Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2017-196, 2017
Manuscript under review for journal Hydrol. Earth Syst. Sci.
Discussion started: 10 May 2017

Hydrology and Earth System Sciences
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Discussions

Comparing soil moisture anomalies from multiple independent sources over different regions across the globe

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Abstract: Agricultural drought events can affect large regions across the World, implying the urge for a suitable global tool for an accurate monitoring of this phenomenon. Soil moisture anomalies are considered a good metric to capture the occurrence of agricultural drought events, and they have become an important component of several operational drought monitoring systems. In the framework of the JRC Global Drought Observatory (GDO, http://edo.jrc.ec.europa.eu/gdo/) the suitability of modelled and/or satellite-derived proxy of soil moisture anomalies was investigated. In this study, three datasets have been evaluated as possible proxies of root zone soil moisture anomalies: (1) soil moisture from the Lisflood distributed hydrological model (LIS), (2) remotely sensed land surface temperature data from the MODIS satellite (LST), and (3) the combined passive/active microwave skin soil moisture dataset developed by ESA (CCI). Due to the independency of these three datasets, the Triple Collocation (TC) technique has been applied, aiming at quantifying the likely error associated to each

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dataset in comparison to the unknown true status of the system. TC analysis was performed on five macro-regions (namely North America, Europe, India, Southern Africa and Australia) detected as suitable for the experiment, providing insight into the mutual relationship between these datasets as well as assessment of the accuracy of each method. A clear outcome of the TC analysis is the good performance of remote sensing datasets, especially CCI, over dry regions such as Australia and Southern Africa, whereas the outputs of LIS seem to be more reliable over areas that are well monitored through meteorological ground station networks, such as North America and Europe. In a global drought monitoring system, these results can be used to design an ensemble system that exploits the advantages of each dataset.

1. Introduction

Drought is a recurring natural extreme, triggered by lower than normal rainfall, often exacerbated by a strong evaporative demand due to high temperatures and strong winds. Drought events may occur in all climates and in most parts of the world, since drought is defined as a temporary deviation from the local normal condition. Due to the usually wide extension of the interested area, drought affects millions of people across the Globe each year (Wilhite, 2000).

On the basis of the economic and natural sectors impacted by this phenomenon, a drought event is usually classified in meteorological, agricultural and hydrological drought, depending on the persistence of the water deficit within the hydrological cycle. Of particular interest for this study are the agricultural (or ecosystem) drought events, defined as prolonged periods with drier than usual soils that negatively affect vegetation growth and crop production, and, as a consequence, human welfare (Dai, 2011).

Soil moisture is commonly seen as one of the most suitable variables to monitor and quantify the impact of water shortage on vegetated lands due to its effects on the terrestrial biosphere and the feedback into the atmospheric system, as highlighted by the inclusion of soil moisture anomalies in numerous drought monitoring systems at regional to continental scales (i.e., European Drought Observatory, United States Drought Monitor, African Flood and Drought Monitor, among others).

Soil moisture monitoring over large areas is usually obtained through either distributed hydrological models or land-surface schemes of climate models (Crow et al., 2012; Sheffield et al., 2004), as well as by thermal or passive/active microwave remote sensing-derived quantities (see e.g., Anderson et al., 2007; Houborg et al., 2012; Mo et al., 2010). In the context of a global drought monitoring system, remote sensing-based approaches have the advantage of an intrinsic worldwide coverage, but the drawbacks, in the case of microwave sensors, of exploring only the first few centimeters of soil and a decreasing sensitivity with the increase of vegetation coverage (Jackson, 2006). In the case of thermal data, the lack of coverage during cloudy conditions and the nontrivial connection between thermal and soil moisture signals (Price, 1980) are other limitations. On the contrary, diagnostic models allow for a continuous monitoring of soil moisture at the desired soil depths, but the accuracy of the data is constrained by uncertainties in the parameterization of soil hydrological characteristics, as well as by the actual availability of near-real time reliable meteorological forcing data. Generally, the use of in-situ observations for large area monitoring is

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limited, mainly due to the lack of long records, the sparseness of recording stations and the high spatial heterogeneity of soil moisture fields.

It follows that both satellite measurements and model predictions are subject to errors and uncertainties that need to be accounted for in their interpretation and application (Gruber et al., 2016). This also suggests that a monitoring system based on a single model is rarely capable to provide global reliable estimates, and a combination of different data sources is desirable in order to minimize the errors in the detection of drought events. Recently, Cammalleri et al. (2015) demonstrated the value of an ensemble of modelled soil moisture anomalies for drought monitoring over Europe, similarly to the findings of the U.S. National Land Data Assimilation System (NLDAS) (Dirmeyer et al., 2006). However, a key point in combining different modelled data is the need to estimate the affinity and divergence between the models across the modelling domain.

In the most recent years, the Triple Collocation (TC) technique (Stoffelen, 1998) has been established as a practical approach to evaluate the unknown error variance (with respect to the truth) of three mutually independent measurement systems without knowing the “true” status of the system (Yilmaz and Crow, 2014). This technique has been widely applied in hydrology to estimate errors in soil moisture, as well as to evaluate precipitation and vegetation property indicators (Dorigo et al., 2010; McColl et al., 2014). One key requirement in TC is the existence of linearity between the three estimates and the truth, which can fail in the case of strongly seasonal geophysical variables such as soil moisture (Su et al., 2014). Luckily, drought monitoring systems are usually based on soil moisture anomalies rather than actual values, hence providing a partial remedy to this problem and making soil moisture anomalies directly suitable for this methodology (Miralles et al., 2010).

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In the frame of the operational monitoring of agriculture and ecosystem drought conditions in the Global Drought Observatory (GDO, http://edo.jrc.ec.europa.eu/gdo/), developed by the Joint Research Centre (JRC) of the European Commission, the soil moisture outputs of the Lisflood hydrological model and the land surface temperature (LST) anomalies derived from the Moderate-Resolution Imaging Spectroradiometer (MODIS) onboard the Terra satellite have been detected as suitable datasets for a near-real time monitoring. In particular, Cammalleri and Vogt (2016) have highlighted how LST anomalies represent the best proxy of soil moisture variations across different climates in Europe when compared to other LST-derived quantities.

As a third dataset for the TC analysis, the combined active/passive microwave soil moisture dataset produced by the European Space Agency (ESA) in the context of the Climate Change Initiative (CCI) is used; even if this dataset is not updated in near-real time, it represents a valuable reference dataset for a global consistent time-series of microwave-based soil moisture maps. The use of three independent sources of data (hydrological model, thermal and microwave remote sensing) helps ensuring to fulfill a key hypothesis of TC, which is the independency between the errors of the three models.

The overall goal of this study is twofold. First, the agreement between the monthly anomalies of the three models is evaluated, in order to identify the macro-areas where a reliable monitoring of soil moisture extreme conditions can be performed according to the available datasets. Second, the TC analysis is performed over those macro-areas to quantify the spatial distribution of the expected random errors for each model compared to the unknown true status in order to develop a suitable combination procedure for a near-real time detection of the occurrence of ecosystem drought events. Both goals will contribute to the development of a robust agricultural drought monitoring index within the GDO system.

2. Methods

Drought events are commonly defined as prolonged periods during which a given drought indicator significantly deviates from the usual condition for the specific site and period (e.g., soil moisture content is lower than the climatology). Following this definition, this study will focus on standardized z-score values in order to make directly comparable the different datasets (i.e., minimizing the differences related to seasonality, soil depth, etc.). Specifically, monthly z-score values, or anomalies, are evaluated as:

$$z_{x,i,k} = \frac{x_{i,k} - \mu_{x,i}}{\sigma_{x,i}} \quad (1)$$

where $x_{i,k}$ is the monthly average variable for the i-th month at the k-th year, $\mu_{x,i}$ and $\sigma_{x,i}$ are the long-term average and standard deviation of the variable x for the i-th month, respectively. The baseline period adopted to compute the reference μ and σ twelve monthly values should be of 15-30 years in order to ensure a stable benchmark. The three datasets used here, as described in the next section, are the root zone soil moisture data from the Lisflood model (x = LIS), the ESA skin soil moisture microwave combined product (x = CCI) and the thermal remote sensing derived land surface temperature (x = LST); in the case of LST data, the sign of the anomalies is reversed due to the expected inverse relationship between soil moisture and LST.

