

DroughtDemo

January 23, 2020

1 Drought Indices

Different types of droughts:

Concentrating on meteorological droughts:

1.1 Standardized Precipitation Index (SPI):

Standardized Precipitation Index (SPI): The Standardized Precipitation Index (SPI) is a widely used index to characterize meteorological drought on a range of timescales. On short timescales, the SPI is closely related to soil moisture, while at longer timescales, the SPI can be related to groundwater and reservoir storage. The SPI can be compared across regions with markedly different climates. It quantifies observed precipitation as a standardized departure from a selected probability distribution function that models the raw precipitation data. The raw precipitation data are typically fitted to a gamma or a Pearson Type III distribution, and then transformed to a normal distribution. The SPI values can be interpreted as the number of standard deviations by which the observed anomaly deviates from the long-term mean. The SPI can be created for differing periods of 1-to-36 months, using monthly input data. For the operational community, the SPI has been recognized as the standard index that should be available worldwide for quantifying and reporting meteorological drought. Concerns have been raised about the utility of the SPI as a measure of changes in drought associated with climate change, as it does not deal with changes in evapotranspiration. Alternative indices that deal with evapotranspiration have been proposed (see SPEI).

1.1.1 Key Strength

- Uses precipitation only; can characterize drought or abnormal wetness at different time scales which correspond with the time availability of different water resources (e.g. soil moisture, snowpack, groundwater, river discharge and reservoir storage)
- More comparable across regions with different climates than the Palmer Severity Drought Index (PDSI)
- Less complex to calculate than the PDSI

1.1.2 Key Limitations

- As a measure of water supply only, the SPI does not account for evapotranspiration, and this limits its ability to capture the effect of increased temperatures (associated with climate change) on moisture demand and availability
- Sensitive to the quantity and reliability of the data used to fit the distribution; 30-50 years recommended
- Does not consider the intensity of precipitation and its potential impacts on runoff, stream-flow, and water availability within the system of interest
- Since temperature is not taken into account, interpret carefully over long time scales.

source: <https://climatedataguide.ucar.edu/climate-data/standardized-precipitation-index-spi>

1.2 Standardized Precipitation Evapotranspiration Index (SPEI):

The SPEI considers not only precipitation but also evapotranspiration (PET) data on its calculation, allowing for a more complete approach to explore the effects of climate change on drought conditions. The SPEI can be calculated at several time scales to adapt to the characteristic times of response to drought of target natural and economic systems, allowing determining their resistance to drought. A major advantage of the SPEI over other multiscalar drought indices such as the SPI is that it considers the role of temperature through its influence on potential evapotranspiration. Thus, the SPEI is adequate for assessing the impact of global warming on droughts.

source: https://www.researchgate.net/publication/252361460_The_Standardized_Precipitation-Evapotranspiration_Index_SPEI_a_multiscalar_drought_index

The cells below need to be executed to show effects of parameters. Data can be downloaded from: https://www.dropbox.com/sh/an281g5o4gfiu7g/AABJxOCjnY7dVUGro5FqK9_8a?dl=0. The file SimMatrix.csv highlights the possible combinations.

```
[1]: #import packages
import pandas as pd
import numpy as np
from bokeh.io import output_notebook, show
from bokeh.models.widgets import Slider
from bokeh.plotting import figure
import numpy as np
import xarray as xr
import holoviews as hv
import geoviews as gv
import geoviews.feature as gf

from cartopy import crs
from geoviews import opts

gv.extension('matplotlib', 'bokeh')

gv.output(size=150)
```

```

import xarray as xr
import cartopy.crs as ccrs

from collections import defaultdict
from bokeh.layouts import row, column, widgetbox, gridplot
from bokeh.models import Slider, LabelSet, Legend, Plot, LinearAxis, Grid,
↳MultiLine, HoverTool
from bokeh.plotting import figure, output_file, show, ColumnDataSource, curdoc
from bokeh.palettes import Spectral5
from bokeh.transform import factor_cmap
from bokeh.models.glyphs import VBar, Wedge, Line, Text
from math import pi
from bokeh.transform import cumsum
from bokeh.models.widgets import Div, Paragraph, Dropdown

```

```

[24]: # Search criteria
#Dataset 1:
dataset1 = 'GLDAS' #option 'GLDAS'
idx1 = 'SPI' #option 'SPI'
scales1 = 6 #option 12
distribution1 = 'gamma' #option 'Pearson'
Calibration_length1 = '15-year' #option '15-year'

#Dataset 2:
dataset2 = 'GLDAS'
idx2 = 'SPEI'
scales2 = 6
distribution2 = 'gamma'
Calibration_length2 = '15-year'

