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Improving meteorological drought monitoring capability over tropical and subtropical water-limited ecosystems: evaluation and ensemble of the Microwave Integrated Drought Index

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Abstract
The monitoring of meteorological drought is critically important for tropical and subtropical water-limited ecosystems, which play key roles in the global carbon cycle and ecosystem services. Satellite remote sensing is the only practical approach for tracking drought changes with high resolution and an instantaneous response. However, the application of remote sensing drought indices derived from optical and infrared bands has been constrained due to cloud contamination. Here the Microwave Integrated Drought Index (MIDI), a multi-sensor microwave remote sensing drought index integrating state-of-the-art multiple satellite microwave-derived precipitation, soil moisture and land surface temperature information, was processed to improve the meteorological drought monitoring capability of satellite remote sensing. The index was evaluated against the 1 to 12 month field-based drought indicators Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) and anomalies in the satellite-derived Enhanced Vegetation Index (EVI) from 1998 to 2014. MIDI with an optimal ensemble of multiple satellite precipitation products showed a better improvement in meteorological drought monitoring capability than MIDI based on an individual satellite precipitation dataset, and had statistically strong correlation in particular with 1 month SPI/SPEI over a wide range of bio-climatic zones spanning from arid to humid. Moreover it showed significantly higher correlations with EVI anomalies than SPI/SPEI. The results demonstrated the reliability and superiority of MIDI in monitoring meteorological drought with the ability to work in all weather conditions. Therefore, MIDI provides a gateway to employing satellite microwave remote sensing for reliable meteorological drought monitoring, with the potential for long-term drought assessments as well as near-real-time drought monitoring using operational satellites.

1. Introduction

Water-limited ecosystems in the tropics and subtropics, where water availability is the main constraint to ecosystem productivity, play key roles in the carbon cycle, ecosystem services and the mitigation of human-induced climate change (Nemani et al 2003, Beer et al 2010, Liu et al 2015). However, these ecosystems are vulnerable to disturbances and climate extremes, especially drought, which causes plant mortality, ecosystem degradation and increased fire risk, ultimately inducing carbon losses (Reichstein et al 2013). These regions have been suffering from frequent droughts and are projected to withstand water stress under climate change in the future (Neelin et al 2006, Dai 2012). Drought is generally defined as a recurring extreme climate event with prolonged deficiency of precipitation (Dai 2011). It is further categorized as meteorological, agricultural, hydrological or socioeconomic drought (American
Meteorological drought usually occurs more frequently and triggers agricultural, hydrological and socioeconomic drought. Reliable meteorological drought monitoring with high spatio-temporal resolution over time is critically important for drought early warning and risk management in water-limited ecosystems.

Meteorological drought was traditionally monitored and evaluated by drought indices based on ground-based meteorological observations or interpolated grids, such as the Standardized Precipitation Index (SPI) (McKee et al. 1993), the Palmer Drought Severity Index (PDSI) (Palmer 1965) and the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al. 2010a, Vicente-Serrano et al. 2010b) at local, regional, and global scales. Among these, SPI is recommended by the World Meteorological Organization as the standard index for worldwide meteorological drought monitoring (Hayes et al. 2011). However, detailed spatio-temporal information about drought is constrained by the relatively coarse spatial resolution for depicting spatial heterogeneity. In addition, the accuracy of these indices is highly dependent on the density of the weather station network (Beck et al. 2017), while ground observations are sparsely distributed over tropical and subtropical regions in particular (Harris et al. 2014). On the other hand, the data products for drought indices are updated with long latency, and often provide monthly time series with, generally, a 1 year lag (Harris et al. 2014); they therefore cannot fulfill the time requirements for global drought assessment and early warning.

At a global scale, satellite remote sensing continuously observes surface environment processes and changes in space and time, providing various drought-related variables, and is becoming a unique tool for monitoring water availability in high spatio-temporal resolution with instantaneous response (AghaKouchak et al. 2015). In recent years, many drought indices based on satellite data have been proposed using individual or multiple variables/indicators, such as the Normalized Multiband Drought Index (NMDI) (Wang and Qu 2007), the Normalized Difference Drought Index (NDDI) (Gu et al. 2007), the Scaled Drought Condition Index (SDCI) (Rhee et al. 2010), the Multivariate Standardized Drought Index (MSDI) (Hao and AghaKouchak 2013), the Drought Severity Index (DSI) (Mu et al. 2013), the Microwave Integrated Drought Index (MIDI) (Zhang and Jia 2013), the Optimized Meteorological Drought Index (OMDI) (Hao et al. 2015) and the Process-based Accumulated Drought Index (PADI) (Zhang et al. 2017c). These drought indices based on multiple variables are more robust, with integrated information from different aspects related to drought such as precipitation, land surface temperature (LST), soil moisture, evapotranspiration and vegetation productivity (Zhang and Jia 2013, AghaKouchak et al. 2015, Zhang et al. 2017b). Moreover, the satellite-derived vegetation greenness of the Enhanced Vegetation Index (EVI) provides an independent reference for drought index evaluations at higher resolution.