The time-series of anomalies computed according to Eq. (1) are characterized by a null average and a unitary standard deviation, making a direct comparison of the different datasets simpler; additionally, in this particular case the Pearson correlation coefficient, R, represents not only a measure of the linear dependency of the two random quantities but also the slope of the linear relationship and a proxy of the difference and biases of the two datasets. In this respect, R can be seen as a good synthetic descriptor of the relationship between two standardized z-score datasets. The statistical significance of the existence of a positive correlation can be evaluated by means of the t-student test (2 sided) by computing the R value corresponding to a significance level $p = 0.05$.

Analysis of the correlation among the datasets is interesting in the framework of the triple collocation (TC) technique and its basic hypotheses. In TC, a first key hypothesis is the existence of linearity between the 'true' status of the system and the three models; this is formally expressed as:

$$z_x = \alpha_x + \beta_x z_\Theta + \varepsilon_x \quad (2)$$

where z_Θ is the unknown true dataset of soil moisture anomalies, α_x and βx are the systematic slope and bias parameters for the dataset x with respect to the truth, and ε_x is the additive zero-mean random noise. It follows that the absence of a statistical significant linear relation between all three models openly violates this hypothesis.

Other key underling hypotheses of TC are the stationarity of both signals and errors, the independency between the errors and the signal (error orthogonality) and the independence between the errors of the three datasets (zero-cross correlation) (Gruber et al., 2016). Under these assumptions, Stoffelen (1998) proposed a formulation to estimate each model error variance, $\sigma^2_{\varepsilon x}$, based on a combination of the covariance between the datasets. In this approach, known as the covariance notation

(Gruber et al., 2016), the error variance values are computed without a common (arbitrary) reference dataset as:

$$\sigma_{\varepsilon_1}^2 = \sigma_1^2 - \frac{\sigma_{12}\sigma_{13}}{\sigma_{23}}$$
$$\sigma_{\varepsilon_2}^2 = \sigma_2^2 - \frac{\sigma_{21}\sigma_{23}}{\sigma_{13}} \qquad (3)$$
$$\sigma_{\varepsilon_3}^2 = \sigma_3^2 - \frac{\sigma_{31}\sigma_{32}}{\sigma_{12}}$$

where, for the sake of simplicity, LIS, LST and CCI where renamed 1, 2, 3, respectively. The first term on the right side of Eqs. (3) represents the single model data variance, whereas the second term represents the so-called sensitivity of the model to variations in the true status, which is a function of the covariance terms between the three models. The advantage of this formulation is to directly estimate the unscaled error variances, which can (eventually) be scaled to a common data space, if needed.

Different performance metrics can be derived from the covariance notation, including relative error variance metrics such as the fractional root-mean-squared-error (fRMSE, Draper et al., 2013) and the correlation coefficient of each model with the underlying true signal (McColl et al., 2014). However, these metrics can be derived from each other by means of simple relationships (see Gruber et al., 2016) and they are analogous to the absolute error values in the case of z-score values that have known unitary dataset variance.

3. Data and Materials

3.1 Lisflood model soil moisture

Root zone soil moisture dynamics are simulated by means of the Lisflood model (de Roo et al., 2000), a GIS-based distributed hydrological rainfall-runoff-routing model designed to reproduce the main hydrological processes that occur in large and trans-national European river catchments. The model simulates all the main hydrological processes occurring in the land-atmosphere system, including infiltration, actual evapotranspiration, soil water redistribution in three sub-layers (surface, root zone and sub-soil), surface runoff rooting to channel, and groundwater storage and transport (Burek et al., 2013).

Static maps used by the model are related to topography (i.e., digital elevation model, local drain direction, slope gradient, elevation range), land use (i.e., land use classes, forest fraction, fraction of urban area), soil (i.e., soil texture classes, soil depth), and channel geometry (i.e., channel gradient, Manning's roughness, bankfull channel depth, channel length, bottom width and side slope). The soil-related quantities are obtained from the ISRIC 1-km SoilGrids database (Hengl et al., 2014), whereas topography data are obtained from the Hydrosheds database (Lehner et al., 2008).

Daily meteorological forcing maps are derived from the European Centre for Medium-range Weather Forecasts (ECMWF) data as spatially resampled and harmonized by the JRC Monitoring Agricultural ResourceS (MARS) group. The dataset includes daily average air temperature, potential evapotranspiration (for soil, water and reference surfaces) and total rainfall at 0.25 degree spatial resolution, which were resampled on the model grid using the nearest neighbors algorithm.

The model run used in this study includes daily maps at 0.1 degree resolution between 1989 and 2015; the grid domain of this dataset is used as reference for the other two, whereas the baseline for the anomalies computation is defined by the period 2001-2015 in order to match the LST data availability.

Monthly data to be used in Eq. (1) are computed as a simple average of all the data available for each month, given that no gaps can be found in this dataset due to its continuous nature as hydrological model. However, some areas where masked out due to the minimum or null temporal dynamic of soil moisture, such are Greenland and the Sahara desert.

3.2 Land Surface Temperature dataset

The use of the land surface temperature (LST) anomalies as a proxy of soil moisture anomalies is based on the well-known role of LST in the surface energy budget as a control factor for the partitioning between latent and sensible heat fluxes. In recent years, the existence of a connection between soil moisture and LST has been analyzed, mainly through the thermal inertia and the triangle methods (e.g., Carlson 2007; Verstraeten et al., 2006), as well as a direct proxy (see e.g., Park et al., 2014; Srivastava et al., 2016). In a study over the pan-European domain, Cammalleri and Vogt (2016) have demonstrated the good agreement between monthly LST and soil moisture z-score values during summer time, where LST outperforms other LST-based indicators such as the day-night difference and the surface-air gradient.

Following these findings, this study adopts the dataset collected by the Moderate-Resolution Imaging Spectroradiometer (MODIS) sensor on board of the Terra satellite (http://terra.nasa.gov/about/terra-instruments/modis) as a source of monthly-scale long records of LST maps. In particular, the MOD11C3 Monthly CMG (Climate Modelling Grid) LST product is used in this study, which is constituted by monthly composited and averaged temperature and emissivity maps at a spatial resolution of 0.05 degrees over a regular latitude/longitude grid; data for the period 2001–2015 are used, as the only fully completed years at the time of the analysis.

This monthly composite product is obtained as an average of the clear-sky data in the MOD11C1 products on the calendar days of the specific month, which are derived after a re-projecting and a re-sampling of the MOD11B1 product. Details on the algorithms used to obtain the daily MOD11B1 maps can be found in Wan et al. (2002); in summary, a double screening procedure is applied, based on: i) the difference between the two independent LST estimates of the day/night algorithm (Wan and Li, 1997) and the generalized split-window algorithm (Wan and Dozier, 1996), and ii) the histogram of the difference between daytime and nighttime LSTs.

LST monthly maps were spatially co-registered to the Lisflood 0.1 degree regular latitude/longitude grid by means of a simple average of the values within each cell, and anomaly maps were computed according to Eq. (1) by using only the data for which LST > 1 °C; this threshold value (commonly used in snowmelt and snow/rainfall discrimination procedures; WMO, 1986) allows removing the data that are likely affected by snow/frost from the analysis.

3.3 Microwave combined dataset

The ESA Climate Change Initiative (CCI) aims at developing a multi-satellite soil moisture dataset by combining data collected in both past and present by passive and active microwave instruments (Dorigo et al., 2016). The current version of the dataset combines data from nine different sensors (SMMR, ERS-1/2, TMI, SSM/I, AMSR-E, ASCAT, WindSat, AMSR2 and SMOS) between 1978 and 2015.

Satellite-based microwave estimates of soil moisture are usually related to the first few centimeters of soil column (i.e., skin layer), which is quite closely related to the soil moisture content in the root zone (Paulik et al., 2014), except for very dry conditions. Additionally, numerous validations against land surface models have highlighted good performance across the globe, with notable exceptions over densely vegetated areas (e.g., Loew et al., 2013).

The algorithm adopted to merge the different data sources is the one developed by Liu et al. (2012), which is a three-step procedure that: i) merges the original passive microwave products, ii) merges the original active microwave products, and iii) blends the two merged products into a single final dataset. The merging procedure of passive datasets includes pixel-scale separation between seasonality and anomalies, rescaling of the data based on the piece-wise cumulative distribution function (CDF) and merging of the dataset using a common reference seasonality. For the active microwave instruments, the CDFs are directly used to rescale the data under the assumption that active datasets have an identical dynamic range, this mainly due to the limited overlap between datasets. The final blending of the two merged datasets is obtained by adopting a common resolution of approximately 25 km and daily frequency, as well as by using the GLDAS-1-Noah model (ftp://agdisc.gsfc.nasa.gov/data/s4pa/) as a reference dataset for the CDF matching.