```

If running locally, change the path to the data.

```

[25]: # Get the master data
global drought_data
drought_data = pd.read_csv('/Users/deborahkhider/Documents/MINT/Drought/SimRuns.
↳csv')
path_file = ('/Users/deborahkhider/Documents/MINT/Drought/results/')

filename1 = drought_data[(drought_data['Index']==idx1)&\
                          (drought_data['Dataset']==dataset1)&\
                          (drought_data['Distribution']==distribution1)&\
                          (drought_data['Scales']==scales1)&\
↳
↳(drought_data['CalibLength']==Calibration_length1)]['Filename'].iloc[0]

filename2 = drought_data[(drought_data['Index']==idx2)&\
                          (drought_data['Dataset']==dataset2)&\

```

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        (drought_data['Distribution']==distribution2)&\
        (drought_data['Scales']==scales2)&\
        ↵
        ↪(drought_data['CalibLength']==Calibration_length2)]['Filename'].iloc[0]

```

```

[27]: #make the plot
d1 = xr.open_dataset(path_file+filename1)
d2 = xr.open_dataset(path_file+filename2)

varname1 = list(d1.data_vars.keys())[0]
dataset1 = gv.Dataset(d1, vdims=varname1)

varname2 = list(d2.data_vars.keys())[0]
dataset2 = gv.Dataset(d2, vdims=varname2)

hg=200

if 'latitude' in d1:
    ensemble1 = dataset1.to(gv.Image, ['longitude', 'latitude'], dynamic=True).
    ↪opts(cmap='BrBG', colorbar=True, backend='bokeh',tools=['hover'], height=hg)
elif 'lat' in d1:
    ensemble1 = dataset1.to(gv.Image, ['lon', 'lat'], dynamic=True).
    ↪opts(cmap='BrBG', colorbar=True, backend='bokeh',tools=['hover'], height=hg)

if 'latitude' in d2:
    ensemble2 = dataset2.to(gv.Image, ['longitude', 'latitude'], dynamic=True).
    ↪opts(cmap='BrBG', colorbar=True, backend='bokeh',tools=['hover'], height=hg)
elif 'lat' in d2:
    ensemble2 = dataset2.to(gv.Image, ['lon', 'lat'], dynamic=True).
    ↪opts(cmap='BrBG', colorbar=True, backend='bokeh',tools=['hover'], height=hg)

gv.output((ensemble1+ensemble2)*gf.coastline()*gf.borders,backend='bokeh')

```

:Layout