Drought monitoring based on infrared and optical satellite observations is weather dependent and constrained by the unfavorable atmospheric conditions due to high cloud cover and aerosol concentration in the tropics and subtropics (Stubenrauch et al. 2013, Reddington et al. 2017). To avoid these constraints, we developed the multiple microwave satellite data-based index MIDI to integrate satellite microwave remote sensing-derived precipitation, soil moisture and LST, which can work in all weather conditions and therefore effectively overcome these problems (Zhang and Jia 2013). MIDI has been successful in monitoring meteorological drought over semi-arid regions and the Continental United States (Zhang and Jia 2013, Zhang et al. 2017b). However, its use in tropical and subtropical regions is limited; thus the capability of MIDI to monitor meteorological drought over pan-tropical water-limited ecosystems, which cover a wide range of bio-climatic zones spanning from arid to humid, needs to be extended.

To some extent, MIDI reduces uncertainty in monitoring drought compared with those indices that use only one variable/indicator because it integrates precipitation, soil moisture and LST in a relative easy way (Zhang and Jia 2013, AghaKouchak et al. 2015, Zhang et al. 2017b). However, even with intensive data quality control and validation the uncertainties still remain because MIDI uses one data source for each variable. Simultaneously, uncertainty is accompanied by the use of different data sources, which differ in retrieval algorithms as well as the sensor characteristics, with their own uncertainty (Kidd and Levizzani 2011, Hou et al. 2014). Ensemble usage of multi-source data has been widely adopted to reduce uncertainty in climate studies (Sheffield et al. 2012, Reddington et al. 2017). In addition, the increasing availability of MIDI-related remote sensing data, in particular satellite-derived precipitation (e.g. Joyce et al. 2004, Huffman et al. 2007, Ashour et al. 2015, Funk et al. 2015, Beck et al. 2017), now provides a unique opportunity to further improve MIDI’s capability in drought monitoring. A MIDI ensemble using multi-source satellite precipitation data is now possible in global drought monitoring.

Given the importance of MIDI in meteorological drought monitoring over pan-tropical regions as well as the increasing availability of MIDI-related satellite remote sensing datasets, here we further develop a regional extended MIDI to improve the meteorological drought monitoring capability of microwave remote sensing over tropical and subtropical water-limited ecosystems. More specifically, we have two main objectives: (1) to develop a regional extended MIDI based on different satellite precipitation datasets and evaluate their capability in monitoring meteorological drought by comparison with SPI and SPEI.
and (2) to verify whether MIDI based on an ensemble of different satellite precipitation datasets can improve drought monitoring capability. The key contribution of this study is providing a robust tool that works in all weather conditions to improve meteorological drought monitoring capability over tropical and subtropical water-limited ecosystems.

2. Data and methods

Several microwave satellite data products were collected and processed to develop a specific MIDI index for tropical and subtropical regions. The datasets continuously covered latitude bands of 38.50°S–38.50°N with 17-year observations from 1998 to 2014, and datasets were further processed to obtain monthly time series at a spatial resolution of 0.25° (table 1).

2.1. Remote sensing data and drought indices

2.1.1. Land cover data

Seven bio-climatic categories were reclassified from land cover types defined by the International Geosphere Biosphere Programme (2012 MCD12C1 051; https://lpdaac.usgs.gov/) with 0.25° resolution by majority class within each grid, including tropical forests (Evergreen Broadleaf forest), other forests (Evergreen/Deciduous Needleleaf forest, Deciduous Broadleaf forest and Mixed forest), shrublands (Closed and Open shrublands), savannas (Woody savannas and Savannas), grasslands (Grasslands), croplands (Croplands and Cropland/Natural vegetation mosaic) and others (Water, Permanent wetlands, Urban and built-up, Snow and ice, and Barren or sparsely vegetated) (figure 1(a)). Drought monitoring capability over the categories of other forests, shrublands, savannas, grasslands and croplands were investigated.

2.1.2. Precipitation data

Five state-of-the-art precipitation datasets, including CHIRPS (Funk et al 2015), CMORPH (Joyce et al 2004), PERSIANN_CDR (Ashouri et al 2015), TMPA (Huffman et al 2007) and MSWEP (Beck et al 2017) (table 1), were employed to evaluate their capability in monitoring meteorological drought. They derive from diverse algorithms and vary in spatial/temporal coverage, resolution and data sources (gauge, satellite and reanalysis). Satellite microwave observations are a major input of precipitation estimation algorithms. The average of annual mean precipitation of five datasets and their standard deviation compared with average precipitation were used to obtain climate characteristic and variance.