In this study, the daily blended dataset is spatially resampled to a 0.1 degree regular latitude/longitude grid (the same used in Lisflood simulations) by means of the nearest neighbor algorithm, and successively aggregated to monthly time scale by simply averaging the data (only if at

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least 8 daily values were available in the specific month). Monthly average maps were converted into z-score maps by using the baseline period 2001-2015 (the timeframe available for the LST dataset).

4. Results and Discussion

Considering the assumption of linearity between each one of the models and the unknown true status of the system in TC, a preliminary analysis on the linear correlation between the three models has been performed in order to detect the macro-areas where the TC procedure can be applied without violating this basic hypothesis. The correlation analysis was performed by using only the monthly data that were available for all three models, and by defining a minimum correlation threshold ($R_{0.05}$) that ensures a statistical significance of the linear relationship on the basis of the t-student test (at $p = 0.05$).

The map in Fig. 1 reports in grey the areas where all three models are significantly linearly correlated according to the described criteria, representing the areas where the first basic hypothesis of the TC is not clearly violated. It is worth to point out that some areas are excluded from the analysis by the lack of data in LIS (low temporal variability, as over Greenland and the Sahara desert), LST (due to the minimum temperature threshold or low temporal variability) or CCI (densely vegetated areas, such as Amazon forest and the Congo basin). These results suggest to focus the successive detailed analysis on five macro-regions (demarked by the boxes in Fig. 1) that have consistent positive correlation values for all the three models; these areas are named, from now on, as: 1) NA (including the contiguous U.S.

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and Mexico), 2) EU (Southern and Central Europe), 3) SA (Southern countries of the African continent and Madagascar), 4) IN (Indian subcontinent), and 5) AU (Australia)*.

The correlation coefficient maps over those regions, obtained by inter-comparing the three models, are reported in Figs. 2 to 4, where the cells in red and yellow are the ones with negative or not-significant correlation, respectively, whereas the blue scale represents the cells with increasing significant linear correlation (from light to dark tones). The comparison between LIS and LST (Fig. 2) shows an overall good agreement between the two datasets, with only minor areas characterized by negative/not-significant correlation values; notably, low correlation can be observed over the Great Lakes and Rocky mountain areas in the U.S., over the Alps in Europe, North Angola and Western Himalaya. Similar results can be observed in Fig. 3, where LIS and CCI datasets are compared; this comparison shows an increasing number of negative values in Western U.S., the Alps, and Southern Turkey, but overall high correlation values across most of the five regions. Finally, the comparison between LST and CCI reported in Fig. 4 shows an increase of areas with low/not-significant correlation in Eastern and Western U.S. and both North- and South-Eastern Europe and the Alps, whereas a high correlation can be observed all over the other regions.

On average, the data in Table 1 summarize the results obtained for all the regions together, as well as for each region independently, showing how CCI and LST are the two datasets best correlated to each other overall, even if this result is mainly driven by the results over AU, SA and IN macro-areas. The data of the LIS model are similarly correlated to the ones of LST and CCI, with a more uniform distribution of the results across the various sub-regions. Another outcome of this analysis is that the

* Consider the countries and boundaries reported here only as indicative of the interested areas, and they may not in any circumstances be regarded as stating an official position of the European Commission.

area with the lowest average correlation between the three models is EU, probably due to the high heterogeneity of this region at the 0.1 degree spatial scale.

Overall, the use of LST as proxy of soil moisture anomalies seems based on a reliable assumption, since there is a clear consistency of LST anomalies with the other two datasets. This consideration allows applying the TC analysis to the LST dataset as well, whereas most of the studies in the literature focus on land modelled and microwave soil moisture datasets (i.e., Dorigo et al., 2010; Gruber et al., 2016; Su et al., 2014) with only few notable exceptions including thermal data (e.g., Hain et al., 2011).

The outputs of the correlation analysis were used to detect the cells suitable for the TC technique; since a key hypothesis of the technique is the existence of a linear relation between each model and the (unknown) truth, a necessary condition (even if not sufficient) is the existence of linear relationships among the three models. As outcome of the correlation analysis, around 10% of the five macro-areas were removed from the TC analysis due to the absence of this basic condition.

The maps in Figs. 5 to 7 show the main outcome of the TC analysis, which is the spatial distribution of the error variance for each model, as detailed by Eqs. (3). The blank areas in those maps correspond to the cells where no significant linear correlation was observed between all three models. The results for LIS (Fig. 5) show how the highest errors are observed over the Western U.S., Northern Cape in South Africa and Western/Southern Australia, whereas low errors are observed over the Eastern U.S. On the opposite, the LST dataset displays the highest errors over the latter area (Fig. 6), whereas the lowest errors are observed over Queensland in Australia, Eastern Cape in South Africa and Lesotho. The maps in Fig. 7 show that the CCI dataset has consistent patterns of low error variance values over most of Australia, Western India and Central U.S.

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Overall, on one hand, it seems evident how CCI tends to outperform the other two methods over dry areas such as Australia and South Africa, but on the other hand, a region like the U.S. is almost equally subdivided among the three models, where LIS performs better in the East, LST in the West and CCI in the center. Differences among models can be partially explained by the differences in the soil layer monitored by each dataset, i.e., microwave system capturing skin soil moisture whereas Lisflood models the full root zone; indeed, even if the use of monthly anomalies allows minimizing some of the discrepancies, skin soil moisture remains more reliable for dry/bare areas (Das et al., 2015).

These findings are summarized in the data reported in Table 2, where the average error variance for each model and macro-area is reported aside its spatial standard deviation. The data in Table 2 confirm that CCI has an overall better performance (lower errors) than LIS and LST, which perform quite closely, mainly thanks to the very low error variance observed over Australia and, to a minor extend, Southern Africa. The LIS model shows to perform better over NA and EU regions, likely due to the better meteorological forcing datasets available over those regions compared to the other macro-areas (due to denser ground networks). The LST dataset seems to perform moderately well over all five macro-regions, with the only notable exception of EU; however, it rarely outperforms the other two datasets, constituting a "second-best" option in most of the cases. It is also worth to point out that the CCI dataset is often masked-out over those regions where the error of microwave techniques are likely high, whereas the data of the other two datasets are mostly produced globally; hence, a possible explanation of the better performance of CCI compared to LIS and LST may be linked to this preliminary screening of the data.

The outcome that LIS slightly outperforms the other two datasets over NA is in agreement with the results reported by Hain et al. (2011), where the Noah land-surface model slightly outperforms (on average) the microwave and thermal datasets over Contiguous U.S. However, it should be pointed out how the spatial distribution of the error estimates for LIS differs from the ones reported for Noah, likely due to the differences in both meteorological forcing and modelling approaches. Similarly, Pierdicca et al. (2015) shows smaller average errors over Europe for the ERA-LAND modelled datasets compared to two microwave-based datasets, similarly to the results obtained in this study. Both these results seem to suggest that land modelling approaches are more reliable, on average, over these regions, likely due to the reliability of meteorological forcing and model parameterizations, even if there can be significant differences among the performances of different land models.

Over AU sub-region, the spatial distribution of the errors in CCI are quite in agreement with the results reported in Su et al. (2014) for two microwave datasets, with larger errors along the South-East Australian coast. This result supports the assumption that microwave data are more reliable over dry bare soil areas, which is further highlighted by the results obtained in SA and IN sub-regions. The subdivision of the NA domain in three main regions is similar to the one observed by Gruber et al. (2016) in comparing ASCAT and AMSR-E microwave datasets, suggesting key differences in the soil moisture behavior over these three sub-regions. Overall, the spatial patterns of microwave and land model errors show similarities with the ones observed by Dorigo et al. (2010), even if no thermal data were included in their analysis.

The error variance values can also be interpreted as the correlation coefficient of each dataset with the underlying true signal, following the definition of McColl et al. (2014). In fact, for the special case

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of anomalies with unitary variance (σ^2_x = 1), the TC-derived R_x of each dataset is simply equal to $\sqrt{1-\sigma^2_{\varepsilon_x}}$, which ranges on average over all five regions (not shown) between 0.91 (for CCI in AU) to 0.66 (for LST over EU); these values show a good capability of the models to capture, on average, temporal variations in soil moisture anomalies.