```

.DynamicMap.I :DynamicMap [time]
:Overlay
.Image.I :Image [lon,lat] (spi)
.Coastline.I :Feature [Longitude,Latitude]
.Borders.I :Feature [Longitude,Latitude]
.DynamicMap.II :DynamicMap [time]
:Overlay
.Image.I :Image [lon,lat] (spei)
.Coastline.I :Feature [Longitude,Latitude]
.Borders.I :Feature [Longitude,Latitude]

```

The cell below contains highlights the uncertainty associated with the data and parameters.

1. Uncertainty associated with the data

time: 2010-08-01 00:00:00

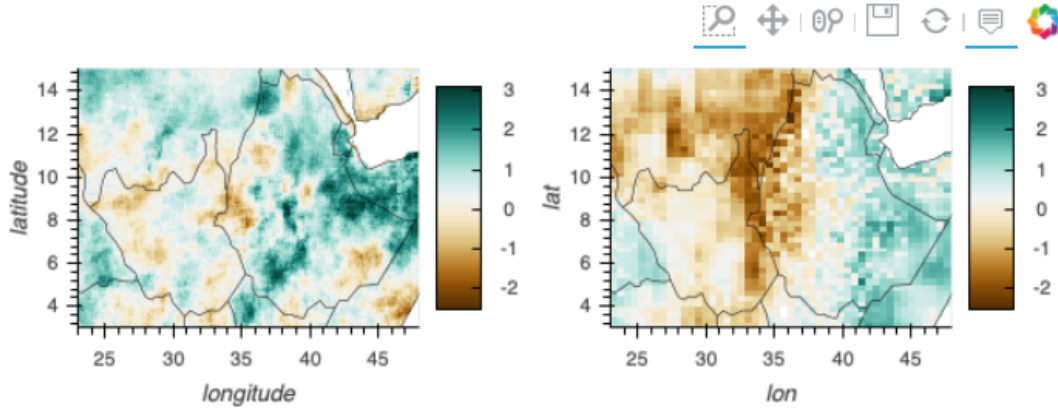
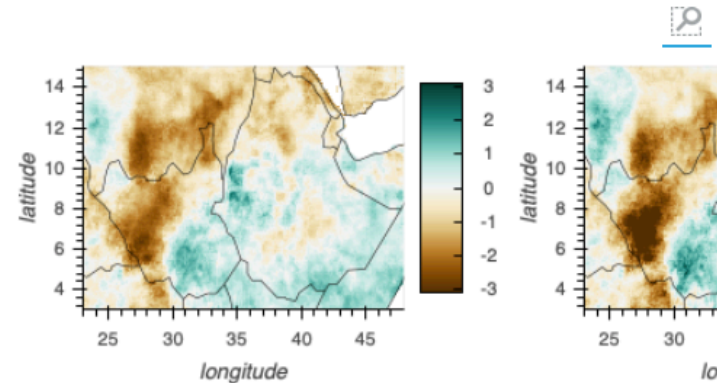


Figure 1:

SPI calculated from CHIRPS (left) and GLDAS (right) for August 2010. CHIRPS suggest wetter than usual conditions over most of South Sudan and Ethiopia while GLDAS suggest much drier conditions.

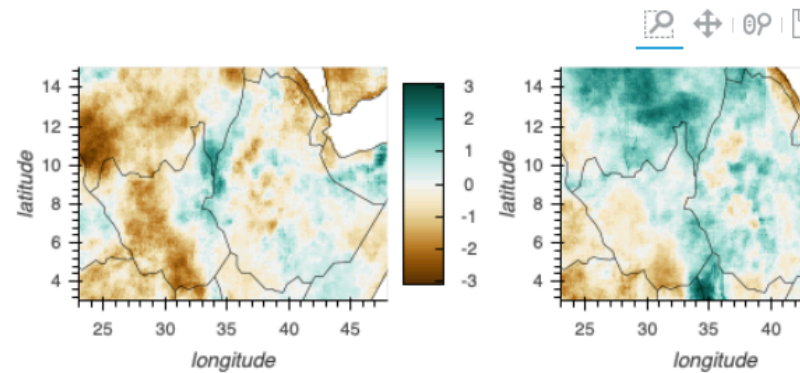
time: 2005-01-01 00:00:00



2. Uncertainty associated with the calibration period.

Figure 2: SPI calculated from CHIRPS using a 30-yr (left) and 15-yr (right) calibration period. Although the results are qualitatively the same, calibrating over a shorter time period leads to more extreme wet/dry conditions.

time: 2008-02-01 00:00:00



3. Uncertainty associated with the timescales.

Figure 3: The SPI was calculated from the CHIRPS dataset as the deviation from the

previous 6month (left) vs previous 12month (right). Establishing the proper period for comparison can be important to place droughts in proper context. This is not a one-size fit all approach. Different scales are appropriate for different months (wet vs dry period).

4. Uncertainty associated with the choice of the index.
time: 2007-12-01 00:00:00

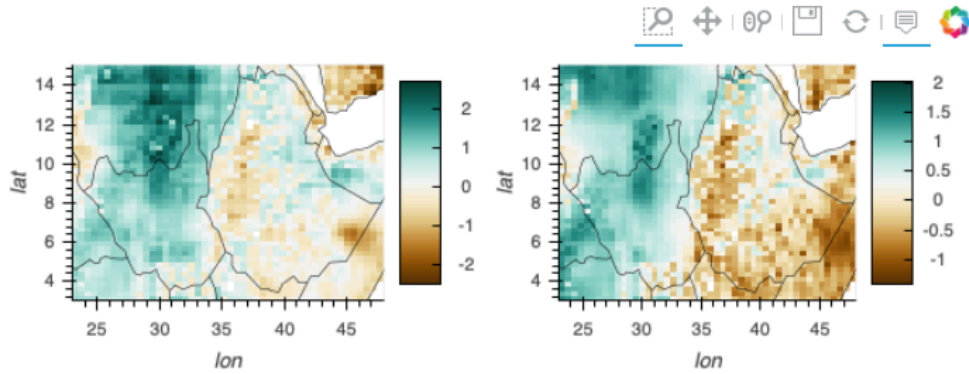


Figure 4: SPI (left) and SPEI (right) calculated from the GLDAS dataset. The difference between the two maps highlights the effect of temperature on drought in the region.

[]: