Difference Vegetation Index (NDVI):
  - (NIR - Red) / (NIR + Red)
- Vegetation Condition Index (VCI):
  - VCI = $\frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$
    - where NDVIi defines observed month NDVI,
    - NDVImin and NDVImax define minimum and maximum values of NDVI values in long term period
- Temperature Condition Index (TCI):
  - TCI = $\frac{LST_{max} - LST_i}{LST_{max} - LST_{min}}$
    - LSTi defines observed month Land Surface Temperature,
    - LSTmin and LSTmax define minimum and maximum values of LST values in long term period
- Vegetation Health Index (VHI):
  - VHI = 0.5 x VCI + 0.5 x TCI

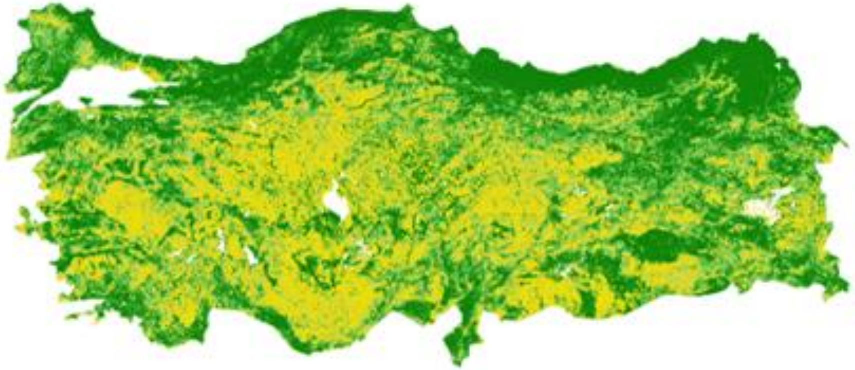
Remote Sensing Indices

- Normalized Difference Drought Index (NDDI)
  - NDDI = $\frac{NDVI-NDWI}{NDVI+NDWI}$
  - NDDI values are scaled between -1 and 1. High NDDI values mean drought conditions.
- Normalized Multiband Drought Index (NMDI)
  - $NMDI_{veg} = \frac{R_{860nm}-(R_{1640nm}-R_{2130nm})}{R_{860nm}+(R_{1640nm}-R_{2130nm})}$
  - NMDI ranges between 0 and 1.
  - Normalized multiband Drought Index (NMDI) is an improved drought index based on soil and vegetation spectral signatures by using NIR wavelength at nearly 860 nm and two SWIR wavelengths at 1640 nm and 2130 nm.

VHI 2004 JULY

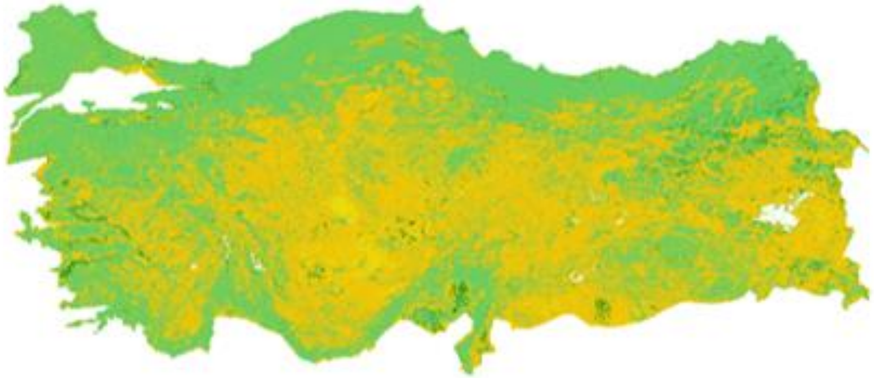
VHI 2007 JULY

NDDI 2004 July



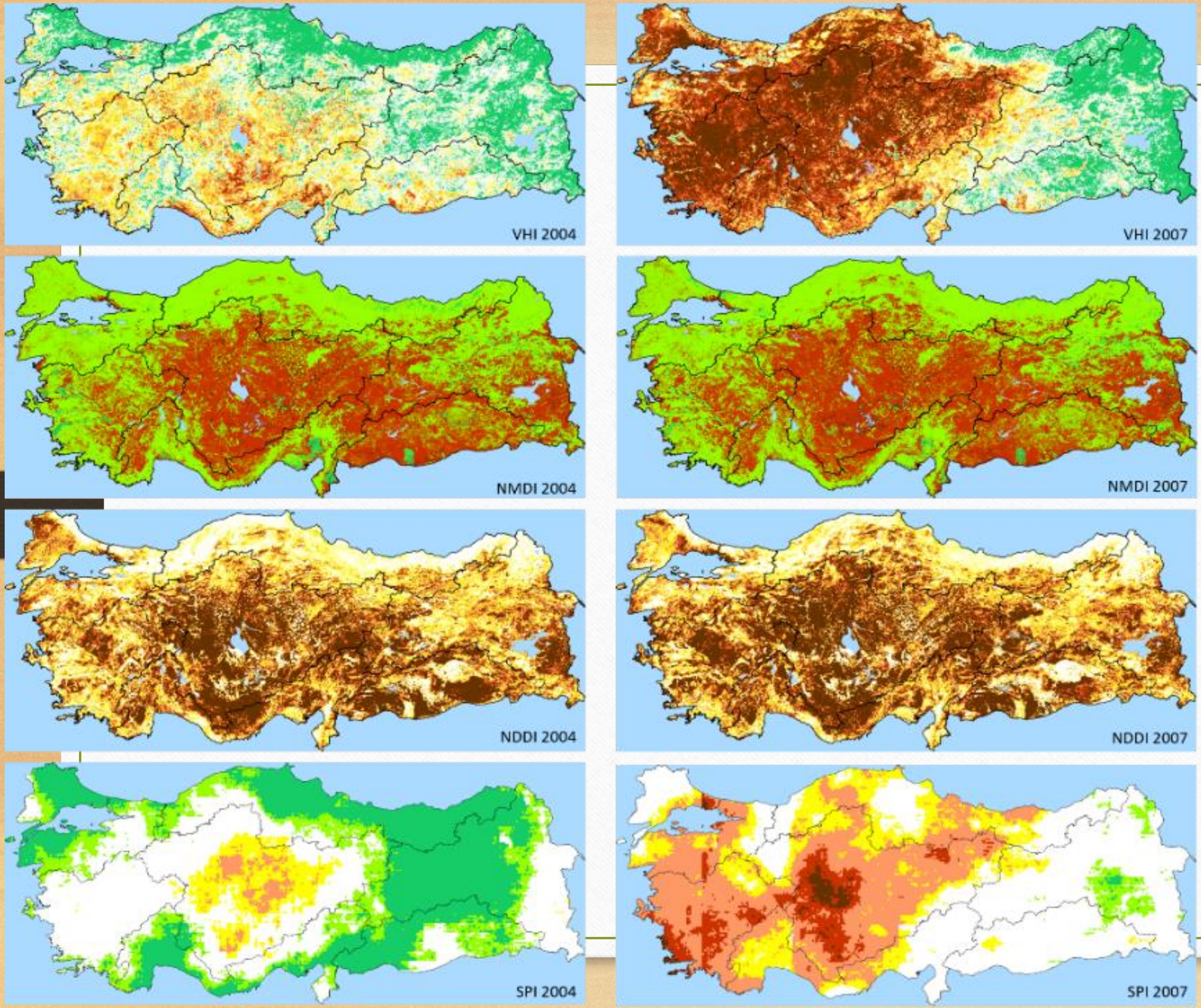
NDDI 2007 July

NMDI 2004 JULY



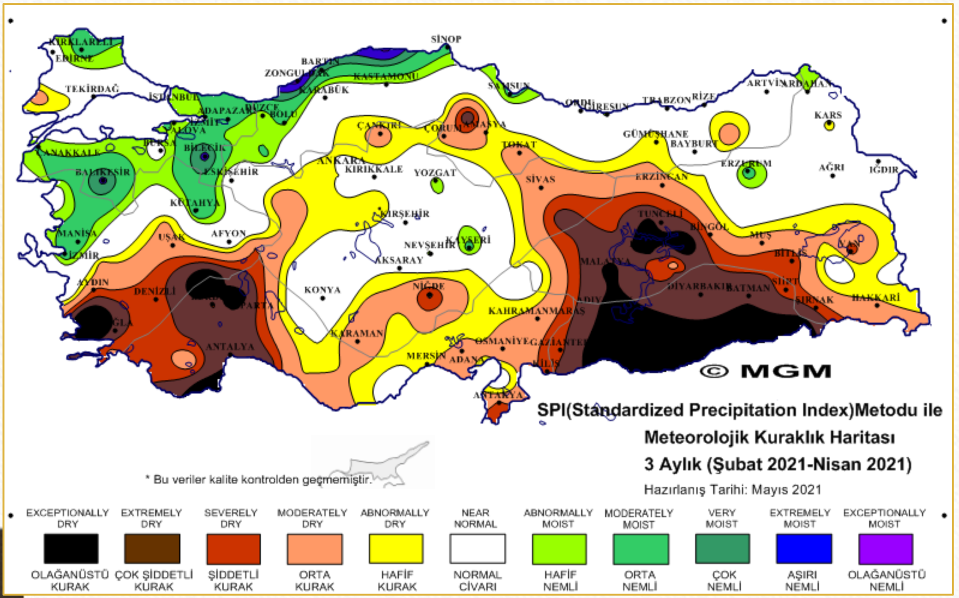
NMDI 2007 JULY

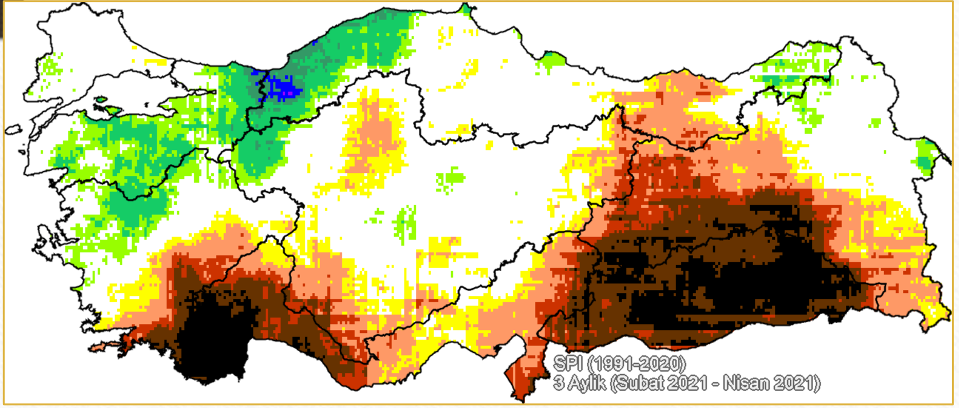
NMDI*100	<20	20-40	40-60	>60
Drought conditions	Extreme Dry	Dry	Wet	Extremely wet
Legend				



2004 was a wet year.
2007 was a dry year.

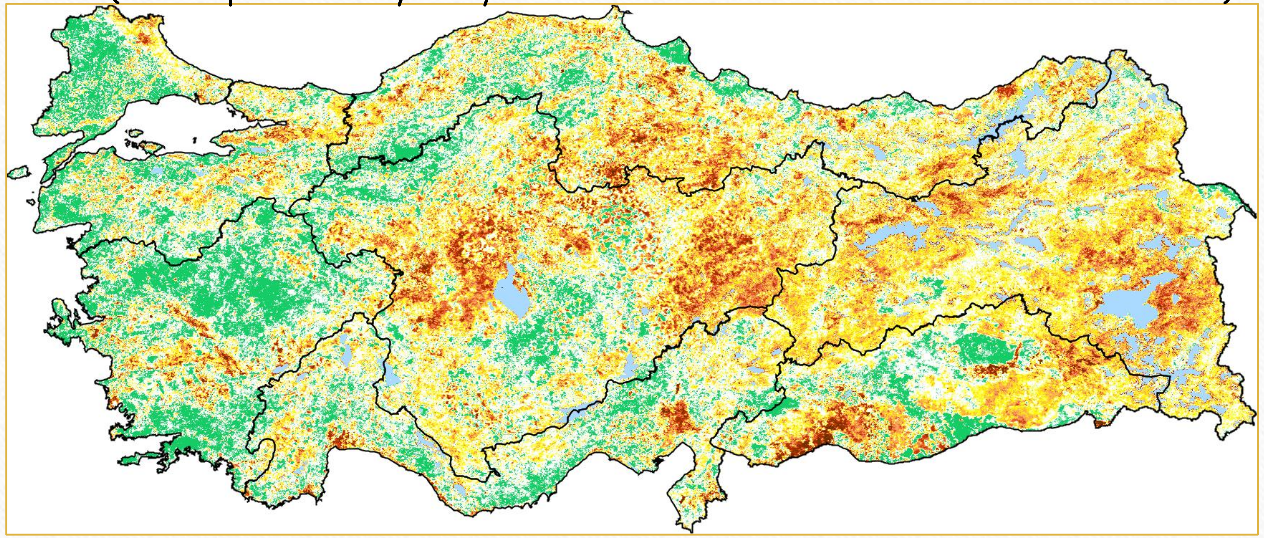
No Data	
Wet	
Normal	
Mild	
Moderate	
Severe	
Extreme	
Drought conditions	Legend



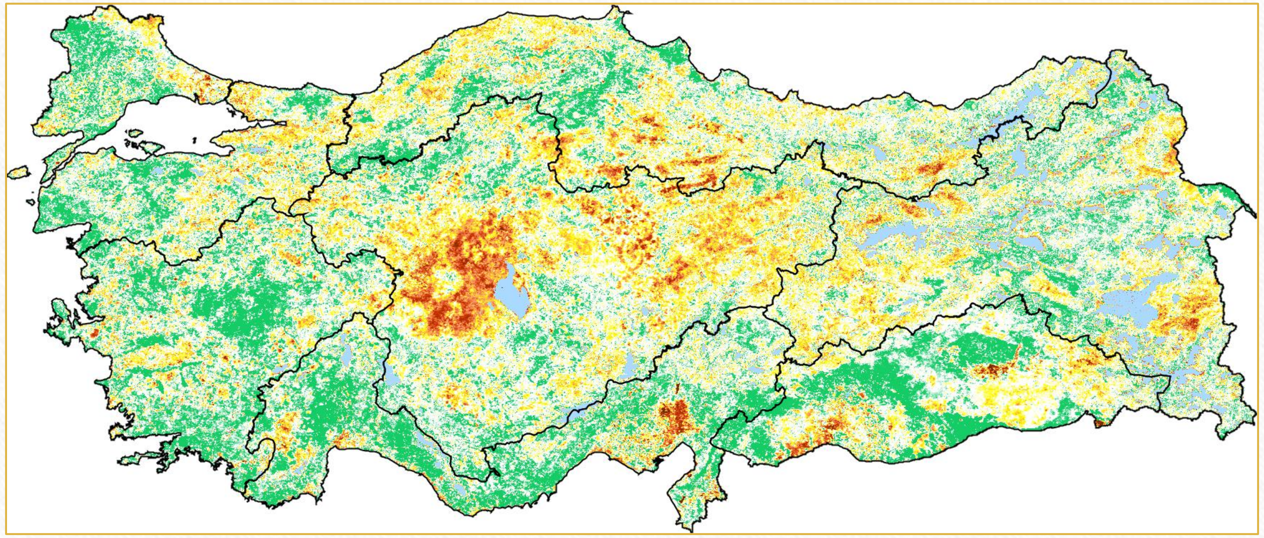


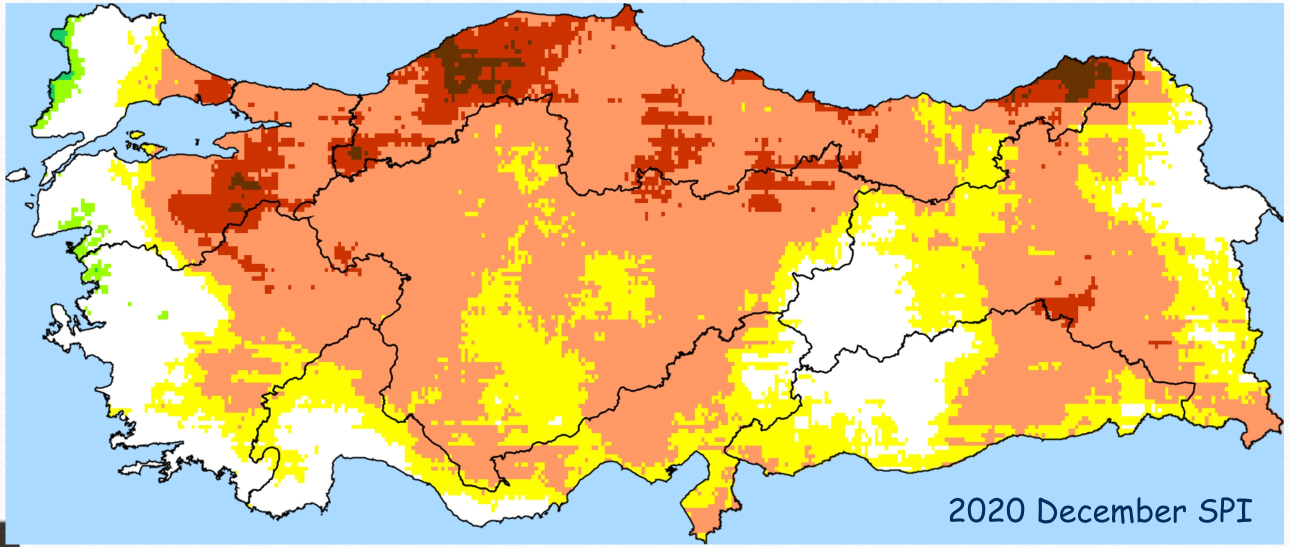
VHI*100	<10	10-20	20-30	30-40	40-60	>60	
Drought conditions	Extreme	Severe	Moderate	Mild	Normal	Wet	No Data
Legend							

VHI (2021 April-Monthly/ 21 year data from MOD09A1.006 and MOD11A2.006)



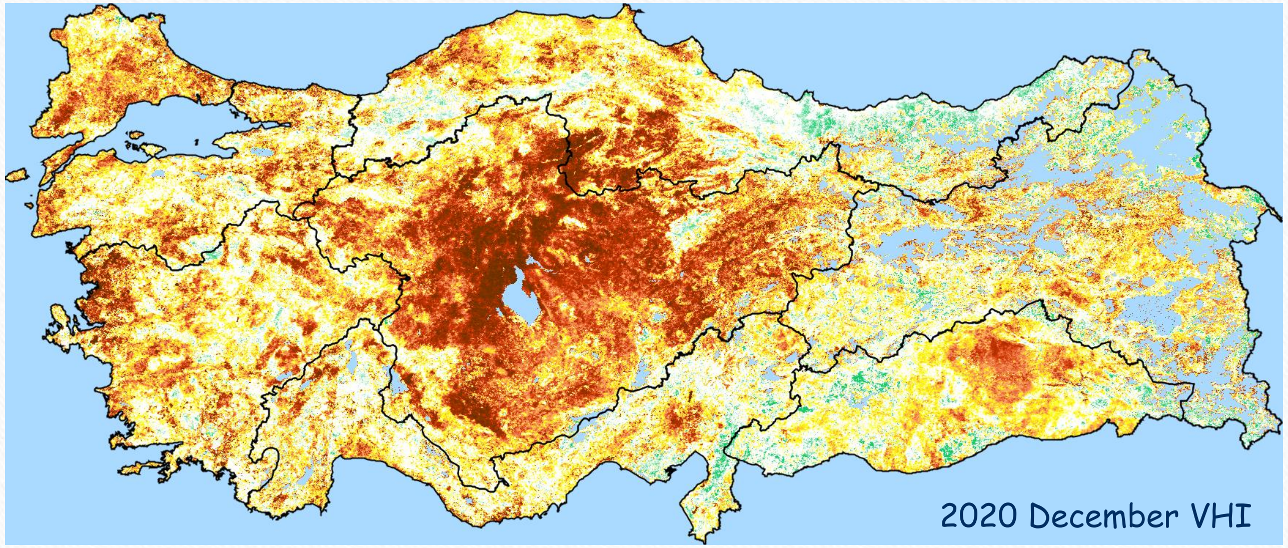
VHI (2021 Feb – April-3 month period / 21 year data from MOD09A1.006)

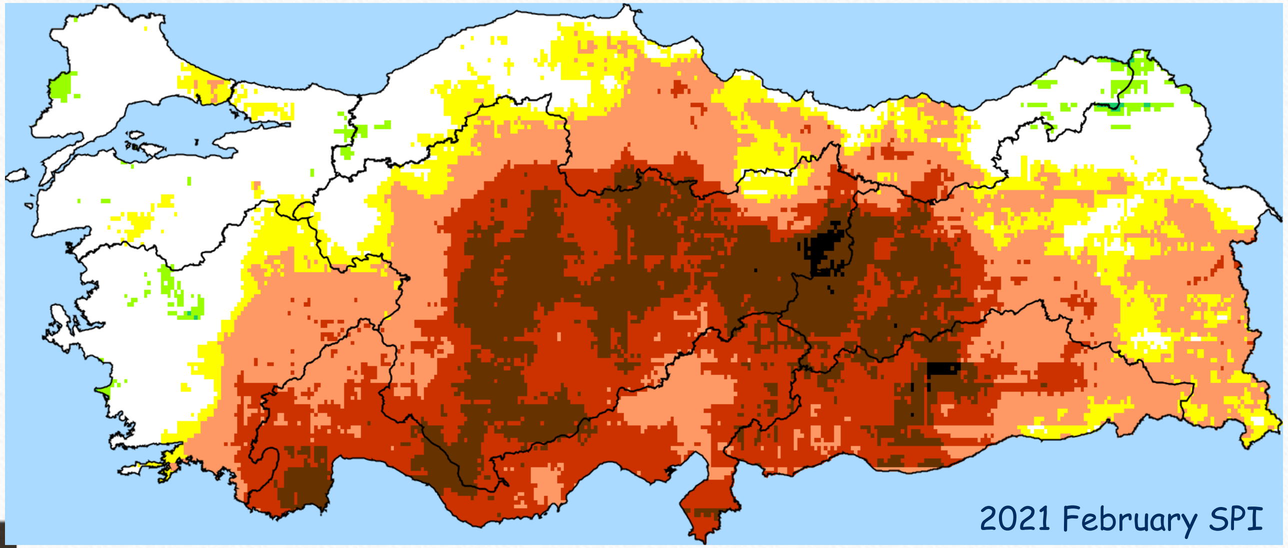



2020 December SPI

Extreme	Severe	Moderate	Mild	Normal	Wet	No Data

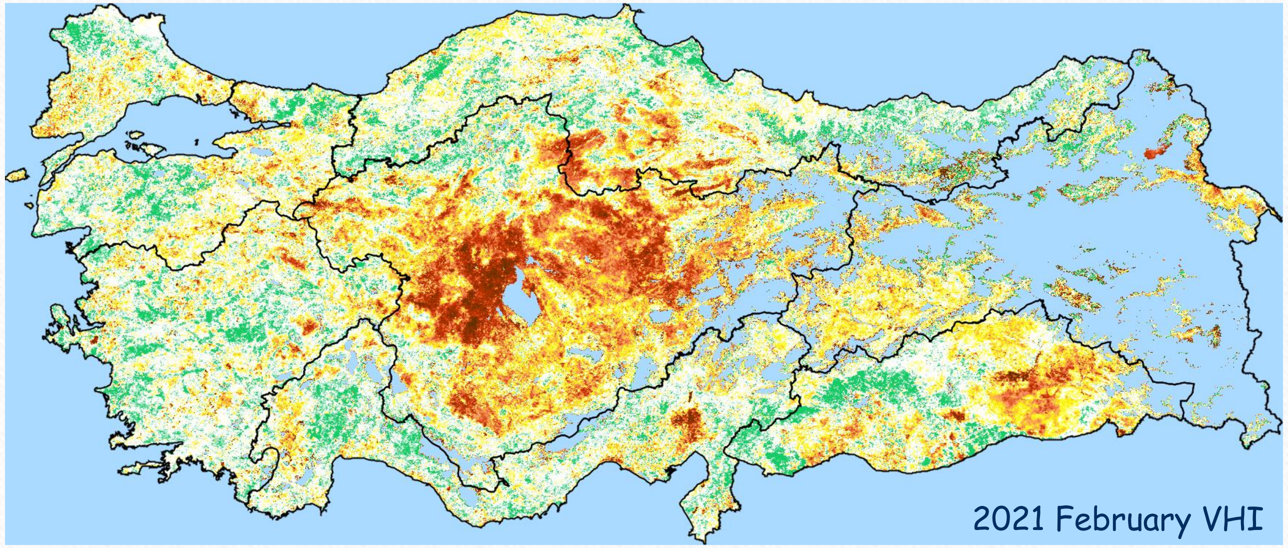
Monthly SPI and VHI (December 2020)

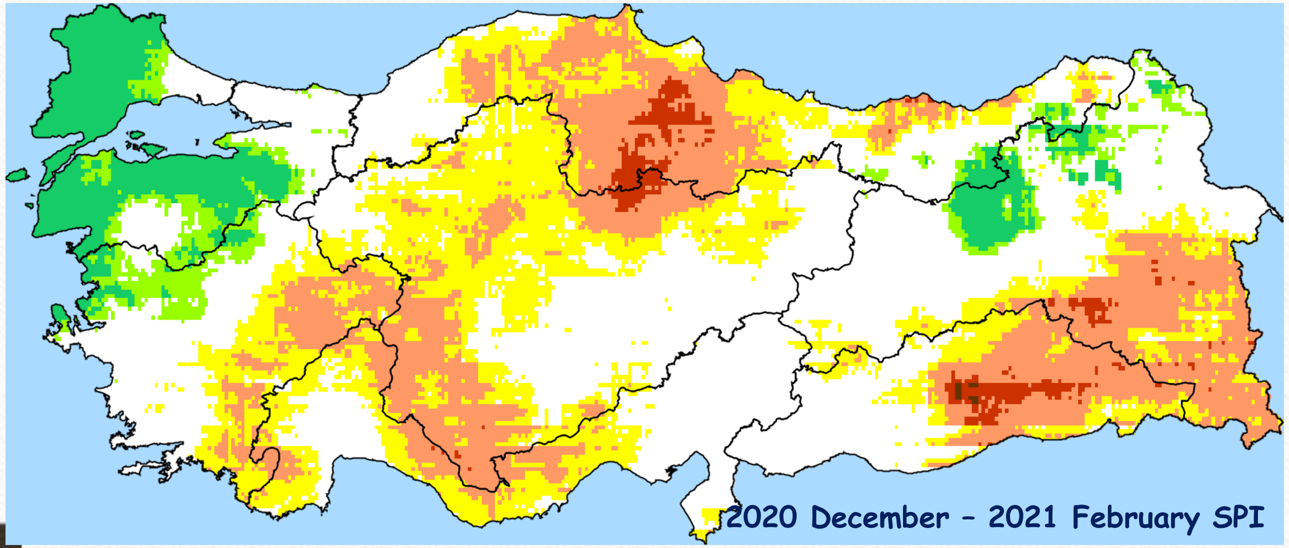

2020 December VHI



Extreme	Severe	Moderate	Mild	Normal	Wet	No Data

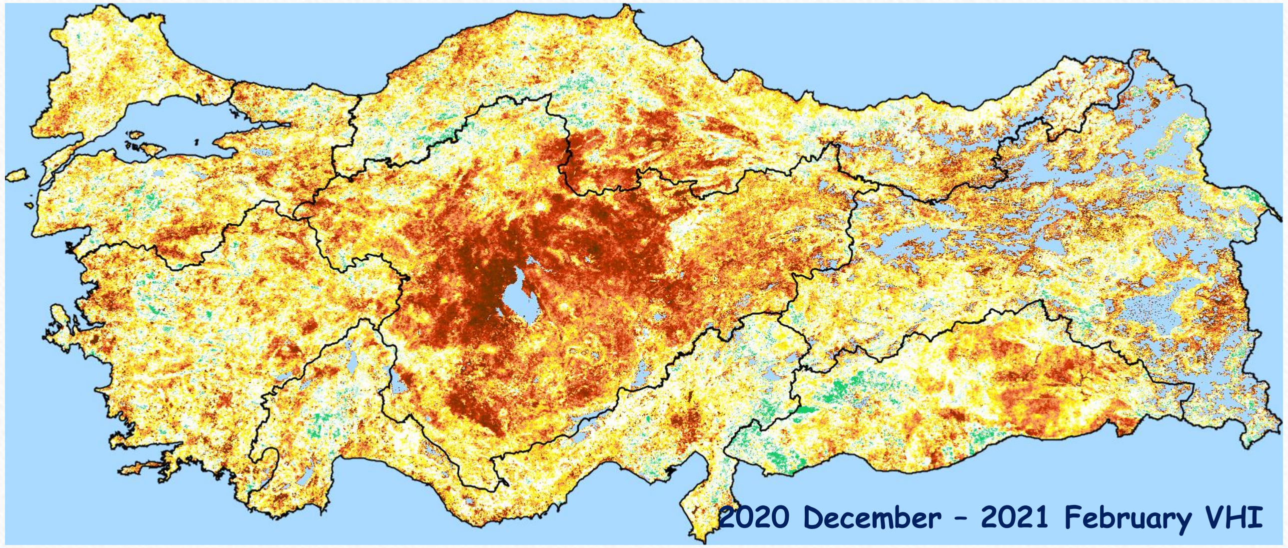
Monthly SPI and VHI (February 2021)





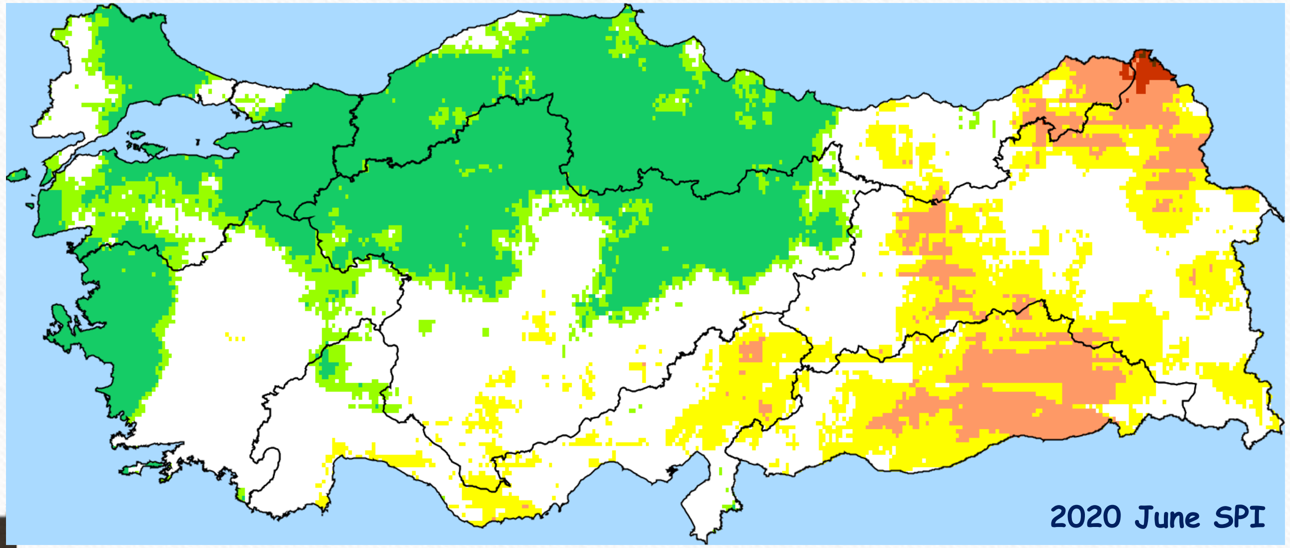
Extreme	Severe	Moderate	Mild	Normal	Wet	No Data

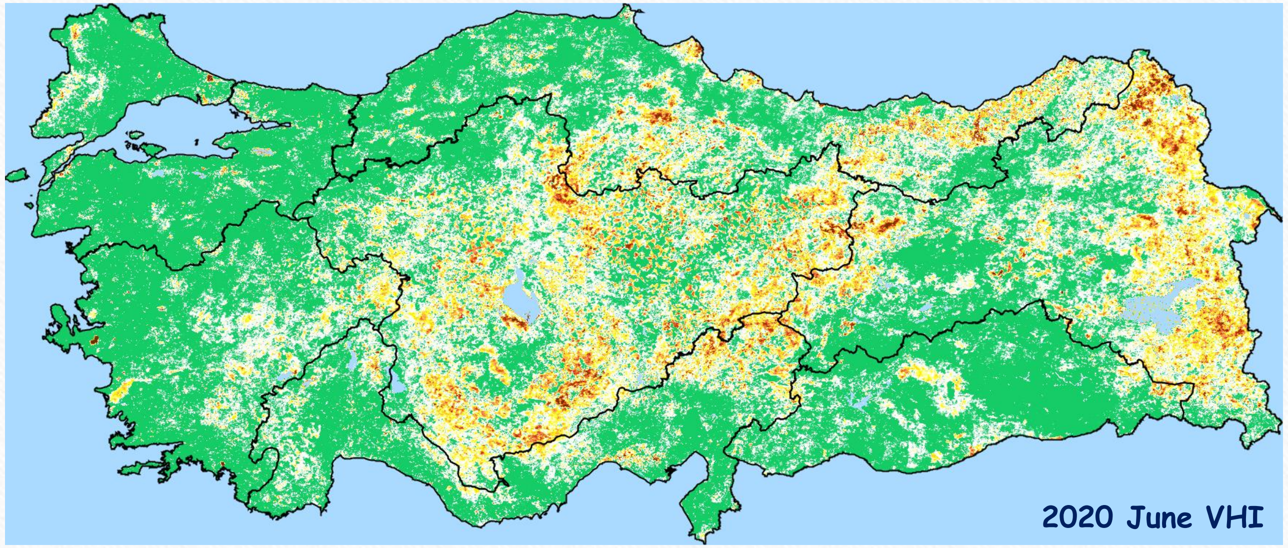
3-Monthly SPI and VHI (December 2020-February 2021)

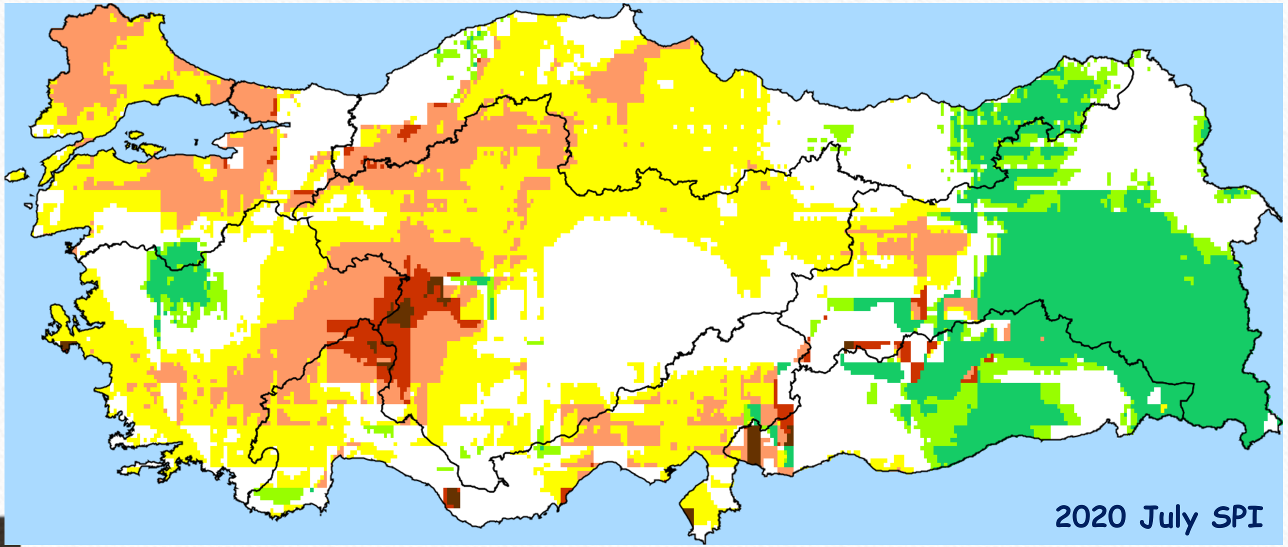


Extreme	Severe	Moderate	Mild	Normal	Wet	No Data

Monthly SPI and VHI (June 2020)

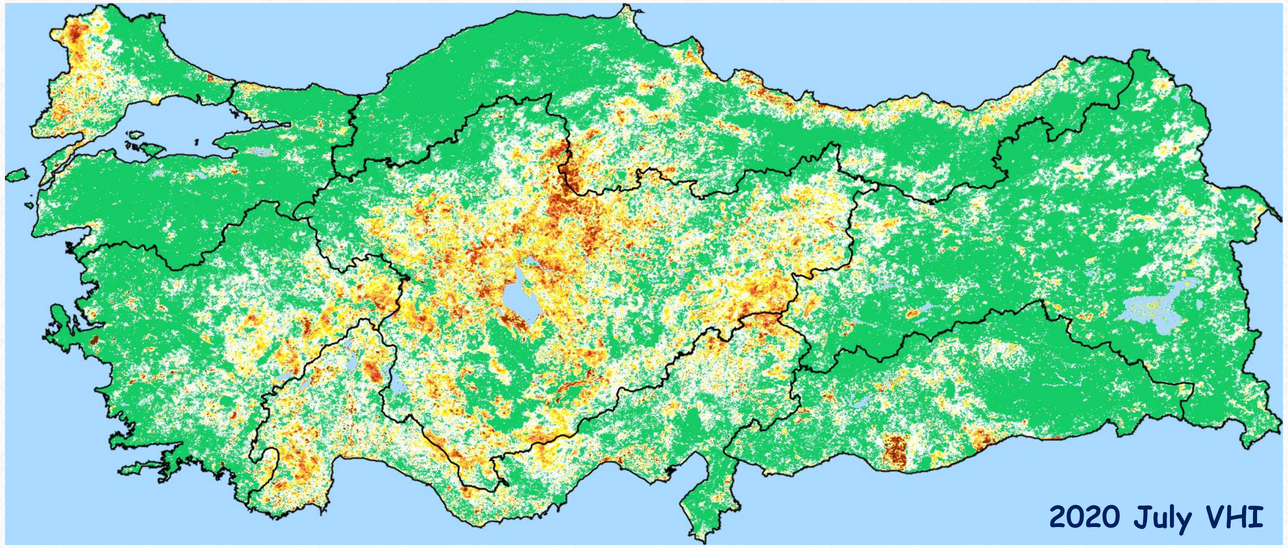


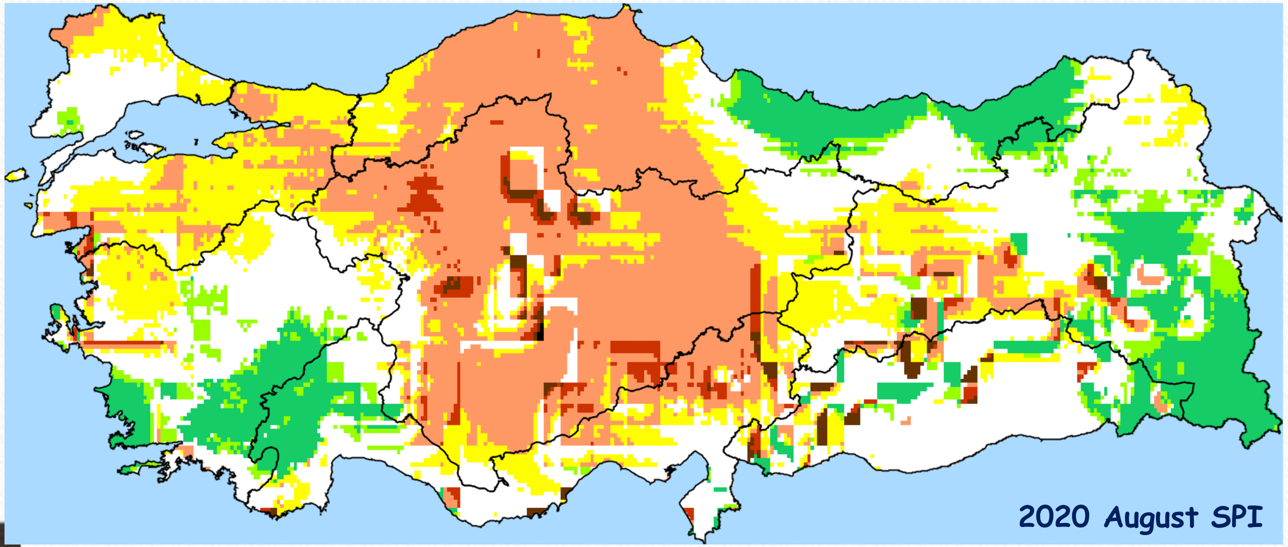




Extreme	Severe	Moderate	Mild	Normal	Wet	No Data

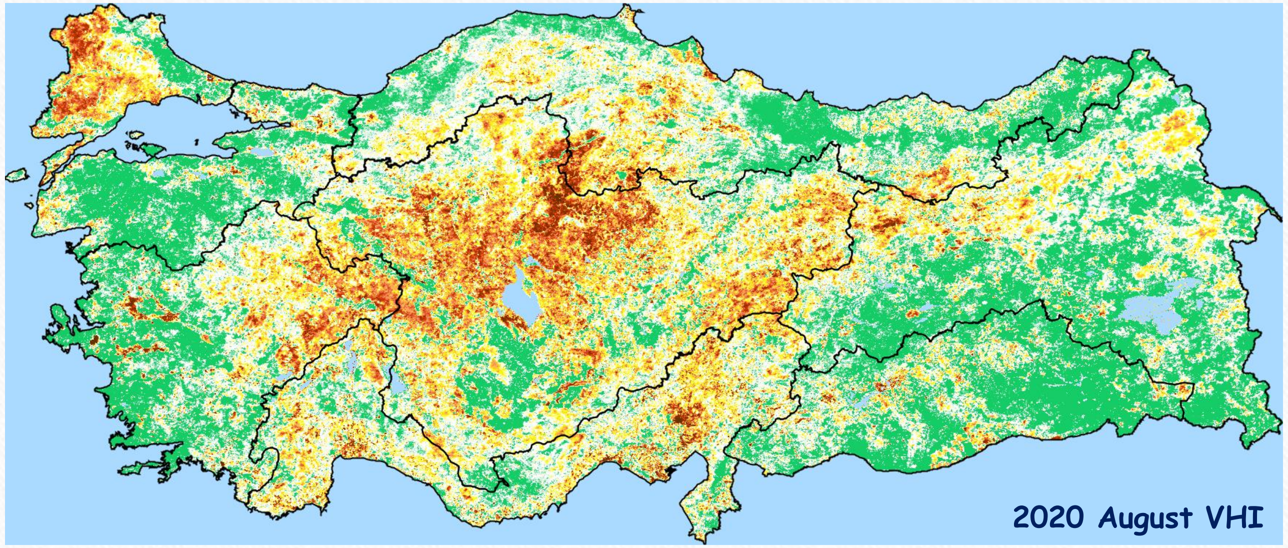
Monthly SPI and VHI (July 2020)

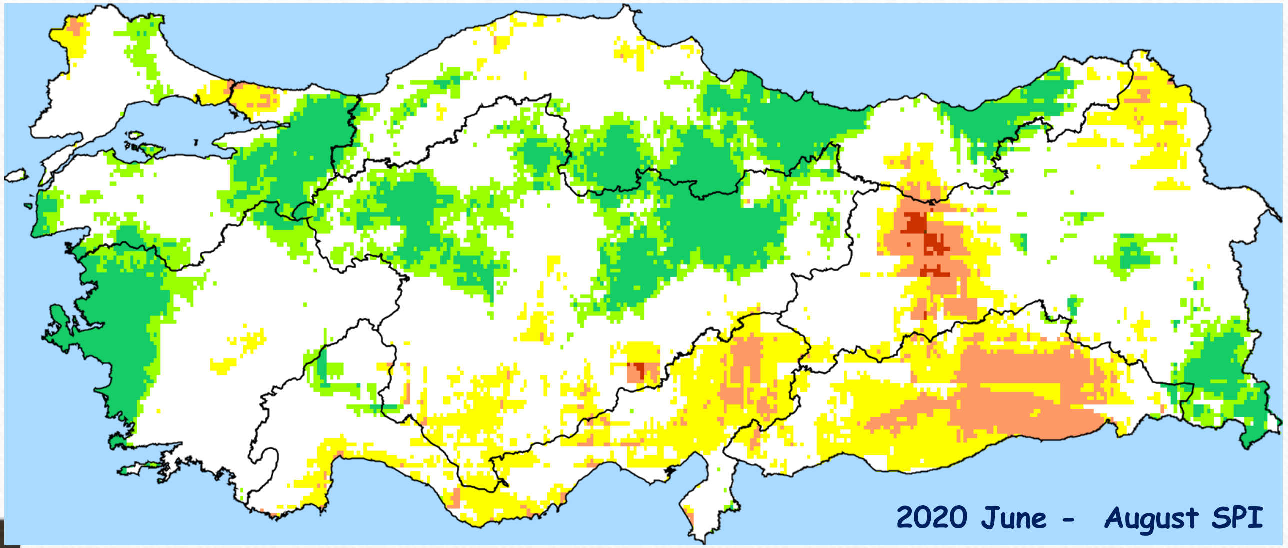




Extreme	Severe	Moderate	Mild	Normal	Wet	No Data

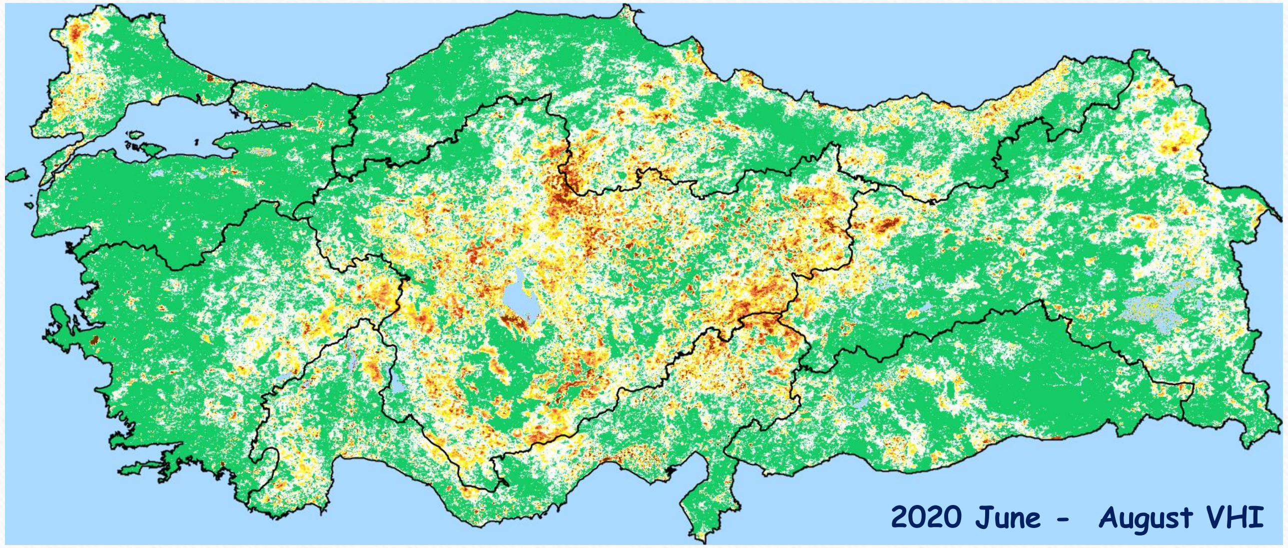
Monthly SPI and VHI (August 2020)





Extreme	Severe	Moderate	Mild	Normal	Wet	No Data

3- Monthly SPI and VHI (June-August 2020)



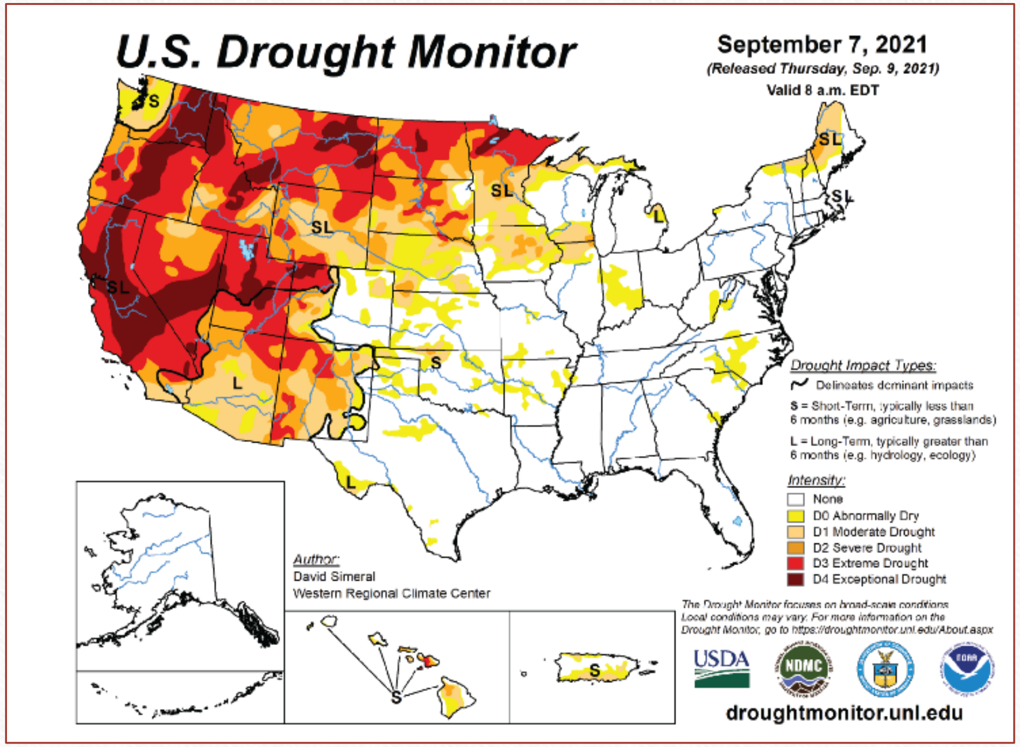
USDM MAPS

U.S. Drought Monitor- Drought Classifications

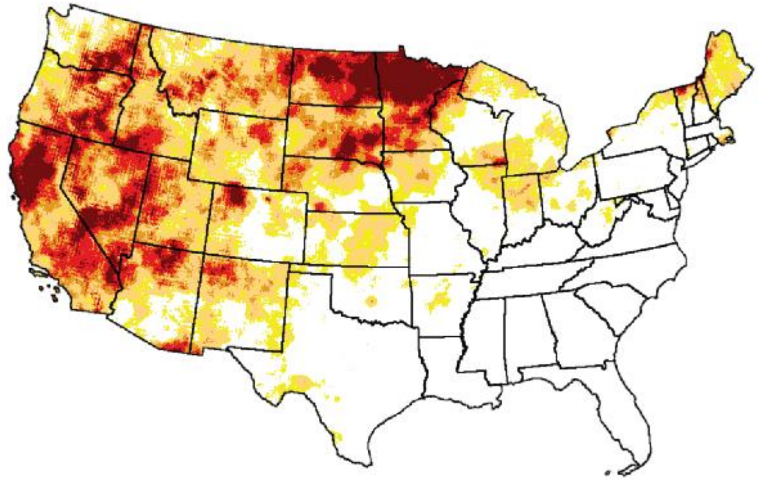
			Ranges				
Category	Description	Possible Impacts	Palmer Drought Severity Index (PDSI)	CPC Soil Moisture Model (Percentiles)	USGS Weekly Streamflow (Percentiles)	Standardized Precipitation Index (SPI)	Objective Drought Indicator Blends (Percentiles)
D0	Abnormally Dry	Going into drought: • short-term dryness slowing planting, growth of crops or pastures Coming out of drought: • some lingering water deficits • pastures or crops not fully recovered	-1.0 to -1.9	21 to 30	21 to 30	-0.5 to -0.7	21 to 30
D1	Moderate Drought	• Some damage to crops, pastures • Streams, reservoirs, or wells low, some water shortages developing or imminent • Voluntary water-use restrictions requested	-2.0 to -2.9	11 to 20	11 to 20	-0.8 to -1.2	11 to 20
D2	Severe Drought	• Crop or pasture losses likely • Water shortages common • Water restrictions imposed	-3.0 to -3.9	6 to 10	6 to 10	-1.3 to -1.5	6 to 10
D3	Extreme Drought	• Major crop/pasture losses • Widespread water shortages or restrictions	-4.0 to -4.9	3 to 5	3 to 5	-1.6 to -1.9	3 to 5
D4	Exceptional Drought	• Exceptional and widespread crop/pasture losses • Shortages of water in reservoirs, streams, and wells creating water emergencies	-5.0 or less	0 to 2	0 to 2	-2.0 or less	0 to 2

Drought Classification | U.S. Drought Monitor (unl.edu)

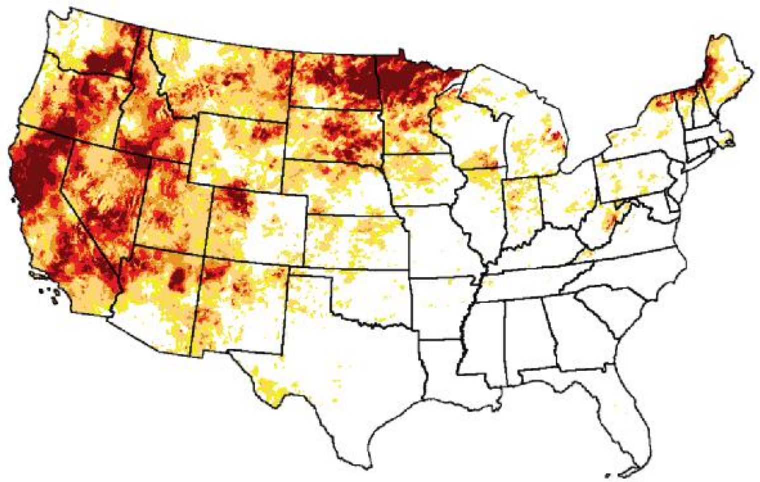
- USDM uses many drought indicators to monitor drought such as:
  - Palmer Drought Severity Index,
  - CPC Soil Moisture Model Percentiles,
  - US Geological Survey Daily Streamflow Percentiles,
  - Percent of Normal Precipitation,
  - Standardized Precipitation Index,
  - Remotely sensed Satellite Vegetation Health Index.
- Blending these indices and addition ancillary indicators Objective Blend of Drought Indicators (OBDI) was developed.
- OBDI is not completely objective because of subjective decisions from authors made contributions.



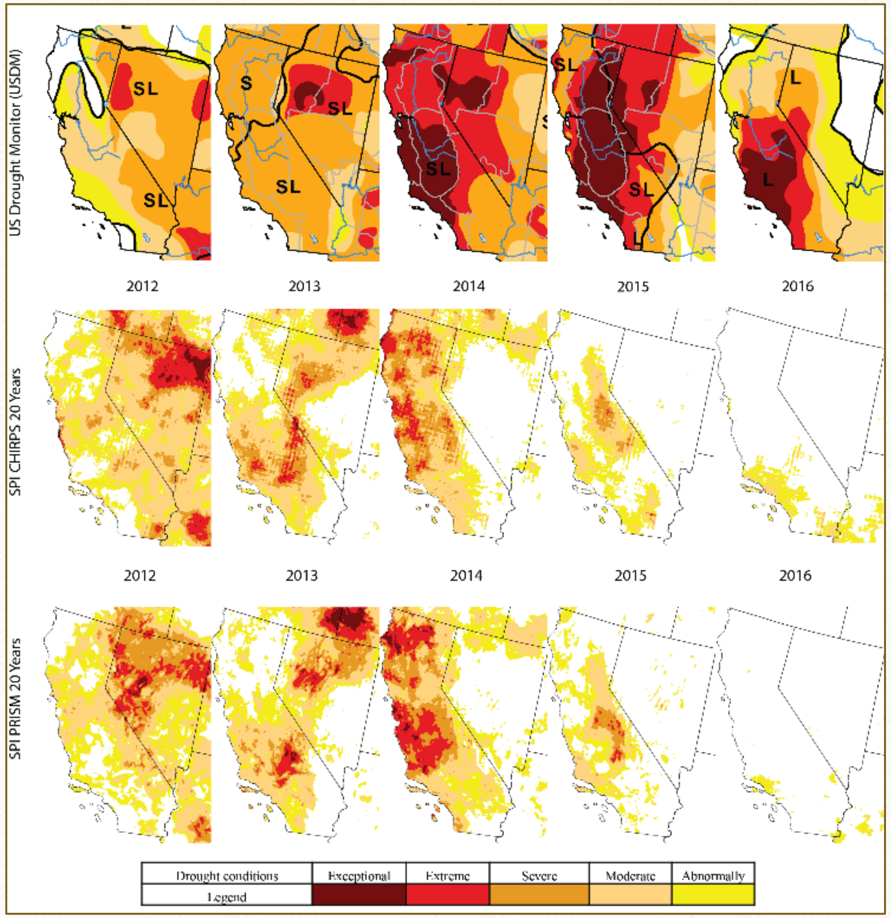
SPI (CHIRPS) 2020 September - 2021 August



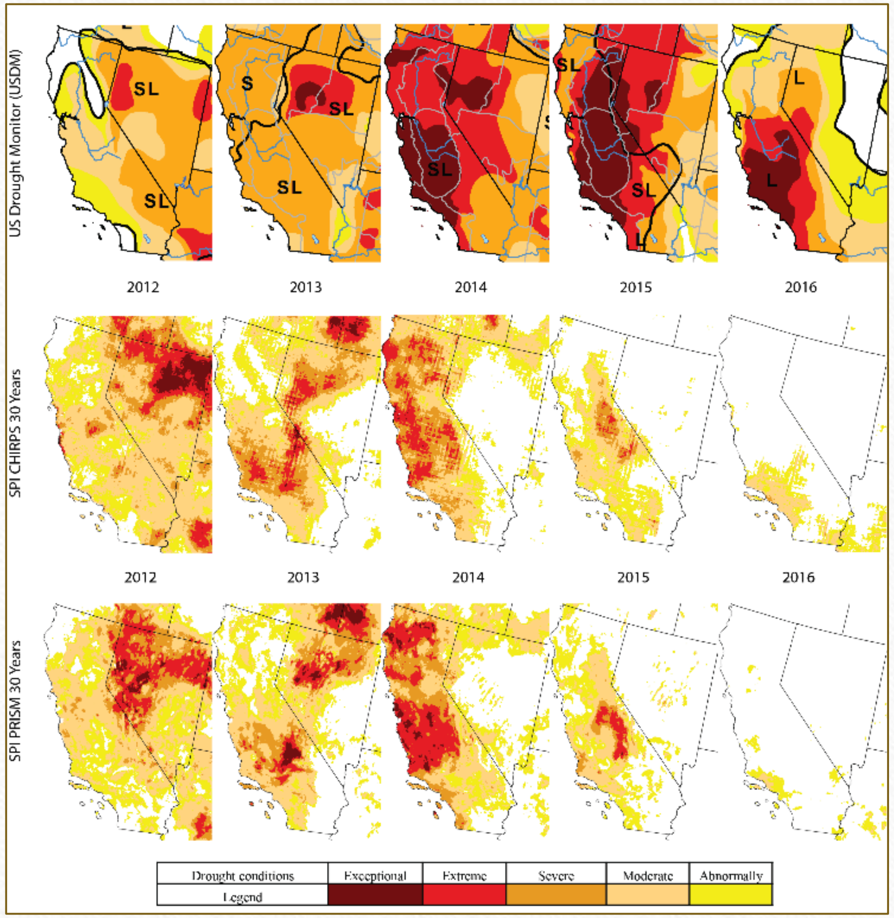
SPI (PRISM) 2020 September - 2021 August



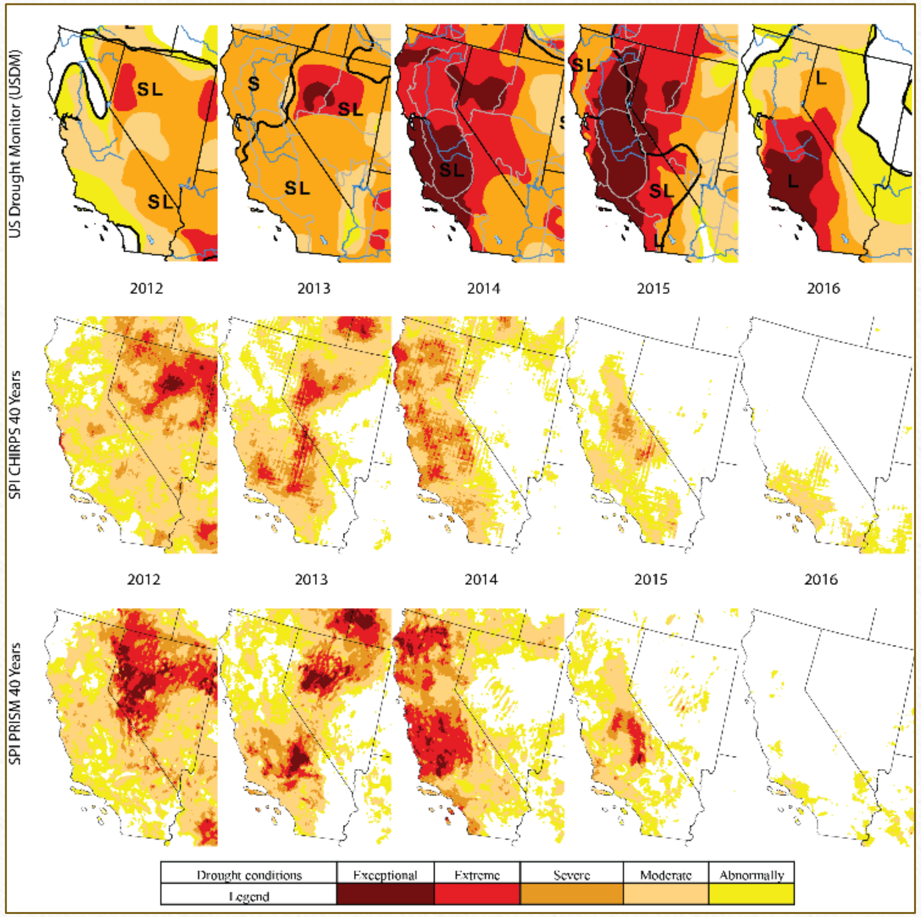
Known drought events in California for years between 2012 to 2016



20 years data- 2001 to 2020



30 years data-1991 to 2020



40 years data- 1981 to 2020

- PRISM derived drought severity maps are closer to USDM maps than CHIRPS derived maps.
- However, CHIRPS also detected drought starting in 2012.
- Both SPI maps show no sign of drought event in 2016 in contrast to USDM.

ML BASED DROUGHT ANALYSIS USING EO DATA

PRILIMINARY RESULTS

Support Vector Machines

- Support Vector Machine (SVM) is a supervised classification method derived from statistical learning theory that often yields good classification results from complex and noisy data.
- Support vector machines (SVMs) is a supervised non-parametric statistical learning technique, therefore there is no assumption made on the underlying data distribution.
- It separates the classes with a decision surface that maximizes the margin between the classes.
- The surface is often called the *optimal hyperplane*, and the data points closest to the hyperplane are called *support vectors*. The support vectors are the critical elements of the training set.

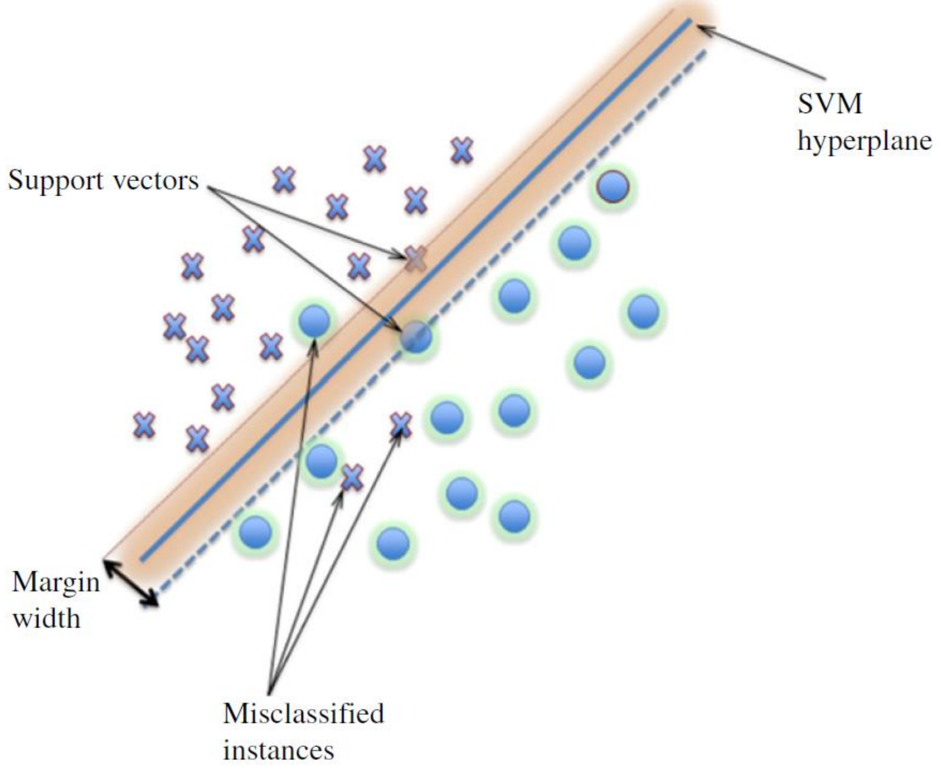


Fig. 1. Linear support vector machine example.
Source: adapted from Burges (1998).

G. Mountrakis et al. / ISPRS Journal of Photogrammetry and Remote Sensing 66 (2011) 247–259

The method is presented with a set of labeled data instances and the SVM training algorithm aims to find a hyper plane that separates the dataset into a discrete predefined number of classes in a fashion consistent with the training examples.

Learning refers to the iterative process of finding a classifier with optimal decision boundary to separate the training patterns (in potentially high-dimensional space) and then to sep arate simulation data under the same configurations (dimensions)

Support Vector Machines

- SVM is characterised by an efficient hyperplane searching technique that uses minimal training area and therefore consumes less processing time.
- The method is able to avoid over fitting problem and requires no assumption on data type. Although non-parametric, the method is capable of developing efficient decision boundaries and therefore can minimise misclassification.
- This is done through finding of optimal separating hyperplanes between classes by focusing on the training cases (support vectors) that lie at the edge of the class distributions, with the other training cases being excluded

https://iopscience.iop.org/article/10.1088/1755-1315/20/1/012038/pdf

Usage	Returns
`ee.Classifier.libsvm(decisionProcedure, svmType, kernelType, shrinking, degree, gamma, coef0, cost, nu, terminationEpsilon, lossEpsilon, oneClass)`	Classifier

Argument	Type	Details
`decisionProcedure`	*String, default: "Voting"*	*The decision procedure to use for classification. Either 'Voting' or 'Margin'. Not used for regression.*
`svmType`	*String, default: "C_SVC"*	*The SVM type. One of `C_SVC`, `NU_SVC`, `ONE_CLASS`, `EPSILON_SVR` or `NU_SVR`.*
`kernelType`	*String, default: "LINEAR"*	*The kernel type. One of LINEAR (u′×v), POLY ($(\gamma \times u' \times v + coef_0)^{degree}$), RBF ($\exp(-\gamma \times \lvert u-v \rvert^2)$) or SIGMOID ($\tanh(\gamma \times u' \times v + coef_0)$).*
`shrinking`	*Boolean, default: true*	*Whether to use shrinking heuristics.*
`degree`	*Integer, default: null*	*The degree of polynomial. Valid for POLY kernels.*
`gamma`	*Float, default: null*	*The gamma value in the kernel function. Defaults to the reciprocal of the number of features. Valid for POLY, RBF and SIGMOID kernels.*
`coef0`	*Float, default: null*	*The $coef_0$ value in the kernel function. Defaults to 0. Valid for POLY and SIGMOID kernels.*
`cost`	*Float, default: null*	*The cost (C) parameter. Defaults to 1. Only valid for C-SVC, epsilon-SVR, and nu-SVR.*
`nu`	*Float, default: null*	*The nu parameter. Defaults to 0.5. Only valid for nu-SVC, one-class SVM, and nu-SVR.*
`terminationEpsilon`	*Float, default: null*	*The termination criterion tolerance (e). Defaults to 0.001. Only valid for epsilon-SVR.*
`lossEpsilon`	*Float, default: null*	*The epsilon in the loss function (p). Defaults to 0.1. Only valid for epsilon-SVR.*
`oneClass`	*Integer, default: null*	*The class of the training data on which to train in a one-class SVM. Defaults to 0. Only valid for one-class SVM. Possible values are 0 and 1. The classifier output is binary (0/1) and will match this class value for the data determined to be in the class.*

Parameters of SVM classification in GEE platform

Random Forest (RF)

- RF is an ensemble machine-learning algorithm based on CART (Classification and regression tree).
- Multiple decision trees, which have no correlations with each other, are combined to create RF.
- Each tree has its own evaluation process.
- Results of these trees are averaged for RF output.
- Decision trees are weak learners; therefore, weak learners are combined to produce a strong model.
- RF can predict either class variables or regression variables.

Random Forest (RF)

- It has six parameters that can be changed in GEE platform
  - number of trees,
  - variables per split whose default is the square root of the number of variables,
  - minimum leaf population whose default is 1,
  - bag fraction with default 0.5,
  - maximum nodes with unlimited default
  - seed whose default is 0 for randomization.

Home > Products > Google Earth Engine > Reference   Was this helpful?

ee.Classifier.smileRandomForest

Send feedback

Creates an empty Random Forest classifier.

Usage	Returns
`ee.Classifier.smileRandomForest(numberOfTrees, variablesPerSplit, minLeafPopulation, bagFraction, maxNodes, seed)`	Classifier

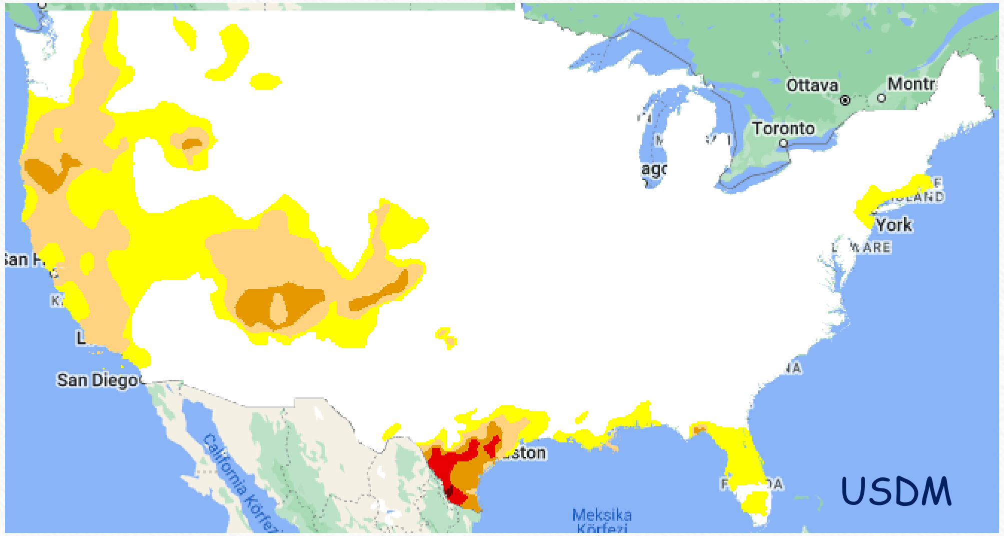
Argument	Type	Details
`numberOfTrees`	Integer	The number of decision trees to create.
`variablesPerSplit`	*Integer, default: null*	*The number of variables per split. If unspecified, uses the square root of the number of variables.*
`minLeafPopulation`	*Integer, default: 1*	*Only create nodes whose training set contains at least this many points.*
`bagFraction`	*Float, default: 0.5*	*The fraction of input to bag per tree.*
`maxNodes`	*Integer, default: null*	*The maximum number of leaf nodes in each tree. If unspecified, defaults to no limit.*
`seed`	*Integer, default: 0*	*The randomization seed.*

ML model parameters

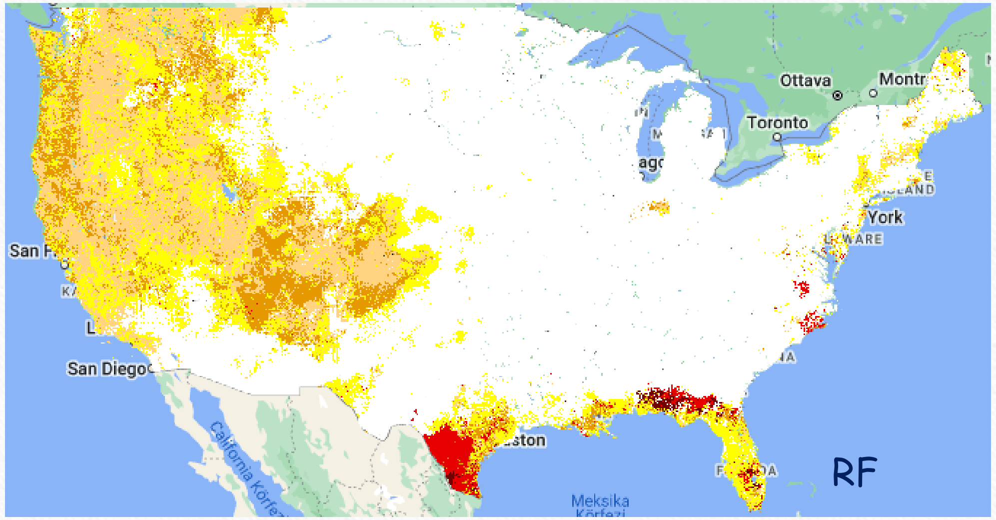
- Random Forest Classification
  - Number of trees: 100
- Support Vector Classification
  - Kernel: RBF
  - Gamma: 2^-15
  - Cost: 2^13
- Above machine learning algorithms with their respectful parameters had been trained on indices which are defined previously.
- USDM maps are used as reference for ML algorithms.
- For each class stratified sampled points.

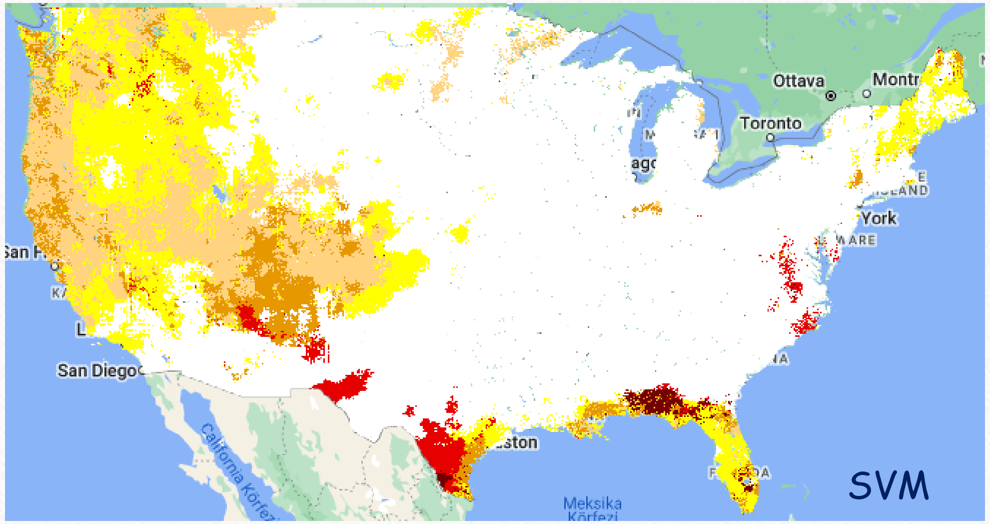
Datasets for ML-based Modeling

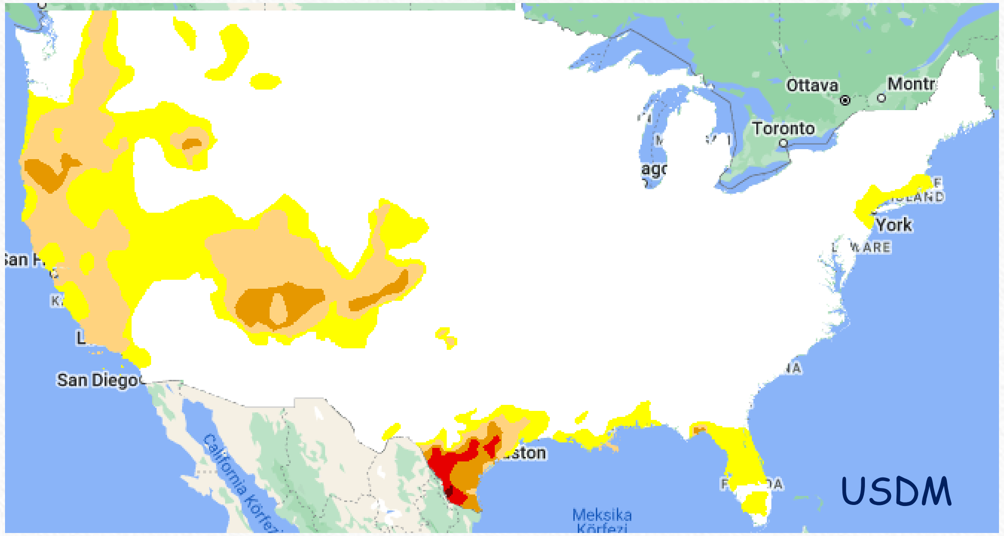
- SPI(1,3,6,12), weekly precipitation <- CHIRPS
- (VHI, VCI, TCI)(1,3,6,12) <- MODIS
- SSM (Soil Surface Moisture) <- SMAP (resampled to ~10 km)
- PDSI (Palmer Drought Severity Index) <- Terra Climate (resampled to ~5 km)
- AET (actual evapotranspiration) <- Terra Climate (resampled to ~5 km)
- Fire <- MODIS
  - Soil Surface Moisture obtained from The NASA-USDA Enhanced SMAP Global soil moisture data.
  - Palmer Drought Severity Index and Actual Evapotranspiration are collected from Terra Climate data.
  - Fire data obtained from Terra Thermal Anomalies & Fire data.
  - Climate Hazards Group InfraRed Precipitation With Station Data is used for precipitation data.



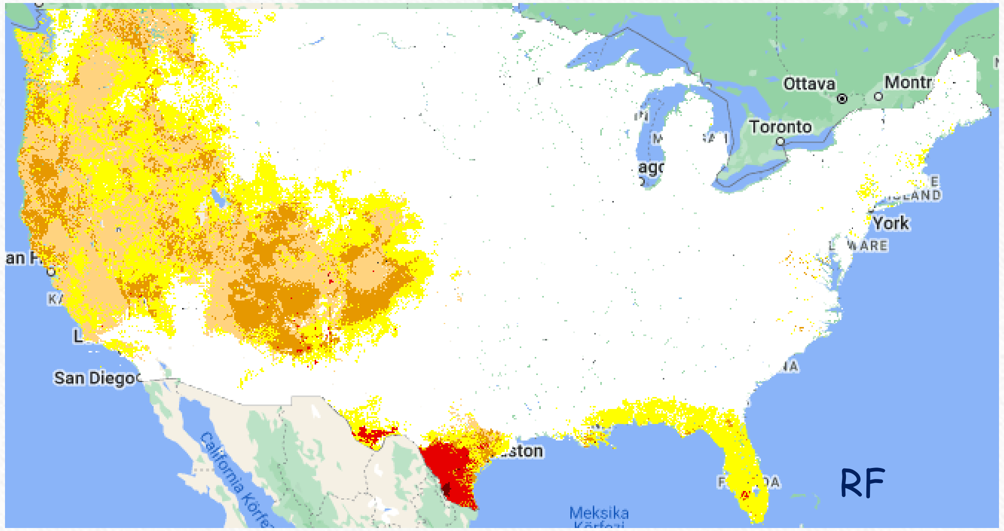
- **2020-WEEK 12**
  - SPI12, SPI6, SPI3,
  - TCI_12, VCI_12, VHI_12,
  - TCI_6, VCI_6, VHI_6,
  - TCI_3, VCI_3, VHI_3,
  - TCI_1, VCI_1, VHI_1

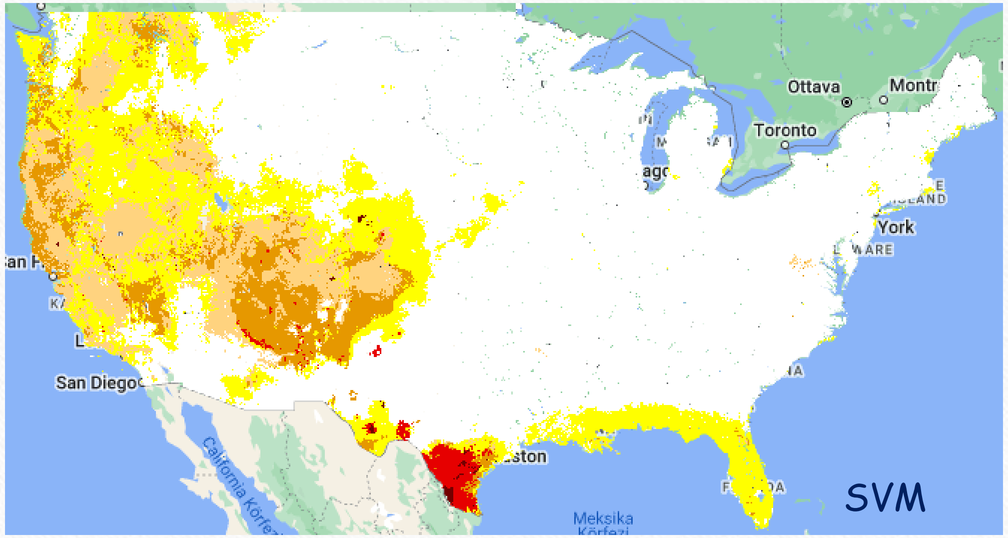


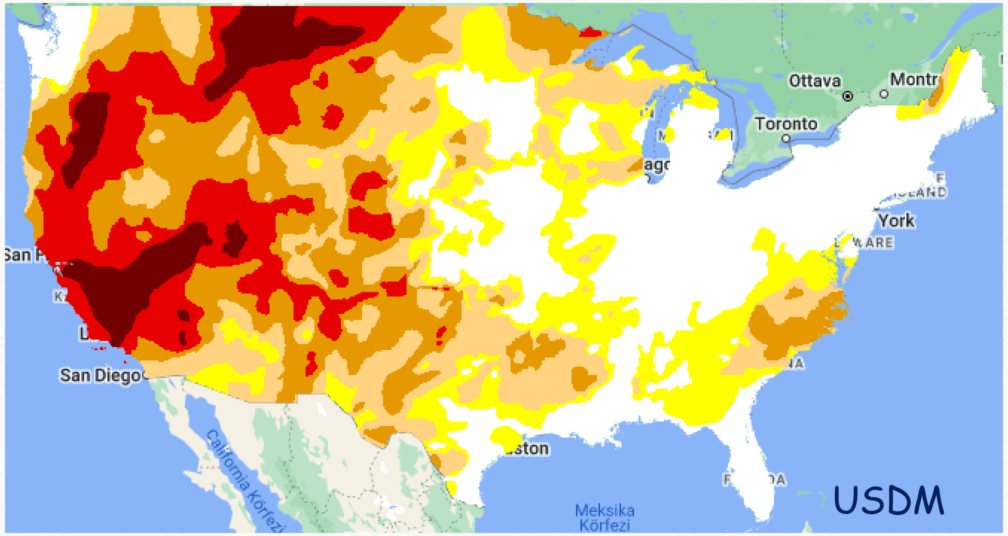




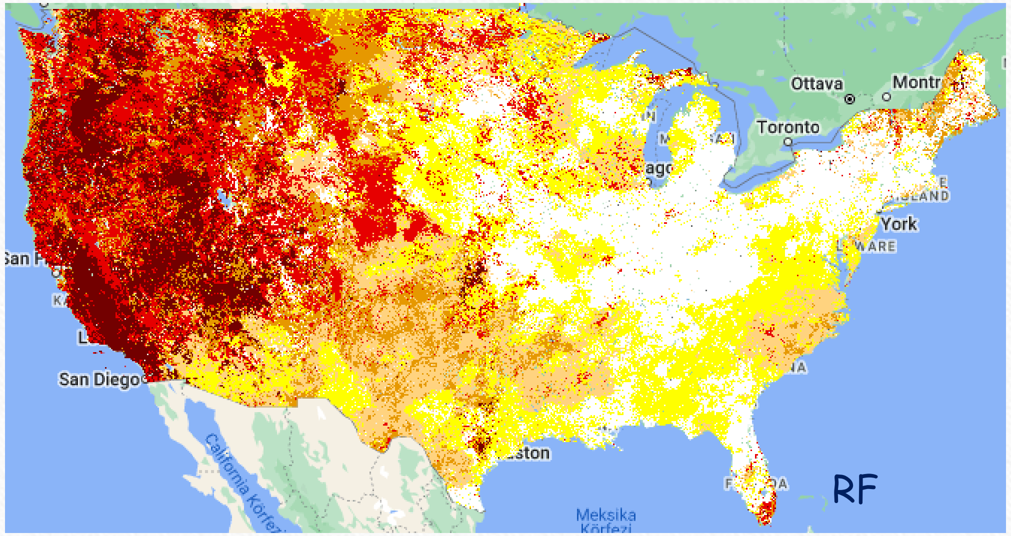
- **2020-WEEK 12**
  - SPI12, SPI6, SPI3,
  - TCI_12, VCI_12, VHI_12,
  - TCI_6, VCI_6, VHI_6,
  - TCI_3, VCI_3, VHI_3,
  - TCI_1, VCI_1, VHI_1,
  - SSM,
  - PDSI,
  - AET,
  - Fire,
  - Precipitation

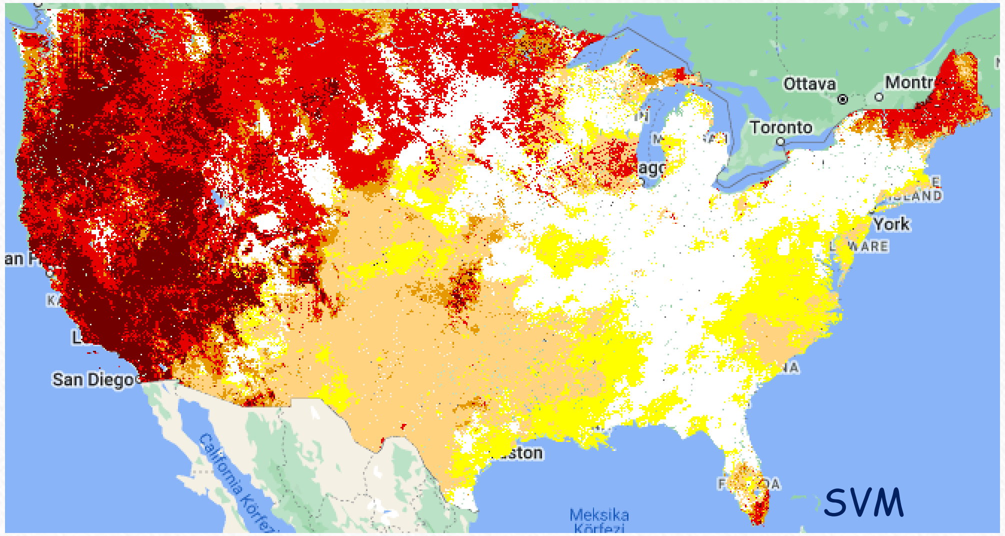


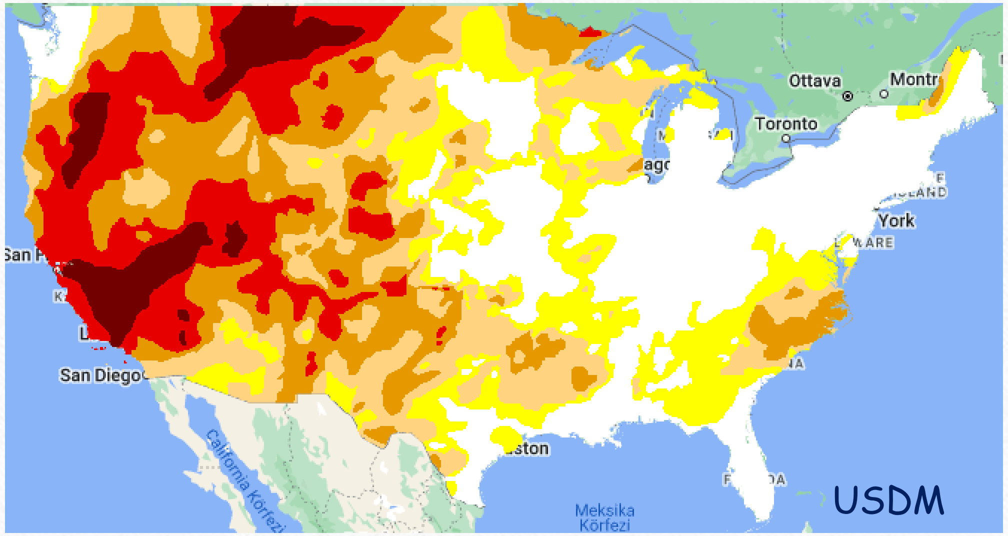




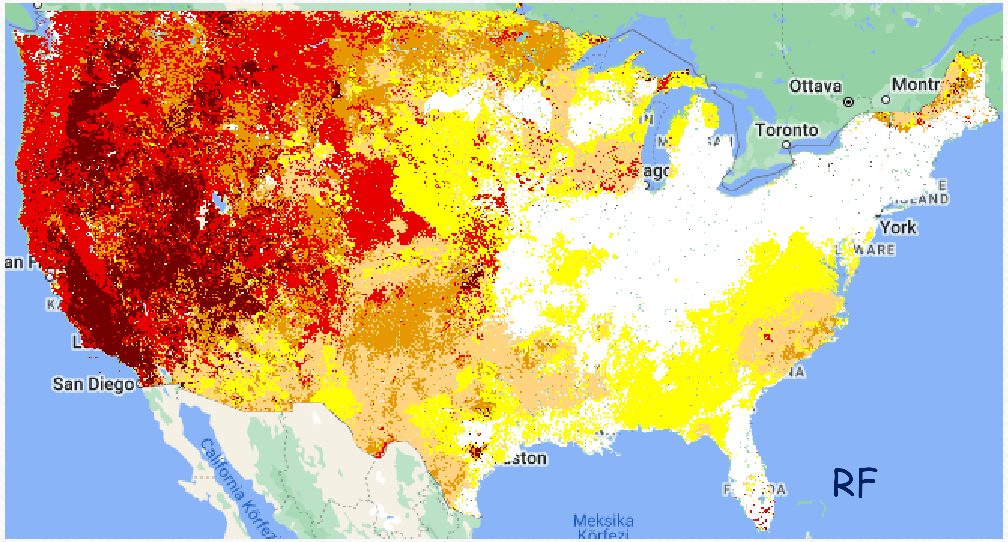
- 2021-WEEK 49
  - SPI12, SPI6, SPI3,
  - TCI_12, VCI_12, VHI_12,
  - TCI_6, VCI_6, VHI_6,
  - TCI_3, VCI_3, VHI_3,
  - TCI_1, VCI_1, VHI_1

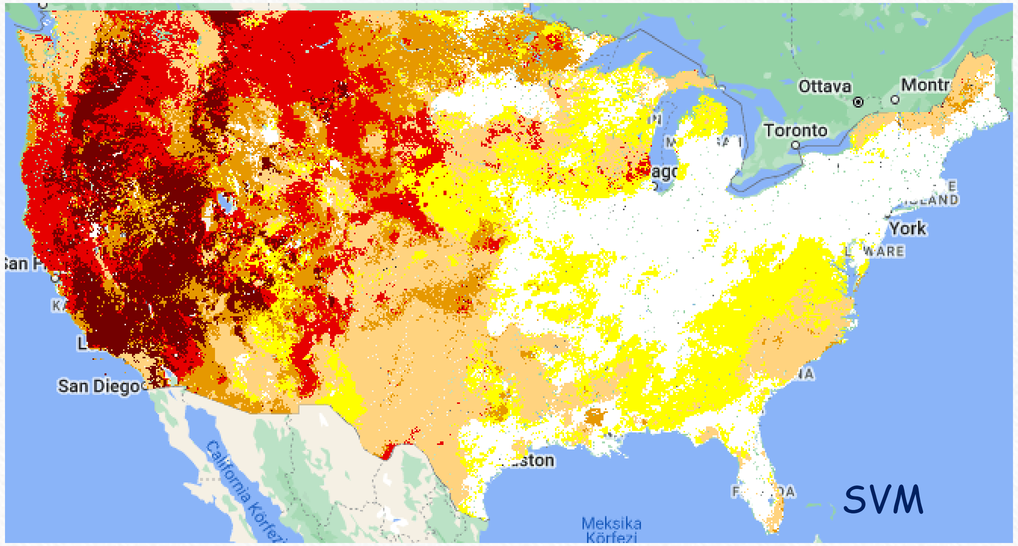






- **2021-WEEK 49**
  - SPI12, SPI6, SPI3,
  - TCI_12, VCI_12, VHI_12,
  - TCI_6, VCI_6, VHI_6,
  - TCI_3, VCI_3, VHI_3,
  - TCI_1, VCI_1, VHI_1,
  - SSM,
  - PDSI,
  - AET,
  - Fire,
  - Precipitation





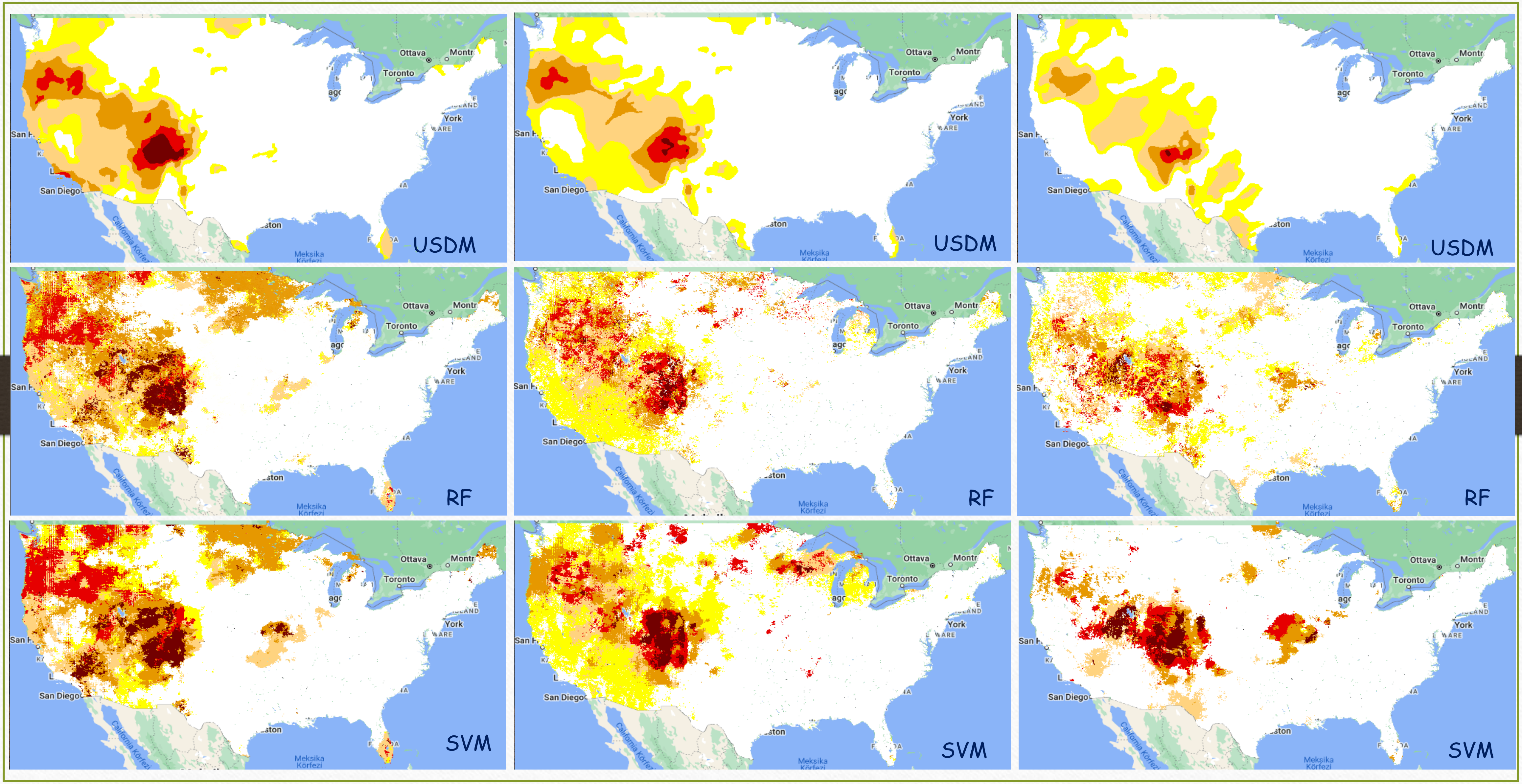
2019 ML BASED DROUGHT EXPERIMENTS

	January		February		March		April		May		June		July		August		September		October		November		December	
	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample
Non-Drought	5379878	100	5440696	100	5731662	100	6184107	100	7025333	100	6784303	100	7014857	100	6312129	100	5490549	100	4722416	100	5614778	100	5311947	100
D0	705450	34	1127538	40	1147373	40	1161288	39	569133	31	595600	32	525391	31	1138281	39	1518766	46	1567639	50	957720	38	1572430	47
D1	870559	36	698948	34	695142	34	378194	30	193771	27	372189	29	205553	27	299204	29	668674	34	1038878	41	728664	35	550060	33
D2	579623	32	375602	30	177073	27	68525	26	3878	25	40029	25	46314	25	42500	26	98537	26	401640	31	449723	31	349649	30
D3	168016	26	136646	27	38108	25	0	0	0	0	0	0	0	0	0	0	15589	25	61554	26	41236	26	8034	25
D4	88587	25	12684	25	2755	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

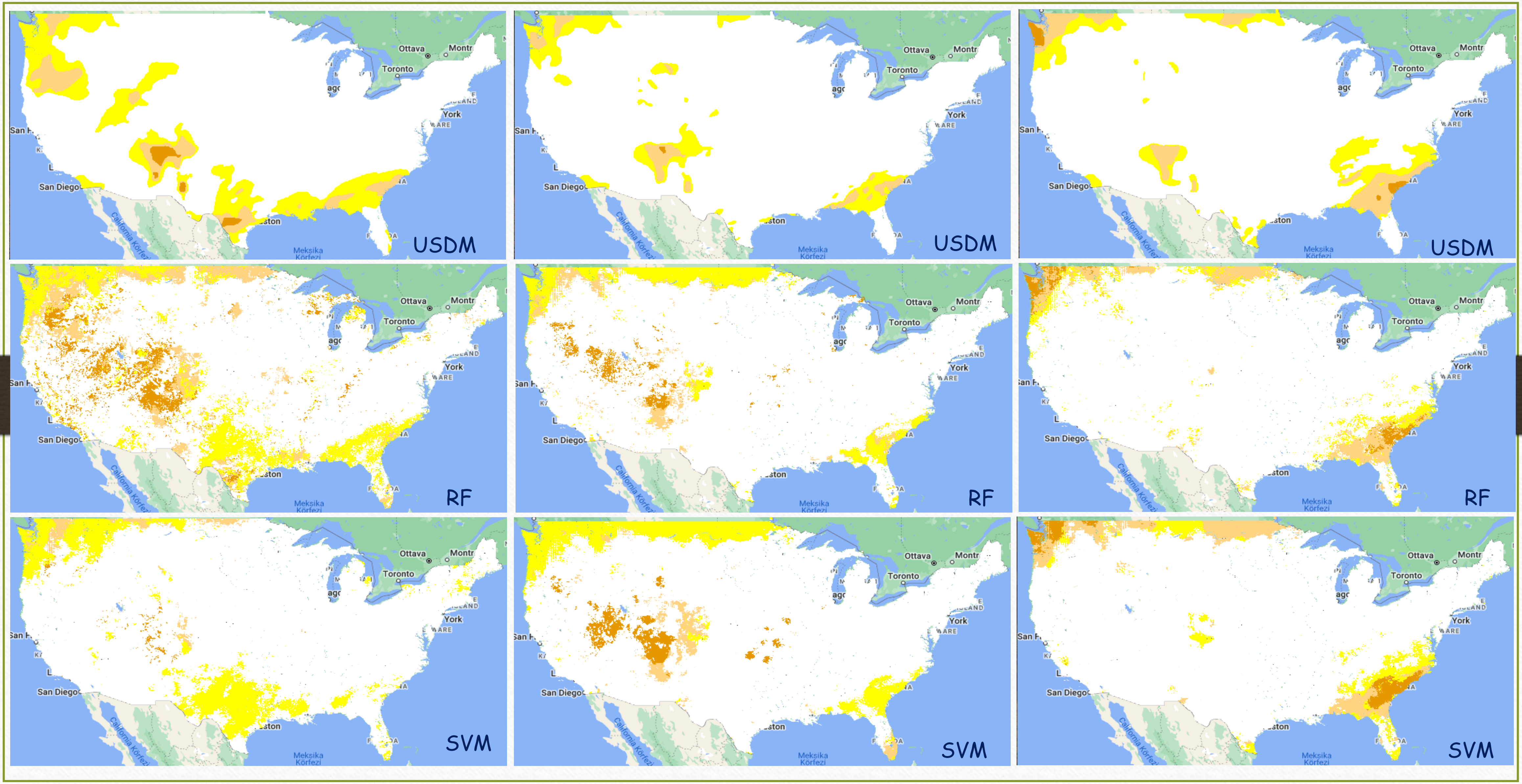
INPUTS

- ✓ SPI12, SPI6, SPI3, SPI1,
- ✓ TCI_12, VCI_12, VHI_12,
- ✓ TCI_6, VCI_6, VHI_6,
- ✓ TCI_3, VCI_3, VHI_3,
- ✓ TCI_1, VCI_1, VHI_1

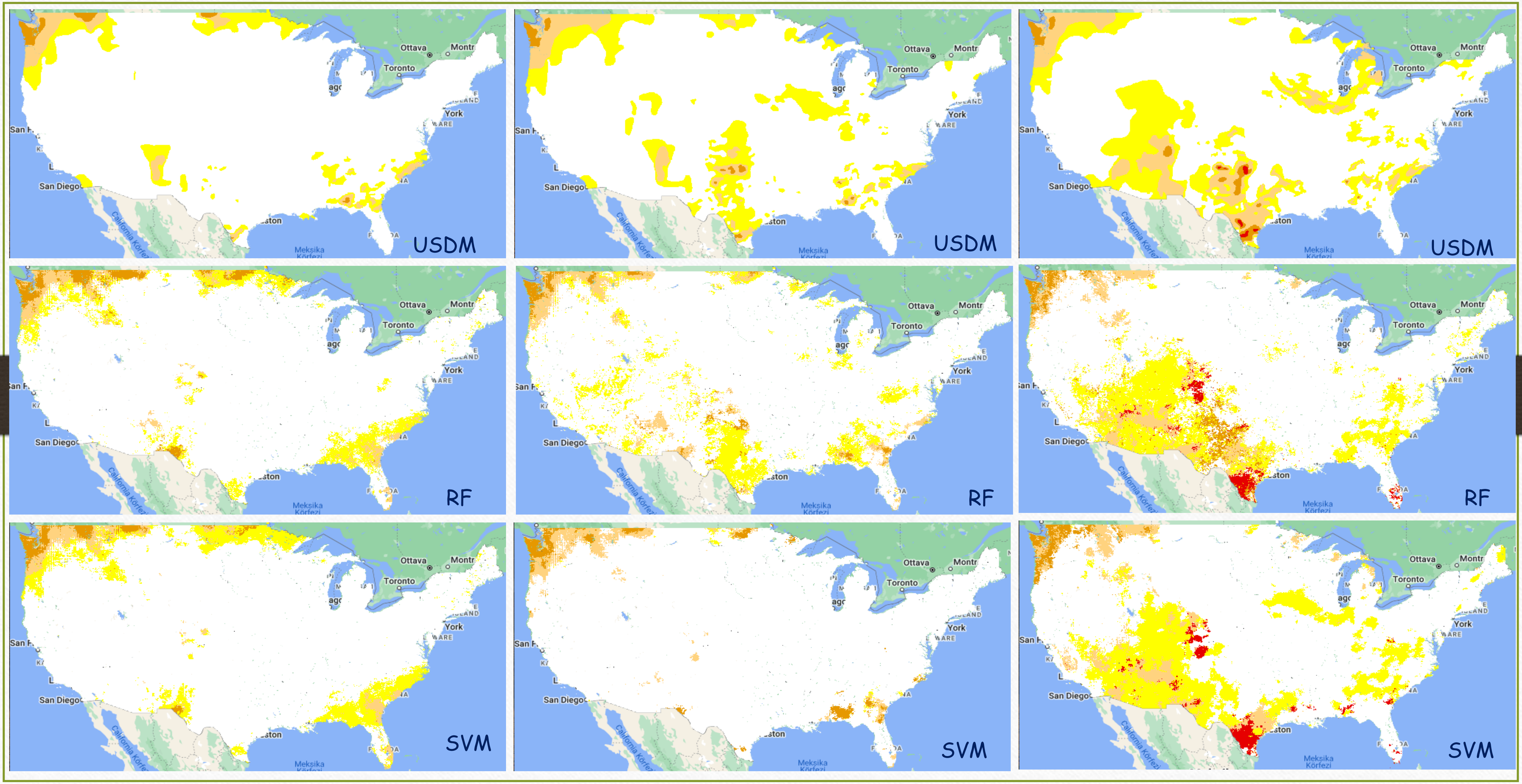
JANUARY 2019 FEBRUARY 2019 MARCH 2019



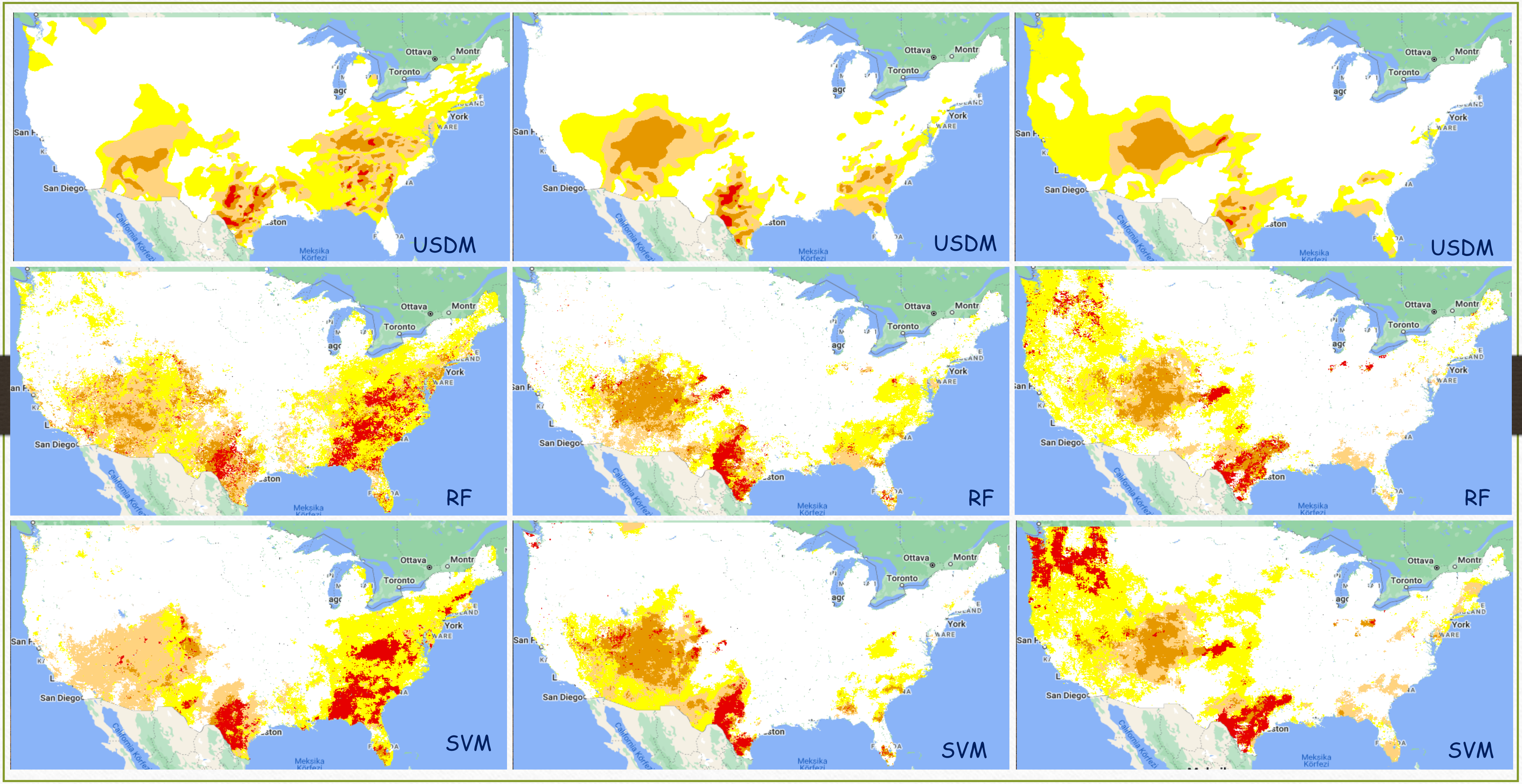
APRIL 2019 | MAY 2019 | JUNE 2019



JULY 2019 AUGUST 2019 SEPTEMBER 2019



OCTOBER 2019 NOVEMBER 2019 DECEMBER 2019



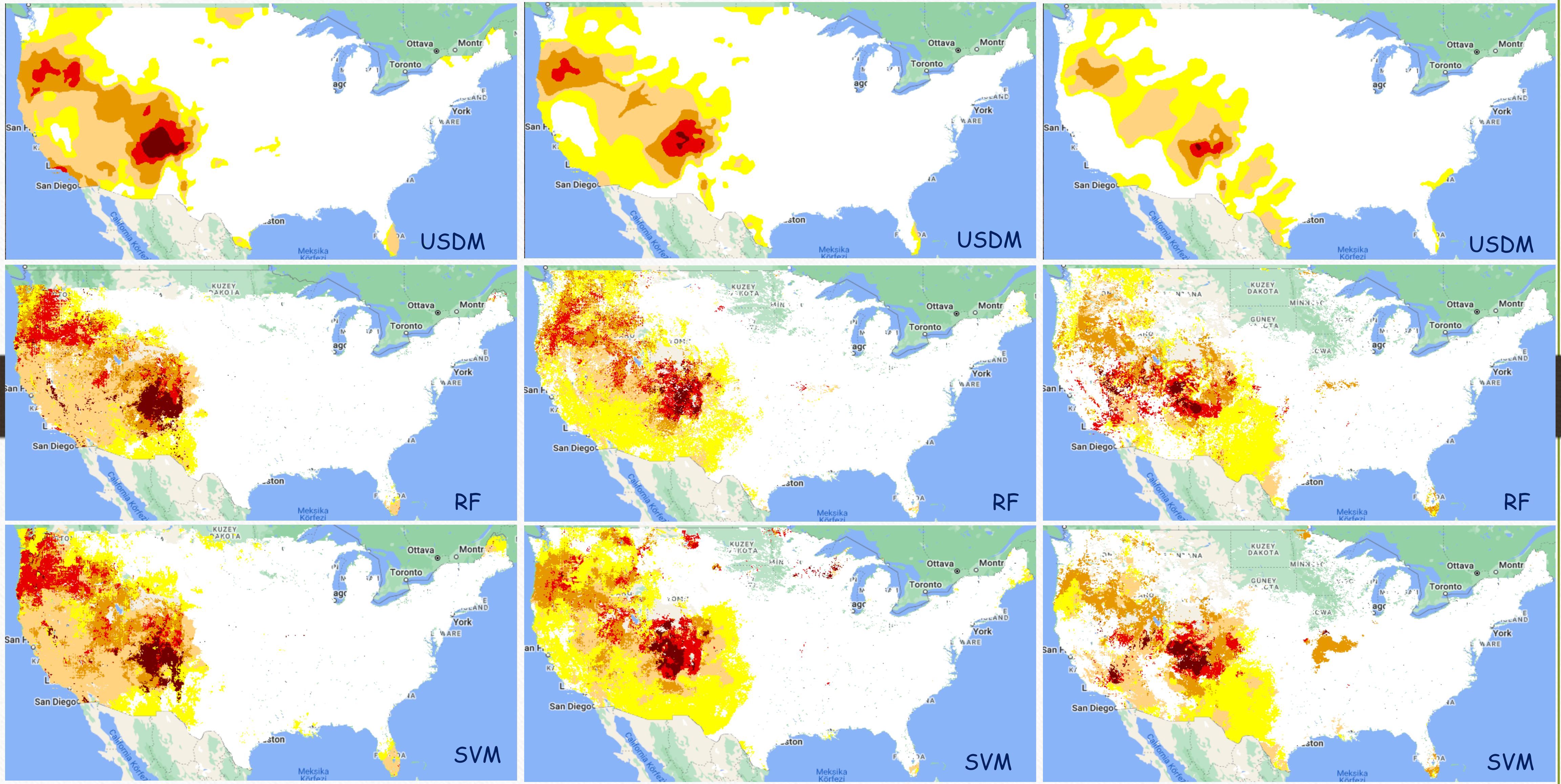
2019 ML BASED DROUGHT EXPERIMENTS

	January		February		March		April		May		June		July		August		September		October		November		December	
	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample
Non-Drought	5379878	100	5440696	100	5731662	100	6184107	100	7025333	100	6784303	100	7014857	100	6312129	100	5490549	100	4722416	100	5614778	100	5311947	100
D0	705450	34	1127538	40	1147373	40	1161288	39	569133	31	595600	32	525391	31	1138281	39	1518766	46	1567639	50	957720	38	1572430	47
D1	870559	36	698948	34	695142	34	378194	30	193771	27	372189	29	205553	27	299204	29	668674	34	1038878	41	728664	35	550060	33
D2	579623	32	375602	30	177073	27	68525	26	3878	25	40029	25	46314	25	42500	26	98537	26	401640	31	449723	31	349649	30
D3	168016	26	136646	27	38108	25	0	0	0	0	0	0	0	0	0	0	15589	25	61554	26	41236	26	8034	25
D4	88587	25	12684	25	2755	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

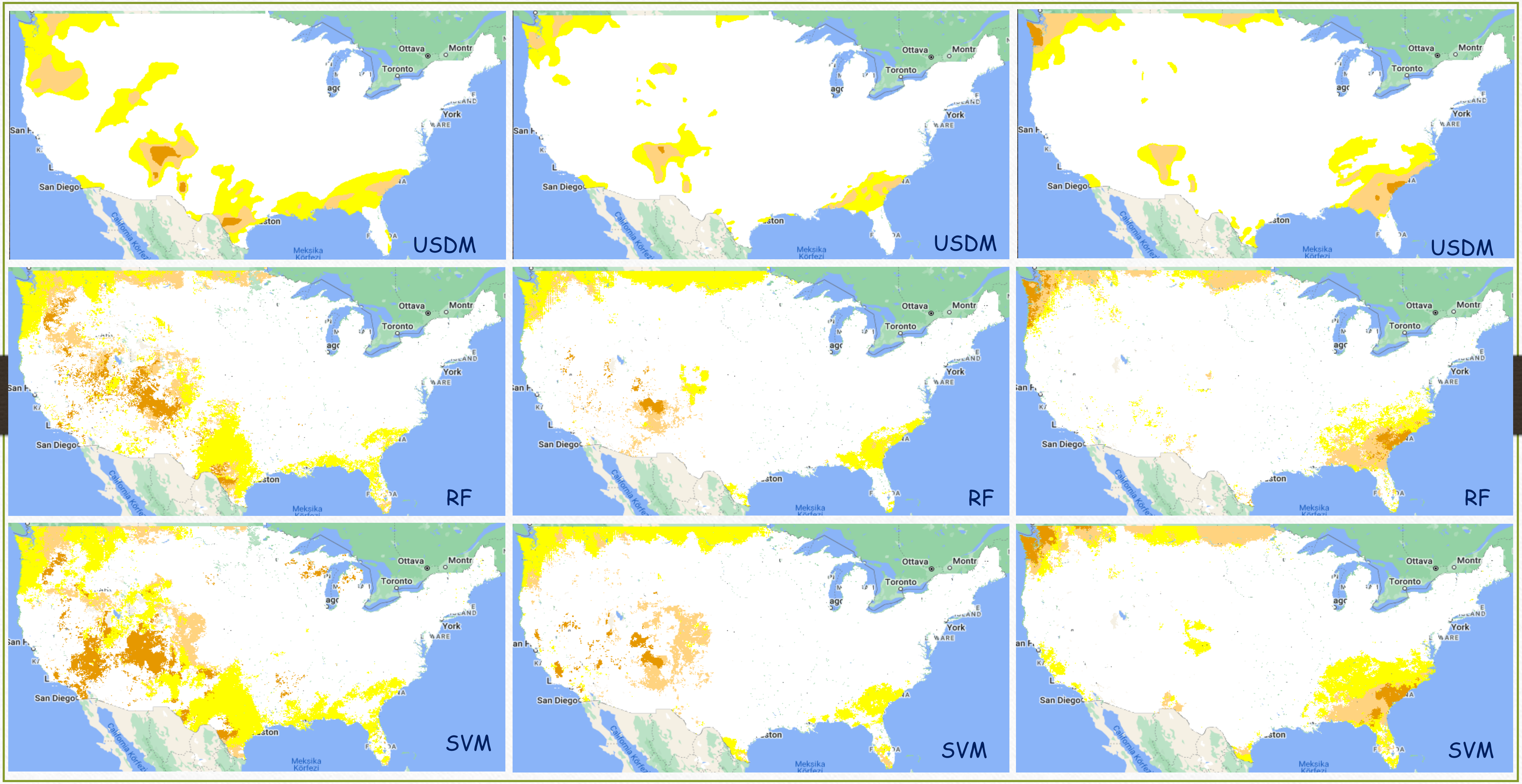
INPUTS

- ✓ SPI12, SPI6, SPI3, SPI1,
- ✓ TCI_12, VCI_12, VHI_12,
- ✓ TCI_6, VCI_6, VHI_6,
- ✓ TCI_3, VCI_3, VHI_3,
- ✓ TCI_1, VCI_1, VHI_1
- ✓ SSM,
- ✓ PDSI,
- ✓ ET/PET, Fire, precipitation

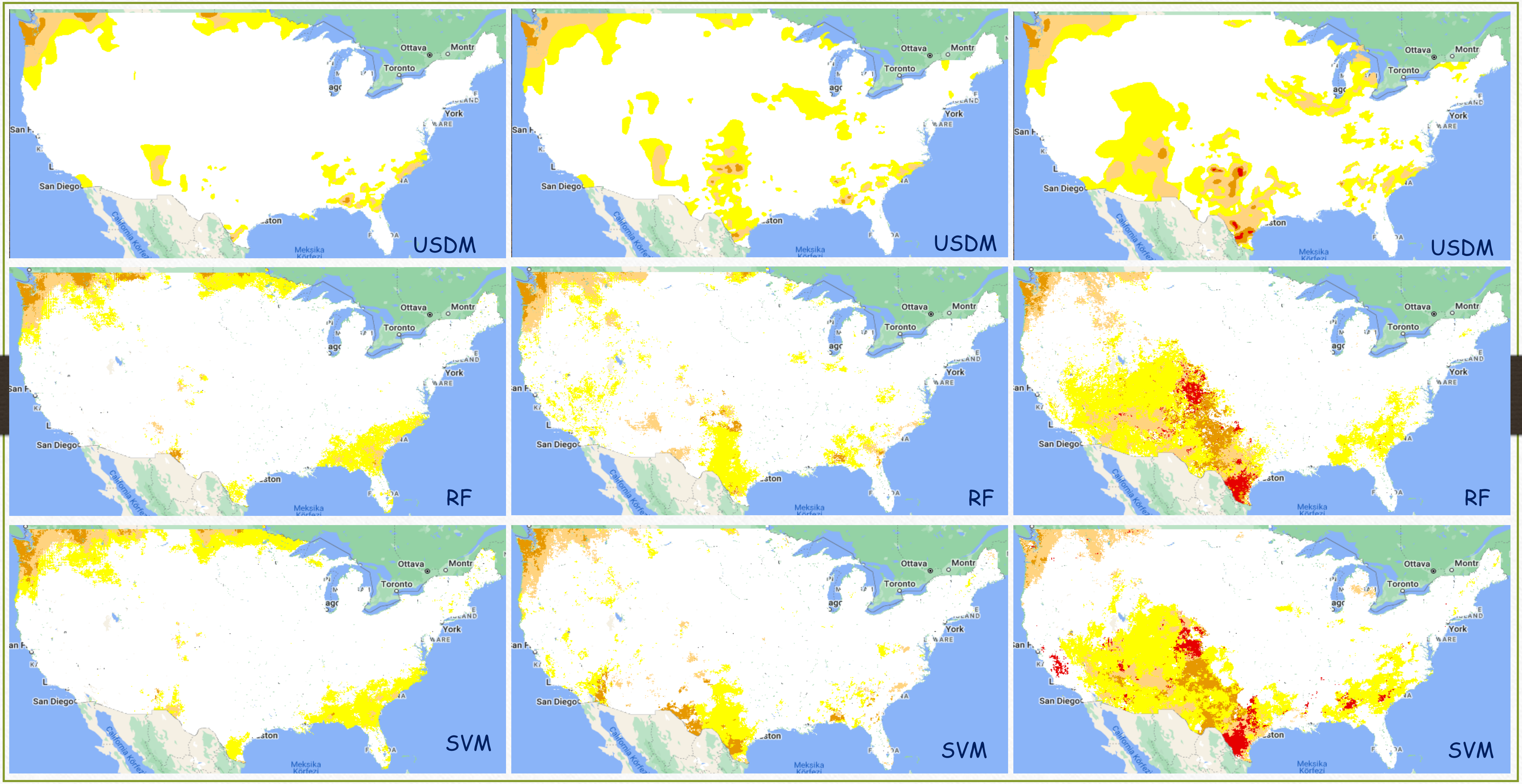
JANUARY 2019 FEBRUARY 2019 MARCH 2019



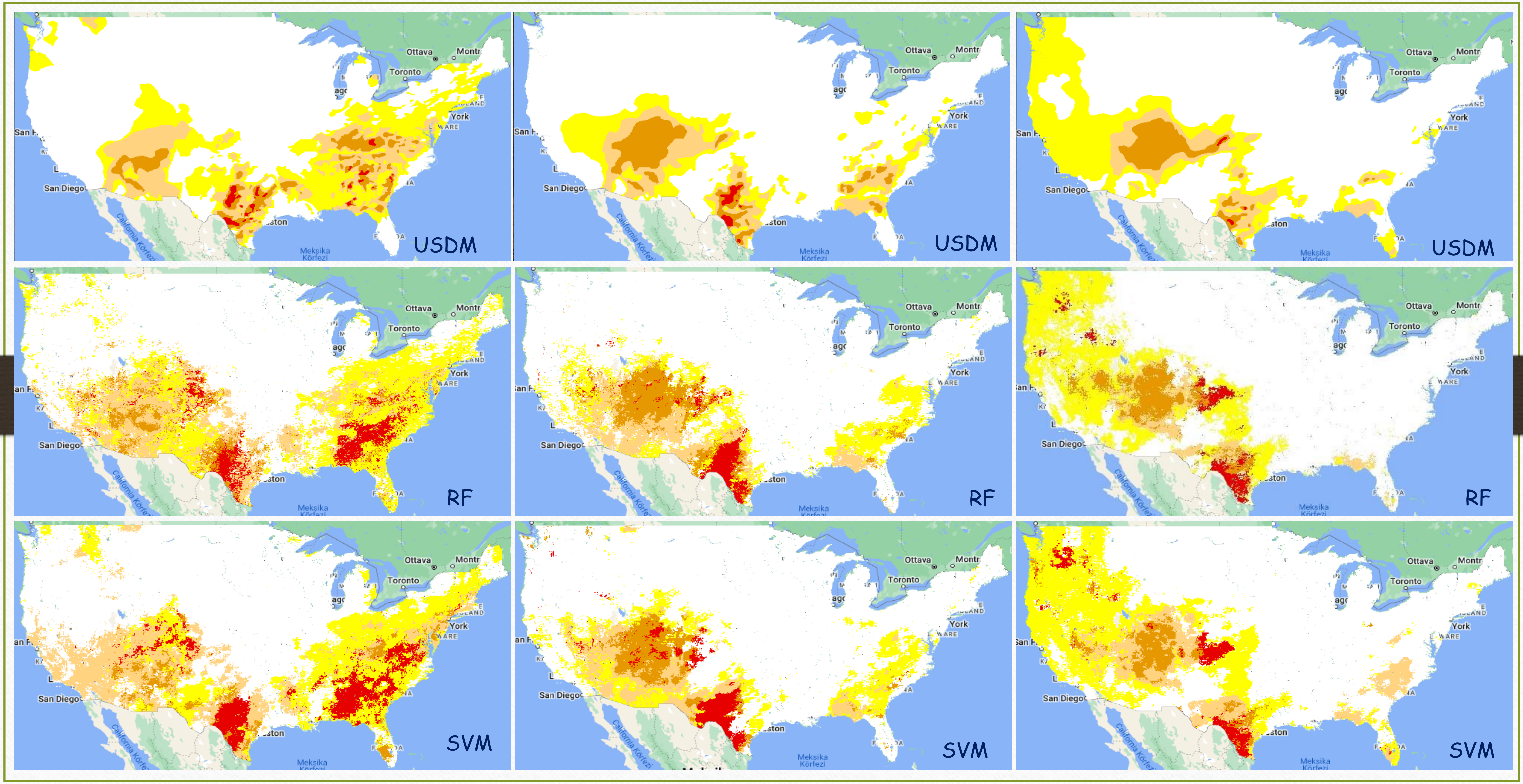
APRIL 2019 MAY 2019 JUNE 2019



JULY 2019 | AUGUST 2019 | SEPTEMBER 2019



OCTOBER 2019 NOVEMBER 2019 DECEMBER 2019



2021 ML BASED DROUGHT EXPERIMENTS

	January		February		March		April		May		June	
	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample
Non-Drought	2993223	100	2777114	100	2987333	100	2777117	100	2677005	100	3194520	100
D0	1234024	42	1448219	52	1175413	42	1504420	54	1487162	55	1192082	39
D1	1002492	34	1114378	40	1220108	43	1118519	40	1115931	41	1029947	34
D2	919162	31	864516	31	959260	35	814696	29	754317	27	740164	25
D3	905813	31	904202	33	788121	29	882682	32	1053265	38	874566	29
D4	737406	25	683684	25	661878	25	694680	25	704433	25	760839	26

	July		August		September		October		November		December	
	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample	Area (km)	Sample
Non-Drought	3309411	100	3570116	100	3516777	100	2932221	100	2899854	100	2181720	100
D0	798305	27	612378	26	720126	28	1161858	44	1166589	47	1282096	62
D1	825265	28	567699	25	771934	30	855514	35	1158242	47	1436264	69
D2	1089559	35	1016592	36	913412	33	1042189	40	1166087	47	1501748	72
D3	1030681	34	1330434	44	1276652	43	1249568	47	953850	40	1002742	51
D4	738892	25	694894	28	593213	25	550763	25	447491	25	387545	25