In order to provide a simple synthetic representation of the likely best model for each area, the map in Fig. 8 depicts for each cell the dataset with the lowest error variance by associating different colors to the three models (red for LIS, blue for LST and green for CCI). Even if this approach is rather simplistic, as it cannot account for two models performing really close over some areas, the major relevant features, like the predominance of the CCI model over Australia, are made evident by these maps.

The maps in Fig. 8 confirm CCI as the dataset with the lowest error variance values over most of AU, SA and IN, whereas the three models almost equally split the other two macro-areas; this is even more evident in the data reported in Table 3, where the percentage of sub-areas where each model is the best is reported. These data confirm the good performance of CCI over AU, SA and IN macro-regions, whereas the NA territory is almost equally divided among the three datasets and LIS outperforms both LST and CCI over 50% of EU domain. In the latter, the areas where the LIS dataset outperforms the other two datasets partially resemble the results obtained by Pierdicca et al. (2011) for the ERA-LAND model; however, the present study includes also remote sensing thermal data and not only microwave-derived datasets. Overall, the CCI dataset outperforms the other two datasets in about 50% of cells, with the remaining almost equally split between LIS and LST.

5. Summary and Conclusions

Three datasets have been compared as proxy of the unknown true status of soil moisture anomalies in the context of the global drought monitoring system under development by the JRC of the European Commission. Key assumption of the study is the inability of a single dataset to accurately capture the soil moisture dynamic over the large range of variability of conditions that can be observed at continental to global scale.

The inter-comparison between the three datasets, namely the outputs of the Lisflood hydrological model (LIS), the MODIS-based land surface temperature (LST) and the combined active/passive satellite microwave (CCI) data, confirms inconsistencies between the three datasets over some areas, as well as the difficulties in comparing the three datasets over certain areas (e.g., Sahara desert, Amazon rainforest) due to the lack of coverage from one or more datasets. Focusing the analysis only on the areas where the three models are substantially in agreement (following a linear regression analysis), five macro-regions were detected as suitable for further investigations according to the Triple Collocation (TC) technique. This analysis allows quantifying the likely random error associated with each model (with regard to the true status) even in absence of an observation of the "truth", under the hypothesis that certain criteria are met.

The main outcome of the TC analysis further confirms the need of a multi-source approach for a reliable assessment of soil moisture anomalies over those five regions, given that no model outperforms the others (in terms of expected error variance) for the entire study domain. Emblematic are the results over North America, where each model outperforms the others in one sub-region, like the LIS approach in Eastern U.S., LST in the South-Western domain and CCI in Central U.S. Overall, remote sensing datasets seem to perform better over dry areas and sparsely monitored areas (e.g., Australia and Southern Africa), whereas the LIS dataset seems more reliable over NA and EU where dense networks of meteorological ground stations are deployed.

It has been highlighted how some differences among models can also be related to the soil layer monitored by each dataset, i.e., the microwave system capturing skin soil moisture whereas Lisflood models the full root zone; indeed, even if the use of monthly anomalies allows minimizing some of the discrepancies, our results confirm that skin soil moisture remains more reliable for dry/bare areas (Das et al., 2015), whereas hydrological models are more suited for agricultural regions. Some analogies between the obtained results and the ones already available in the literature have been found, but the inclusion of thermal data into the analysis enlarges the understanding of the mutual relationship between the different datasets.

The results of this study represent a robust starting point for the development of a global drought monitoring system based on such anomaly datasets, which can exploit the main findings of the TC analysis in order to develop a suitable ensemble product over the investigated regions. Further analyses are required to be able to extend the test to the areas currently not included in this study, especially the ones where the three datasets are available but provide inconsistent or contrasting results.

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Discussion started: 10 May 2017

Tables

Table 1. Summary of the Pearson correlation coefficient values (average ± standard deviation) observed for all the regions.