2.1.3. Microwave-derived soil moisture and land surface temperature

The European Space Agency Climate Change Initiative for soil moisture offers a long-term dataset of merged passive and active microwave observations, providing better performance in evaluating land surface moisture dynamics than retrievals from individual sensors over sparsely and moderately vegetated areas (Liu et al 2011, Liu et al 2012, Wagner et al 2012). It has been widely applied in monitoring land surface moisture changes (Dorigo et al 2017).

LST is derived from passive microwave observations using the Land Parameter Retrieval Model from the TRMM Microwave Imager (TMI) (Holmes et al 2009). The TRMM satellite was launched in late November 1997 and was decommissioned in April 2015 (https://trmm.gsfc.nasa.gov/); it produced continuous year-round observations for 17 years from 1998 to 2014. The LPRM LST was demonstrated to have similar accuracy with infrared observations (Parisussa et al 2008, Holmes et al 2009). The nighttime dataset was used due to its smaller temperature-related errors than daytime retrievals (Owe et al 2008).

2.1.4. MIDI

The Precipitation Condition Index (PCI), Soil Moisture Condition Index (SMCI) and Temperature Condition Index (TCI) were lineary scaled for each pixel based on monthly value (e.g. SM), absolute minimum (SMmin) and maximum values (SMmax) for the same month from 1998 to 2014, based on microwave remotely sensed precipitation, soil moisture and LST, respectively (table 2) (Zhang and Jia 2013): when values change from 0 to 1 this infers that climate changes from dry to wet.

MIDI integrates PCI, SMCI and TCI with flexible weights. Here, weights of 0.5, 0.3 and 0.2 were employed as jointly recommended by former independent evaluations, which both showed the best correlation with short-timescale SPI (Zhang and Jia 2013, Zhang et al 2017b). In addition, the fixed weights help to evaluate the capability of different satellite precipitation-based MIDs with the same criteria. Microwave remote sensing observations are the key input of MIDI, and MIDI can theoretically work in all weather conditions with high temporal resolution (daily datasets; table 1) at multiple timescales (e.g. week, half-month, month, season or year). Here, five individual satellite precipitation datasets of CHIRPS-, CMORPH-, PERSIANN_CDR-, TMPA- and MSWEP-based MIDI (specific MIDs) were processed at monthly intervals. Moreover, the ensemble mean of all five precipitation-based MIDs (Ensemble 5) and the ensemble mean of CHIRPS-, MSWEP-, PERSIANN_CDR- and TMPA-based MIDI (Ensemble 4) were further performed.

2.1.5. The EVI

The monthly (since 2000) MODIS EVI (MOD13C2 V006) with a spatial resolution of 0.05° was used to denote changes in the greenness of terrestrial vegetation. Data with pixel reliability of snow/ice, cloud and estimated were masked out. The standardized
Table 1. Details of satellite remotely sensed datasets related to MIDI. The common spatial and temporal coverage limited this study to latitude bands of 38.5°S–38.5°N and a time period spanning from 1998 to 2014. Datasets were further processed to 0.25° at monthly intervals.

| Short name | Full name and details | Data source(s) | Spatial resolution | Spatial coverage | Temporal resolution | Temporal coverage | References |
|------------|-----------------------|----------------|-------------------|------------------|-------------------|------------------|------------|
| Precipitation |                        |                |                   |                  |                   |                  |            |
| CHIRPS v.2.0 | Climate Hazards group Infrared Precipitation with Stations | Gauge and satellite infrared | 0.05° | 50°S–50°N | Daily, monthly | 1981–present | Funk *et al* (2015) |
| CMORPH_CRT v.1.0 | CPC MORPHing technique (bias corrected) | Satellite passive microwave and infrared | 0.25° | 60°S–60°N | Daily | 1998–present | Joyce *et al* (2004) |
| MSWEP v.1.0 | Multi-Source Weighted-Ensemble Precipitation | Gauge, satellite microwave and infrared, reanalysis | 0.25° | Global | Daily | 1979–present | Beck *et al* (2017) |
| PERSIANN_CDR v.01 | Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks for Climate Data Record | Satellite infrared and passive microwave | 0.25° | 60°S–60°N | Daily | 1983–present | Ashouri *et al* (2015) |
| TMPA 3B43 v.7 | Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis | Gauge, satellite microwave and infrared | 0.25° | 50°S–50°N | Monthly | 1998–2015 | Huffman *et al* (2007) |
| Land Parameter Retrieval Model (LPRM) derived Land Surface Temperature (LST) from TRMM Microwave Imager (TMI) NT_SOILM3.001 | Land Surface Temperature | Satellite passive microwave | 0.25° | 38.5°S–38.5°N | Daily | 1998–2014 | Holmes *et al* (2009) |
| Climate Change Initiative Soil Moisture CCI SM v.02.2 | Climate Change Initiative Soil Moisture | Satellite passive and active microwave merged | 0.25° | Global | Daily | 1978–2014 | Liu *et al* (2011), Liu *et al* (2012), Wagner *et al* (2012) |
anomalies \((a)\) of EVI (hereafter EVI anomalies) in a given month are calculated by the following equation based on the value \((x)\), long-term mean \((m)\) and standard deviation \((s)\) for the specific month:

\[
a = \frac{(x - m)}{s}. \tag{1}
\]

2.2. Meteorological data and drought indices

Global monthly precipitation from the Climate Research Unit (CRU TS3.23) dataset (http://badc.nerc.ac.uk/browse/badc/cru/data/cru_ts/cru_ts_3.23) (Harris et al 2014) from 1901 to 2014 with a spatial resolution of 0.5° was used to generate a 1 to 12 month SPI (McKee et al 1993); the shorter timescales are suitable for monitoring meteorological drought. The global monthly 0.5° gridded SPEI dataset was accessed from the website (http://digital.csic.es/handle/10261/128892) and is based on the CRU TS3.23 dataset. SPEI accounts for the effects of both precipitation and temperature (evapotranspiration) on drought (Vicente-Serrano et al 2010a, Vicente-Serrano et al 2010b). Monthly SPI and SPEI were further interpolated to 0.25° using nearest-neighbor sampling methods so as to be comparable with MIDI. The spatial distribution of ground stations within each pixel was obtained from the dataset (figure S1 is available online at stacks.iop.org/ERL/14/044025/mmedia).

2.3. SPI- and SPEI-based evaluation of MIDI

The correlation coefficients \((R)\) between 1 to 12 month SPI/SPEI and MIDI were calculated using Spearman correlation analysis, which measures the monotonic relationship between two variables based on ranks and is resistant to the effects of outliers (Helsel and Hirsch 2002). A \(p\) value of 0.05 is used to test significance.
The maximum Spearman’s rank correlation coefficient (hereafter the individual maximum correlation) between each precipitation-based MIDI and SPI/SPEI was used to evaluate the capabilities of different precipitation-based MIDIs. The maximum correlation coefficient (hereafter total maximum correlation) was further obtained from individual maximum correlations; and the corresponding MIDI type showed which precipitation performed better in space. Meanwhile, the standard deviation of five individual maximum correlations represented the uncertainty in correlations. Correlation anomalies were individual maximum correlations of specific MIDI or Ensemble MIDI minus total maximum correlations, and the percentages of the corresponding MIDI type (had the maximum correlation of specific MIDI and Ensemble MIDI) were extracted. They represented the improvement of Ensemble MIDI over individual MIDIs in drought monitoring capability.

2.4. EVI-based evaluation of drought indices
The cross-correlation coefficients (lag up to 9 months) between 1 month SPI, SPEI, MIDI and EVI anomalies were calculated using Spearman correlation analysis, and the correlations were used to evaluate the performances of drought indices as an independent reference.

3. Results and discussions
3.1. Evaluation of individual precipitation-based MIDIs
The individual absolute maximum correlations and corresponding timescale between five precipitation-based MIDIs and 1 to 12 month SPI/SPEI showed a similar spatial pattern, with slightly higher values for MIDI and SPEI, especially over South Asia (figures 2 and S1). Overall, overwhelmingly positive correlations were found, with an identical spatial gradient with a decreased correlation coefficient from middle to low latitudes. More significant correlations occurred in North America, southeastern South America, South Africa, eastern China and Australia, with correlation coefficients above 0.7, and moderate correlations (0.3 to 0.6) were found across lower latitudes, demonstrating reasonable performance of MIDI in monitoring large-scale droughts in these regions. The lowest correlations across tropical Africa were insignificant or even negative (figures 2(a)–(e) and S2(a)–(e)).

The percentages for individual maximum correlations with the corresponding SPI (SPEI) timescale were 73.8%, 62.6%, 72.9%, 73.4% and 71.5% (81.2%, 71%, 80.4%, 80.8% and 80.1%) of the CHIRPS-, CMORPH-, MSWEP-, PERSIANN_CDR- and TMPA-based MIDIs populated with 1 month SPI (SPEI) (figures 2 and S2). The ground weather station
density controlled the timescale distribution between PCI/MIDI and SPI/SPEI, the higher the density the higher the percentage in 1 month timescale (figures 2 and S1–4); a large part of Africa had the maximum correlations at scales over 2 months, owing to insufficient descriptions of drought heterogeneity in space and time monitored by SPI/SPEI as a result of sparsely distributed ground observations. Meanwhile, the meteorological drought index SPI or SPEI (SPEI covered an area about 10% greater in 1 month) and types of precipitation retrieval algorithm (CMORPH MIDI covered an area about 10% smaller) also influenced the percentages. The correlation analyses suggested that monthly MIDI derived from different satellite precipitation data was reliable in monitoring short-term drought, in particular meteorological drought.

3.2. Improved capability of ensemble MIDI in drought monitoring

The total maximum correlation showed similar spatial patterns to the individual maximum correlation (figures 3(a) and S5(a)). The CHIRPS-, CMORPH-, MSWEP-, PERISIANN_CDR- and TMPA-based MIDIs accounted for 29.8%, 2.7%, 20.3%, 26.2% and 21% (26.6%, 2.2%, 22.1%, 26.6%, and 22.5%) of the area of the corresponding total maximum correlation with SPI (SPEI), showing great heterogeneity in space. In other words none of them are clearly the best correlations individually, therefore no single dataset is superior to the others. Meanwhile, the standard deviation of individual maximum correlation showed relative greater values in general over global dry lands, central and southwestern China and areas neighboring tropical forest in Africa (figures 3(c) and S5(c)), following similar patterns to precipitation variance (figure 1(c)). Therefore, relatively higher uncertainty existed over such areas when using precipitation data from only one source satellite for drought monitoring. Furthermore, the mosaic distribution of MIDI type and approximate percentages provided a possible opportunity for ensemble utilization of a multi-source precipitation-based MIDI to further reduce the uncertainty and increase the capability for drought monitoring.

The statistics for correlation anomaly and percentage of corresponding MIDI type indicated a clear improvement in drought monitoring with an ensemble approach (figure 4). In general, the ensemble approach increased correlations and showed smaller discrepancies from the total maximum correlations than individual MIDIs, whatever MIDI ensemble (4 or 5) was used (figures 4(a) and (c)). In addition MIDI Ensemble 4 had the smallest correlation anomaly, and about 25% of the study regions showed higher correlations than the total maximum correlations. From the perspective of maximum correlation with the
Figure 4. Summary of statistics for correlation anomaly and percentage of corresponding MIDI type.

Figure 5. Maximum correlation between SPI, SPEI and MIDI Ensemble 4 in space and across bio-climatic zones. (a) Spatial patterns of maximum correlations between MIDI and 1 to 12 month SPI. (c) Box plots of the maximum correlation between SPI and MIDI Ensemble 4 across bio-climatic zones (the mean correlation is shown by blue dots). Parts (b) and (e) are the same as (a) and (c) but for correlations between SPEI and MIDI. Statistics of percentages of pixels in correlations are shown in (d).
corresponding MIDI type percentage, MIDI Ensemble 4 showed comparable or better performance than individual MIDIs (figures 4(b) and (d)). These facts indicate that an optimal ensemble effectively reduced the related uncertainty of the individual satellite precipitation-based MIDIs while the precipitation datasets differ in retrieval algorithms as well as sensor characteristics (which have their own uncertainty) (Kidd and Levizzani 2011, Hou et al 2014, Agha-Kouchak et al 2015); such an ensemble was also more reliable and had improved capability in drought monitoring. Consequently, the optimal Ensemble 4 of MIDI (hereafter MIDI) was further assessed.

MIDI showed identical spatial patterns in correlation with SPI and SPEI (figures 5(a) and (b)). Areas with strong correlations ($R > 0.60$) accounted for 40% and 46% of the correlation between SPI/SPEI and MIDI respectively, while limited pixels (8%) showed weak correlations ($R < 0.3$) (figure 5(d)). The mean correlation coefficients between MIDI and SPI (SPEI) were 0.62, 0.60, 0.55, 0.54 and 0.46 (0.62, 0.62, 0.57, 0.55 and 0.48) for categories of other forests, shrublands, croplands, grasslands, and savannas. Meanwhile global mean values were 0.54 and 0.55, respectively. This significant and robust widely distributed agreement suggested that monthly ensemble MIDI was reliable for monitoring meteorological drought. Shrublands exhibited the highest values at the 95th percentile, and savannas held the lowest values at the 5th percentile (figures 5(c) and (e)). The differences in correlations among categories were rather related to their distribution in space rather than bio-climatic type. For example, correlation coefficients for savannas in South America and Australia were much greater than for African savanna.
3.3. Superiority of MIDI in drought monitoring

Ideally, SPI/SPEI based on precipitation datasets with spatial resolution 0.25° may be considered as an appropriate reference for evaluating the performance of MIDI. SPI/SPEI detect drought based on statistical probability from long-term precipitation or evaporation records; the calculation of SPI requires at least 50 years’ precipitation record for drought monitoring periods of 1 year or less (Guttman 1999). However, ground precipitation records at high spatial resolution (0.25°) over 50 years are not available. As an alternative, here we use the satellite vegetation greenness anomalies of EVI to evaluate the drought indices as an independent factor at the same resolution as MIDI.

The correlations between MIDI and EVI anomalies were significantly higher than those between SPI/SPEI and EVI anomalies (figures 6 and 7). This demonstrates the superiority of MIDI for practical drought monitoring and disaster warning applications due to its more robust connections with vegetation as well as its reliability in drought monitoring. The connection between drought and vegetation growth is complex, and many factors may influence the correlations (Vicente-Serrano et al 2013). For example, the insignificant correlation over East Asia may be related to the intense human management in that region (Ouyang et al 2016).

The correlation between SPI/SPEI and MIDI exhibited a gradient that decreased from middle to low latitudes, and the gradient was tightly related to the distribution patterns of density of ground meteorological stations, showing significant and strong correlation (~0.70) by latitude (figure 7(a)). The relatively lower correlations in the tropics, in particular over Africa (figure 5), probably resulted from the bias of description of drought heterogeneity in space and time by SPI/SPEI through interpolation of insufficient ground gauge observations while satellite-derived MIDI directly observed spatio-temporal heterogeneity. Moreover, the correlation discrepancy among EVI and drought indices also provided similar evidence (figure 7(b)).

Maps were created to compare spatial patterns of drought conditions based on monthly MIDI, SPI and SPEI for January over Australia as an example (figures 8, S6 and S7). SPI and SPEI generally showed similar spatio-temporal patterns to that of MIDI except for drought severity and affected area (figures S6 and S7). The discrepancies were mostly related to different reference time periods, with the drought
categories of SPI/SPEI deriving from long-term probability distribution (1901–2014) (McKee et al 1993, Vicente-Serrano et al 2010a, Vicente-Serrano et al 2010b). However, MIDI was calculated only from 17 years of data; therefore, the relatively dry condition of MIDI may not be a dry spell from the point of view of the 100 year reference period for SPEI/SPI, resulting in a larger drought area and higher severity being detected by MIDI. More appropriate MIDI drought categories could be derived in future studies with a longer record of available data.

MIDI detected detailed drought distribution and heterogeneity, showing alleviation around 2006 and 2007 followed by a rebound in 2008. Water supply reached a peak around 2011, bringing exceptional vegetation greenness and a land carbon sink around 2011 (Poulter et al 2014, Zhang et al 2017a). However, water stress quickly intensified, in particular over central and eastern parts during 2013 and 2014, inducing a significant decline in vegetation greenness (figures 8 and S8). MIDI showed a stronger correlation with vegetation greenness than SPI/SPEI (figures 6 and S9), demonstrating the superiority of MIDI in drought monitoring.

The time period of this study is from 1998 to 2014 as a result of common spatial and temporal coverage of all the evaluated remote sensing data; the evaluations have demonstrated the reliability of ensemble MIDI in drought monitoring. The satellite precipitation datasets CHIRPS, MSWEP and PERSIANN_CDR provide archives from 1981, 1979 and 1983 to the present, while the datasets of CCI blended soil moisture and LPRM LST begin in 1978. Therefore, MIDI can be used for long-term drought assessments (~40 years). Beside the datasets used in this study, other datasets of satellite precipitation, soil moisture and LST could be integrated into further development of MIDI.

Satellite precipitation algorithms of CHIRPS, TMPA, CMORPH, MSWEP and PERSIANN, provide daily updated near-real-time retrievals with 2 days' latency. In addition, the Integrated Multi-satellite Retrievals for Global Precipitation Measurement (IMERG) provides better precipitation estimates than the TRMM satellite owing to the advanced onboard instruments (Huffman et al 2018), and it is also updated daily with 2 days' latency and can be included in the MIDI framework after March 2014. The ESA CCI blended soil moisture data is a near-real-time dataset with a maximum latency of 10 days, while the LPRM soil moisture derived data from the Advanced Microwave Scanning Radiometer 2 (AMSR2) routinely offers global daily near-real-time microwave soil moisture and LST with 2 days' latency. Therefore, MIDI has the potential capability to provide near-real time drought monitoring services at multiple timescales (daily, weekly, monthly and seasonal).

4. Conclusion

This study developed and systematically evaluated a broad-scale MIDI index to improve meteorological drought monitoring capability over tropical and subtropical water-limited ecosystems. MIDI was accomplished using state-of-the-art satellite microwave-derived precipitation data products of CHIRPS, CMORPH, MSWEP, PERSIANN_CDR, and TMPA, ESA CCI soil moisture and LPRM LST. The individual precipitation-based MIDI and ensemble of multiple precipitation-based MIDs were evaluated against 1 to 12 month SPI/SPEI/monthly EVI anomalies.