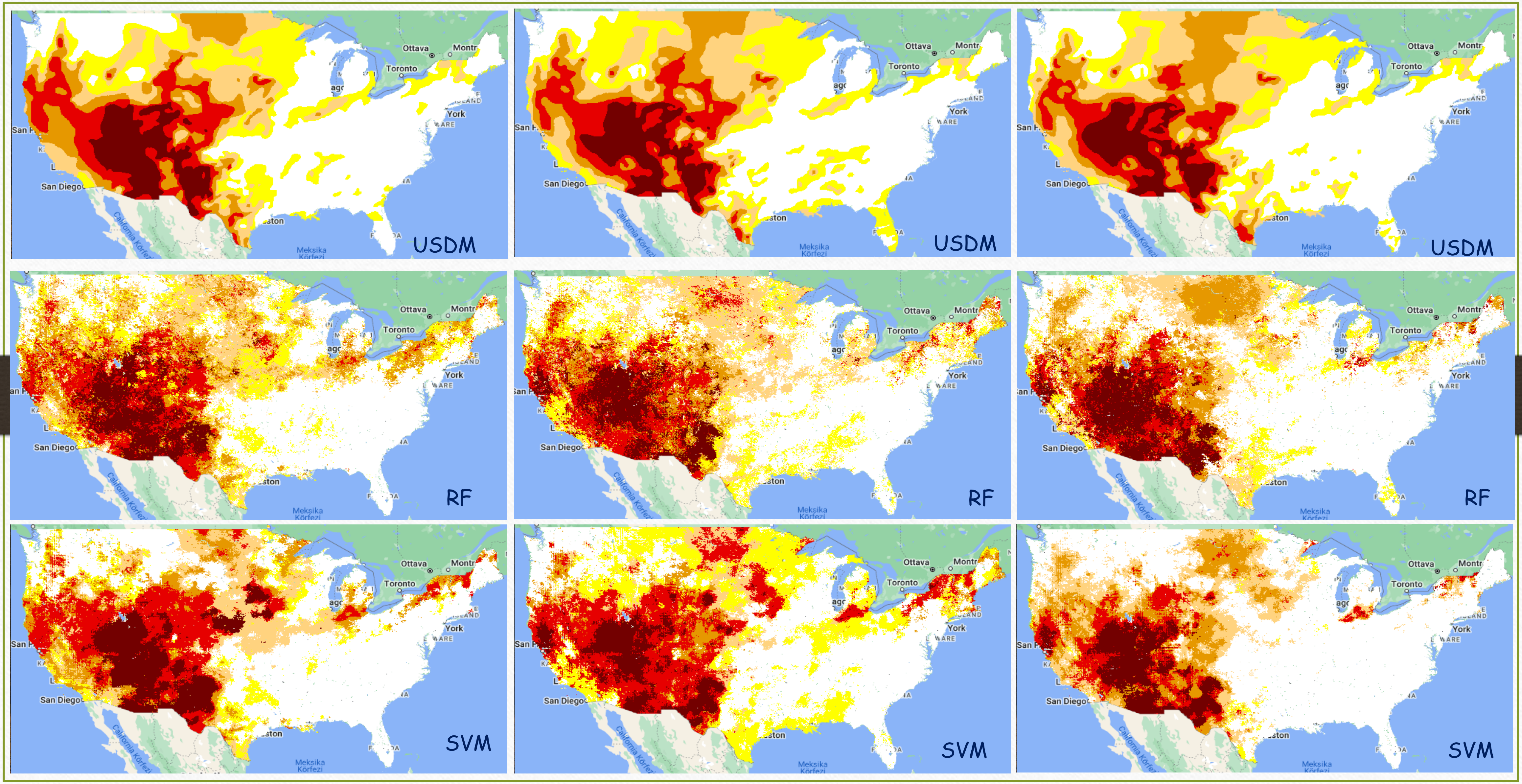
INPUT1

- ✓ SPI12, SPI6, SPI3, SPI1,
- ✓ TCI_12, VCI_12, VHI_12,
- ✓ TCI_6, VCI_6, VHI_6,
- ✓ TCI_3, VCI_3, VHI_3,
- ✓ TCI_1, VCI_1, VHI_1

INPUT2

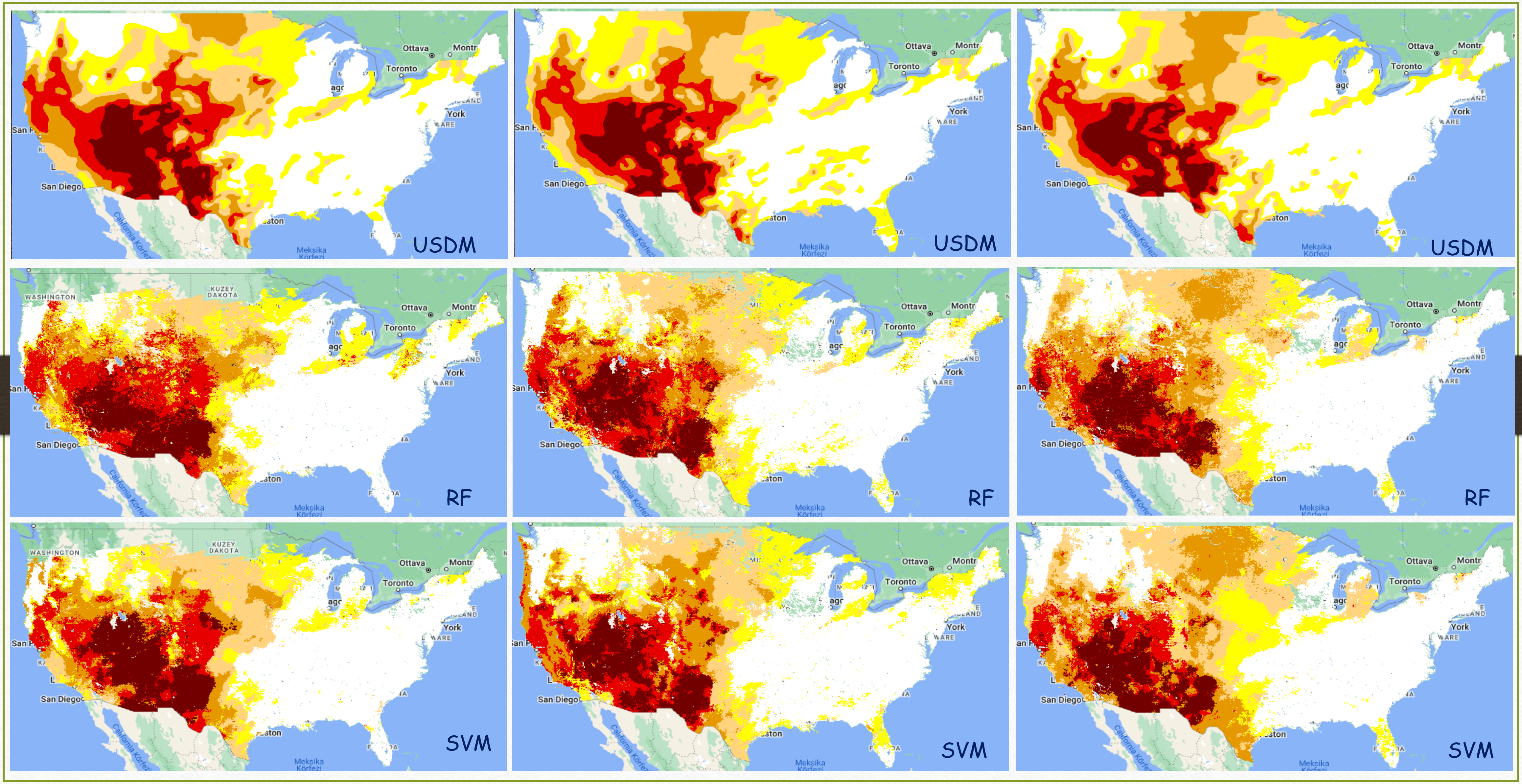
- ✓ SPI12, SPI6, SPI3, SPI1,
- ✓ TCI_12, VCI_12, VHI_12,
- ✓ TCI_6, VCI_6, VHI_6,
- ✓ TCI_3, VCI_3, VHI_3,
- ✓ TCI_1, VCI_1, VHI_1
- ✓ SSM,
- ✓ PDSI,
- ✓ ET/PET, Fire, precipitation

JANUARY 2021 FEBRUARY 2021 MARCH 2021



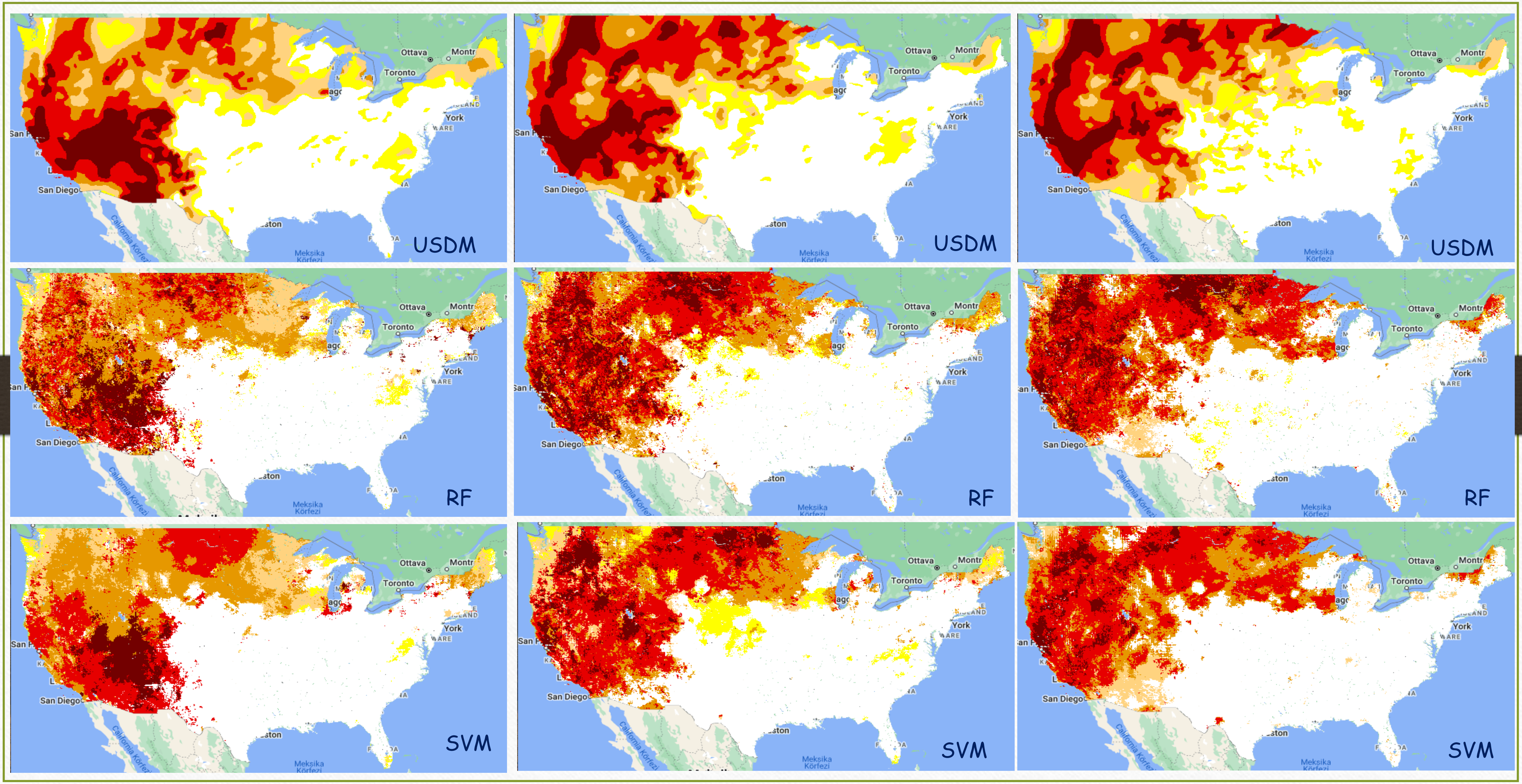
SPI12, SPI6, SPI3, SPI1, TCI_12, VCI_12, VHI_12, TCI_6, VCI_6, VHI_6, TCI_3, VCI_3, VHI_3, TCI_1, VCI_1, VHI_1

JANUARY 2021 **FEBRUARY 2021** **MARCH 2021**



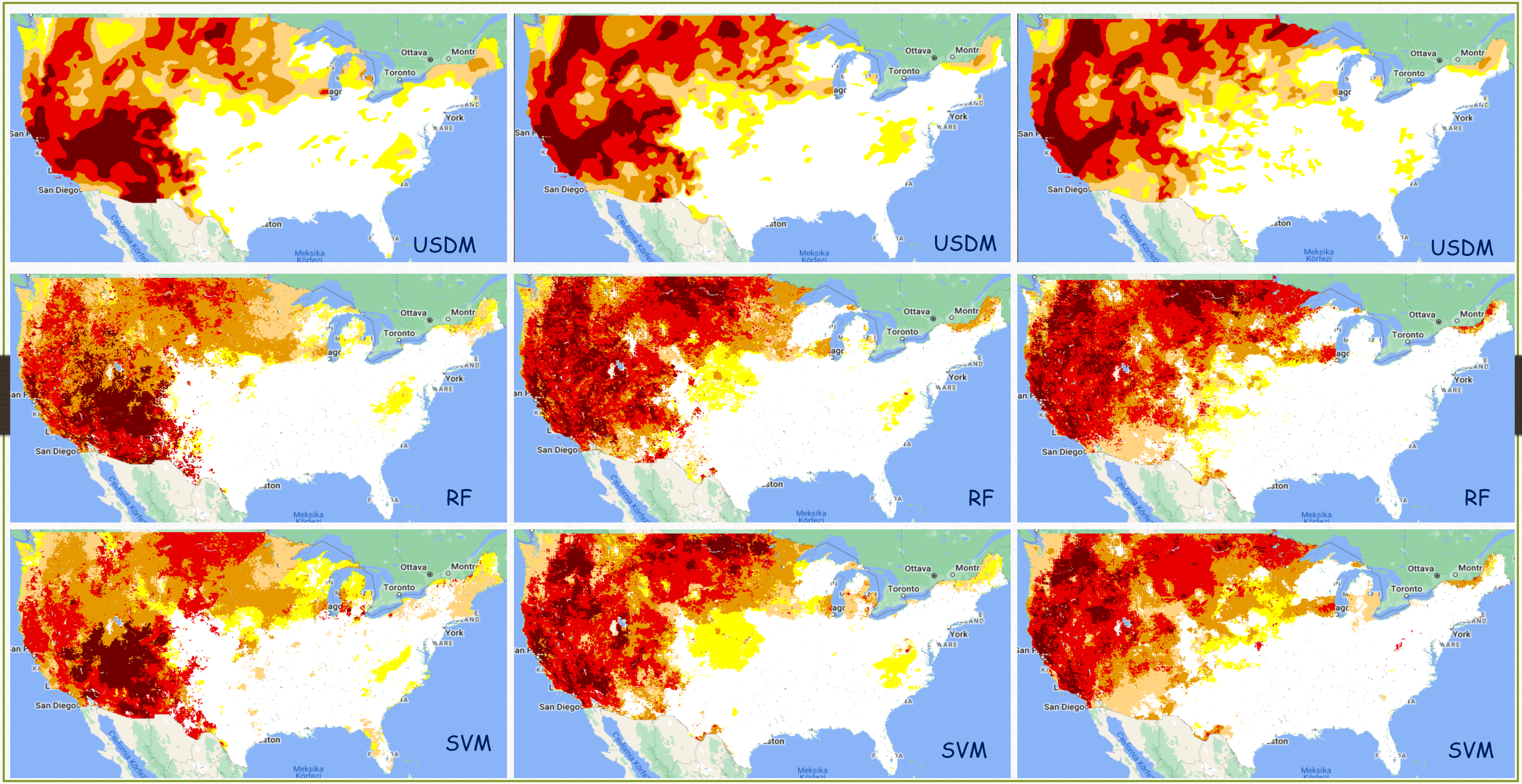
SPI12, SPI6, SPI3, SPI1, TCI_12, VCI_12, VHI_12, TCI_6, VCI_6, VHI_6, TCI_3, VCI_3, VHI_3, TCI_1, VCI_1, VHI_1, SSM, PDSI, ET/PET, Fire, precipitation

JULY 2021 AUGUST 2021 SEPTEMBER 2021



SPI12, SPI6, SPI3, SPI1, TCI_12, VCI_12, VHI_12, TCI_6, VCI_6, VHI_6, TCI_3, VCI_3, VHI_3, TCI_1, VCI_1, VHI_1

JULY 2021 AUGUST 2021 SEPTEMBER 2021



SPI12, SPI6, SPI3, SPI1, TCI_12, VCI_12, VHI_12, TCI_6, VCI_6, VHI_6, TCI_3, VCI_3, VHI_3, TCI_1, VCI_1, VHI_1, SSM, PDSI, ET/PET, Fire, precipitation

TEST ACCURACY ASSESSMENT

25 reference location for each drought class

	January		February		March		April		May		June		July		August		September		October		November		December	
	SVM	RF	SVM	RF	SVM	RF	SVM	RF	SVM	RF	SVM	RF	SVM	RF	SVM	RF	SVM	RF	SVM	RF	SVM	RF	SVM	RF
2019 SPI VHI	0.37	0.45	0.49	0.51	0.49	0.53	0.32	0.42	0.65	0.64	0.54	0.60	0.64	0.67	0.45	0.48	0.43	0.47	0.38	0.40	0.58	0.63	0.64	0.63
2019 ALL	0.47	0.56	0.52	0.51	0.55	0.53	0.48	0.46	0.67	0.64	0.59	0.65	0.60	0.62	0.49	0.53	0.45	0.52	0.43	0.47	0.58	0.62	0.68	0.67
2021 SPI VHI	0.49	0.49	0.33	0.43	0.42	0.45	0.49	0.45	0.47	0.43	0.43	0.44	0.39	0.42	0.39	0.45	0.38	0.37	0.41	0.41	0.37	0.43	0.37	0.47
2021 ALL	0.41	0.58	0.52	0.45	0.50	0.48	0.51	0.49	0.49	0.49	0.44	0.45	0.46	0.43	0.40	0.41	0.41	0.40	0.47	0.48	0.39	0.47	0.44	0.56

Challenges

- Lack of reliable and spatially dense reference data
- No Data values specifically in snowy and cloudy regions
- Different data periods for different datasets
- Scalability, transferability and generalizability
- Different results with different ML methods

Future Work

- Trying more features related with drought in ML models:
  - Different RS based drought indices for different periods,
  - Different precipitation indices,
  - LST data,
  - Soil moisture data
- Different ML algorithms:
  - XGBoost will be the next.
- Explanaible ML to better explain the results and impacts of different fatures.
- Analyzing different data periods and reference times.
- Further investigation of time series to better understand the relationship between optical remote sensing drought severity indices and meteorological drought severity indices.
- Cross-validate the scalability and the generalizability of the proposed models spatio-temporally.
- GeoAI based models for drought monitoring.

Refences

- Aksoy, S., Gorucu O., & Sertel E. (2019). “Drought Monitoring using MODIS derived indices and Google Earth Engine Platform”. In 2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics). Istanbul, Turkey: IEEE.
- Aksoy, S., & Sertel, E. (2021). Comparison of drought monitoring indices derived from MODIS and CHIRPS data using Google Earth Engine. In 9th Global Conference on Global Warming (GCGW-2021), Croatia, 4p.
- Aksoy, S., & Sertel E. (2022). “Comparison of Landsat and MODIS derived vegetation health indices for drought monitoring using google earth engine platform”. International Symposium on Applied Geoinformatics (ISAG 2021).

THANKS FOR YOUR ATTENTION..

sertele@itu.edu.tr