Individual precipitation-based MIDs had statistically high correlation in particular with 1 month SPI/SPEI, and showed similar spatial patterns. However, none of them was superior in holding the best correlations. Importantly, we further modified MIDI with an optimal ensemble of multiple precipitation, and the ensemble MIDI performed better than the individual precipitation-based MIDs. Moreover, ensemble MIDI showed significantly higher correlations with vegetation greenness than SPI/SPEI, demonstrating that ensemble MIDI has an increased drought monitoring capability. Therefore MIDI is suggested to be a reliable spatial indicator in monitoring meteorological drought across wide range of bio-climate zones spanning from arid to humid over tropical and subtropical water-limited ecosystems.

The study provides an option to employ satellite microwave remote sensing for reliable meteorological drought monitoring, with the potential for long-term drought assessments as well as near-real-time drought monitoring using operational satellites, benefiting decision making and operational applications.

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References

AghaKouchak A, Farahmand A, Melton F S, Teixeira J, Anderson M C, Wardlow B D and Hain C R 2015 Remote sensing of drought: progress, challenges and opportunities Rev. Geophys. 53 452–80
American Meteorological Society 1997 Meteorological drought policy statement Bull. Am. Meteorol. Soc. 78 847–9
Ashouri H, Hsu K-L, Sorooshian S, Braithwaite D K, Knapp K R, Cecil L D, Nelson B R and Prat O P 2015 PERSIANN-CDR:
daily precipitation climate data record from multisatellite observations for hydrological and climatic studies Bull. Am. Meteorol. Soc. 96 69–83
Beck H E, Van Dijk A J, Levizzani V, Schellekens J, Gonzalez Miralles D, Martens B and De Roo A 2017 MSWEP: 3-hourly 0.25 global gridded precipitation (1979–2015) by merging gauge, satellite, and reanalysis data Hydrol. Earth Syst. Sci. 21 389–615
Beer C et al 2010 Terrestrial gross carbon dioxide uptake: global distribution and covariation with climate Science 329 834–8
Dai A 2011 Drought under global warming: a review Wiley Interdiscip. Rev. Clim. Change. 2 45–65
Dai A 2012 Increasing drought under global warming in observations and models Nat. Clim. Change 3 52–8
Dorigo W et al 2017 ESA CCI soil moisture for improved Earth system understanding: state-of-the art and future directions Remote Sens. Environ. 203 185–215
Friedl M A, Sulla-Menashe D, Tan B, Schneider A, Ramankutty N, Sibley A and Huang X 2010 MODIS collection 5 global land cover: algorithm refinements and characterization of new datasets Remote Sens. Environ. 114 168–82
Funk C et al 2015 The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes Sci. Data. 2 150066
Gu Y, Brown J F, Verdin J P and Wardlow S 2007 A five-year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States Geophys. Res. Lett. 34 L06407
Guttmann N B 1999 Accepting the standardized precipitation index: a calculation algorithm J. Am. Water Resour. Assoc. 35 311–22
Hao C, Zhang J and Yao F 2015 Combination of multi-sensor remote sensing data for drought monitoring over Southwest China Int. J. Appl. Earth Obs. Geoinf. 35 270–83
Hao Z and AghaKouchak A 2013 Multivariate standardized drought index: a parametric multi-index model Adv. Water Resour. 57 12–8
Harriss I, Jones P D, Osborn T J and Lister D H 2014 Updated high-resolution grids of monthly climatic observations—the CRU TS3.10 dataset Int. J. Climatol. 34 623–42
Hayes M, Svoboda M, Wall N and Widhalm M 2011 The Lincoln Declaration on drought indices: universal meteorological drought index recommended Bull. Am. Meteorol. Soc. 92 485–8
Helsel D R and Hirsch R M 2002 Statistical Methods in Water Resources Techniques of Water Resources Investigations, Book 4, chapter A3 US Geological Survey (https://pubs.usgs.gov/twi/twi4a3/)
Holmes T R H, De Jeu R A M, Owe M and Dolman A J 2009 Land surface temperature from Ka band (37 GHz) passive microwave observations J. Geophys. Res. 114 D04113
Hou A Y, Kakar R K, Neeck S, Arzabanin A A, Kummerow C D, Kojima M, Oto R, Nakamura K and Iguchi T 2014 The global precipitation measurement mission Bull. Am. Meteorol. Soc. 95 701–22
Huffman G J, Bolvin D T, Braithwaite D, Hsu K, Joyce R, Kidd C, Nelkin E J, Sorooshian S, Tan J and Xie P 2018 GPM Integrated Multi-Satellite Retrievals for GPM (IMERG) Algorithm Theoretical Basis Document (ATBD)V5.2 (https://pmm.nasa.gov/sites/default/files/document_files/IMERG_ATBD_V5_2_0.pdf)
Huffman G J, Bolvin D T, Nelkin E J, Wolff D B, Adler R F, Gu G, Hong Y, Bowman K P and Stocker E F 2007 The TRMM multisatellite precipitation analysis (TMPA): quasi-global, multiyear, combined-sensor precipitation estimates at fine scales J. Hydrometeorol. 8 38–55
Joyce R J, Janowiak J E, Arkin P A and Xie P 2004 CMORPH: a method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolutions J. Hydrometeorol. 5 487–503
Kidd C and Levizzani V 2011 Status of satellite precipitation retrievals Hydrol. Earth Syst. Sci. 15 1109–16
Liu Y, Dorigo W A, Parinussa R M, de Jeu R A M, Wagner W, McCabe M F, Evans J P and van Dijk A J J M 2012 Trend-preserving blending of passive and active microwave soil moisture retrievals Remote Sens. Environ. 123 280–97
Liu Y, Parinussa R M, Dorigo W A, de Jeu R A M, Wagner W, van Dijk A J J M, McCabe M F and Evans J P 2011 Developing an improved soil moisture dataset by blending passive and active microwave satellite-based retrievals Hydrol. Earth Syst. Sci. 15 425–39
Liu Y, van Dijk A J J M, de Jeu R A M, Canadell J G, McCabe M F, Evans J P and Wang G 2015 Recent reversal in loss of global terrestrial biomass Nat. Clim. Change 5 470–4
McKeever T B, Doesken N J and Kleist J J 1993 The relationship of drought frequency and duration to time scales Proc. of the 8th Conf. on Applied Climatology (Anaheim, CA: American Meteorological Society) pp 179–84 (http://droughtresearch.info/literature/AMS_Relationship_of_Drought_Frequency_and_Duration_1993.pdf)
Mu Q, Zhao M, Kimball J S, McDowell N G and Running S W 2013 A remotely sensed global terrestrial drought severity index Bull. Am. Meteorol. Soc. 94 83–98
Neelis JD, Munnich M, Su H, Meyerson J F and Holloway CE 2006 Tropical drying trends in global warming models and observations Proc. Natl. Acad. Sci. USA 103 6110–5
Nemani R R, Keeling C D, Hashimoto H, Jolly W M, Piper S C, Tucker C J, Myneni R B and Running S W 2003 Climate-driven increases in global terrestrial net primary production from 1982 to 1999 Science 300 1560–3
Ouyang Z et al 2016 Improvements in ecosystem services from investments in natural capital Science 352 1455–9
Owe M, de Jeu R and Holmes T 2008 Multisensor historical climatology of satellite-derived global land surface moisture J. Geophys. Res. 113 F01002
Palmer W 1965 Meteorological Drought 45 US Department of Commerce, Weather Bureau Research Paper
Parinussa R M, de Jeu R A M, Holmes T R H and Walker J P 2008 Comparison of microwave and infrared land surface temperature products over the NAFeO6 research sites IEEE Geosci. Remote Sens. Lett. 5 783–7
Poulter B et al 2014 Contribution of semi-arid ecosystems to interannual variability of the global carbon cycle Nature 509 660–3
Reddington C L et al 2017 The Global Aerosol Synthesis and Science Project (GASSP): measurements and modeling to reduce uncertainty Bull. Am. Meteorol. Soc. 98 1857–77
Reichstein M et al 2013 Climate extremes and the carbon cycle Nature 500 287–95
Rhee J, Im J and Carbone G J 2010 Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data Remote Sens. Environ. 114 2875–87
Shields J, Wood E F and Roderick M L 2012 Little change in global drought over the past 60 years Nature 491 435–8
Stubenrauch C J et al 2013 Assessment of global cloud datasets from satellites: project and database initiated by the GEWEX radiation panel Bull. Am. Meteorol. Soc. 94 1031–49
Vicente-Serrano S M, Beguña S and López-Moreno J I 2010a A new environmental record for monitoring soil and vegetation moisture with satellite remote sensing Geophys. Res. Lett. 34 L19405

Zhang A and Jia G 2013 Monitoring meteorological drought in semiarid regions using multi-sensor microwave remote sensing data. *Remote Sens. Environ.* 134 12–23

Zhang A, Jia G, Epstein H E and Xia J 2017a ENSO elicits opposing responses of semi-arid vegetation between hemispheres. *Sci. Rep.* 7 42281

Zhang L, Jiao W, Zhang H, Huang C and Tong Q 2017b Studying drought phenomena in the Continental United States in 2011 and 2012 using various drought indices. *Remote Sens. Environ.* 190 96–106

Zhang X, Chen N, Li J, Chen Z and Niyogi D 2017c Multi-sensor integrated framework and index for agricultural drought monitoring. *Remote Sens. Environ.* 188 141–63