Comparison	ALL	NA	EU	SA	IN	AU
LIS vs. LST	0.44 ± 0.09	0.41 ± 0.08	0.39 ± 0.07	0.48 ± 0.09	0.44 ± 0.07	0.50 ± 0.10
LIS vs. CCI	049 ± 0.10	0.47 ± 0.09	0.42 ± 0.08	0.48 ± 0.10	0.48 ± 0.08	0.58 ± 0.11
CCI vs. LST	0.56 ± 0.13	0.49 ± 0.14	0.37 ± 0.09	0.63 ± 0.09	0.52 ± 0.10	0.68 ± 0.07

Table 2. Summary of the TC error variance analysis, reporting the spatial average (± standard deviation) values observed over each macro-region.

Model	ALL	NA	EU	SA	IN	AU
LIS	0.48 ± 0.13	0.42 ± 0.14	0.44 ± 0.12	0.54 ± 0.11	0.49 ± 0.10	0.54 ± 0.14
LST	0.44 ± 0.13	0.46 ± 0.15	0.56 ± 0.10	0.37 ± 0.10	0.48 ± 0.09	0.38 ± 0.11
CCI	0.36 ± 0.18	0.46 ± 0.16	0.54 ± 0.12	0.30 ± 0.14	0.38 ± 0.16	0.17 ± 0.10

Table 3. Fraction of each macro-area (as percentage) where one model outperforms the other two.

Model	ALL	NA	EU	SA	IN	AU
LIS	25.5	39.2	50.0	10.6	28.2	4.3
LST	25.7	28.8	23.1	36.0	20.3	18.6
CCI	48.8	32.0	26.9	53.4	51.5	77.1

Figures

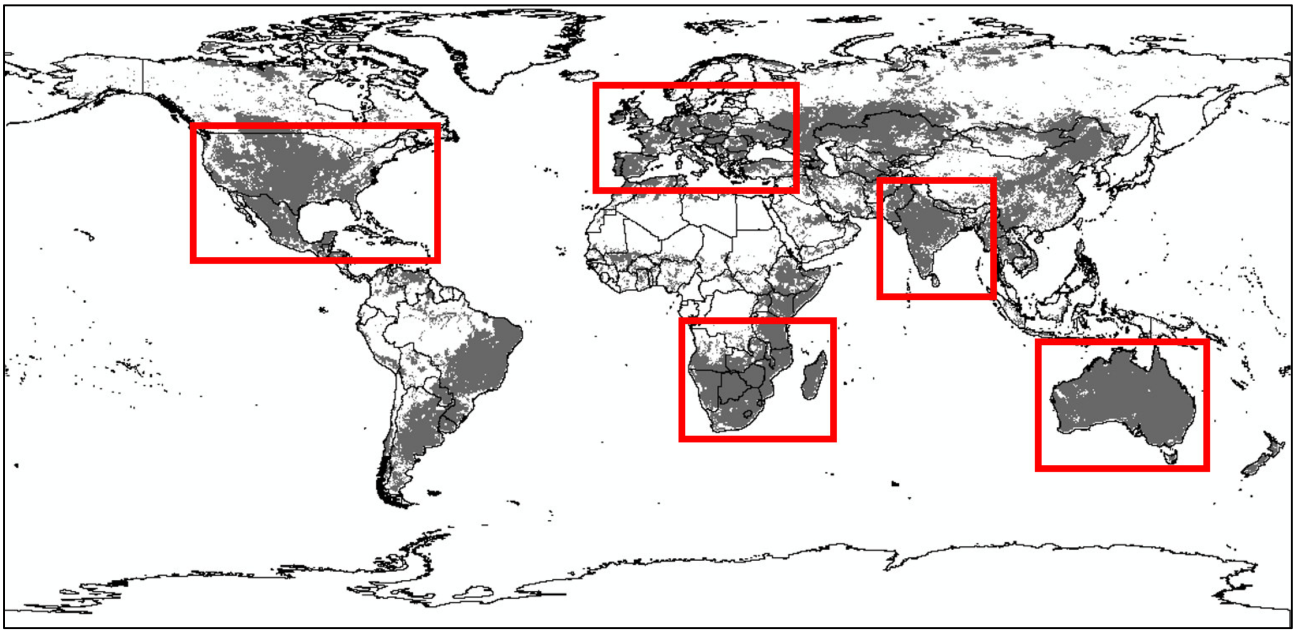

Fig. 1. Map of the areas where all the three models are positively significantly linearly correlated (cells in grey) according to the t-student test at $p = 0.05$. The boxes delimitate the macro-regions selected for the successive analyses.

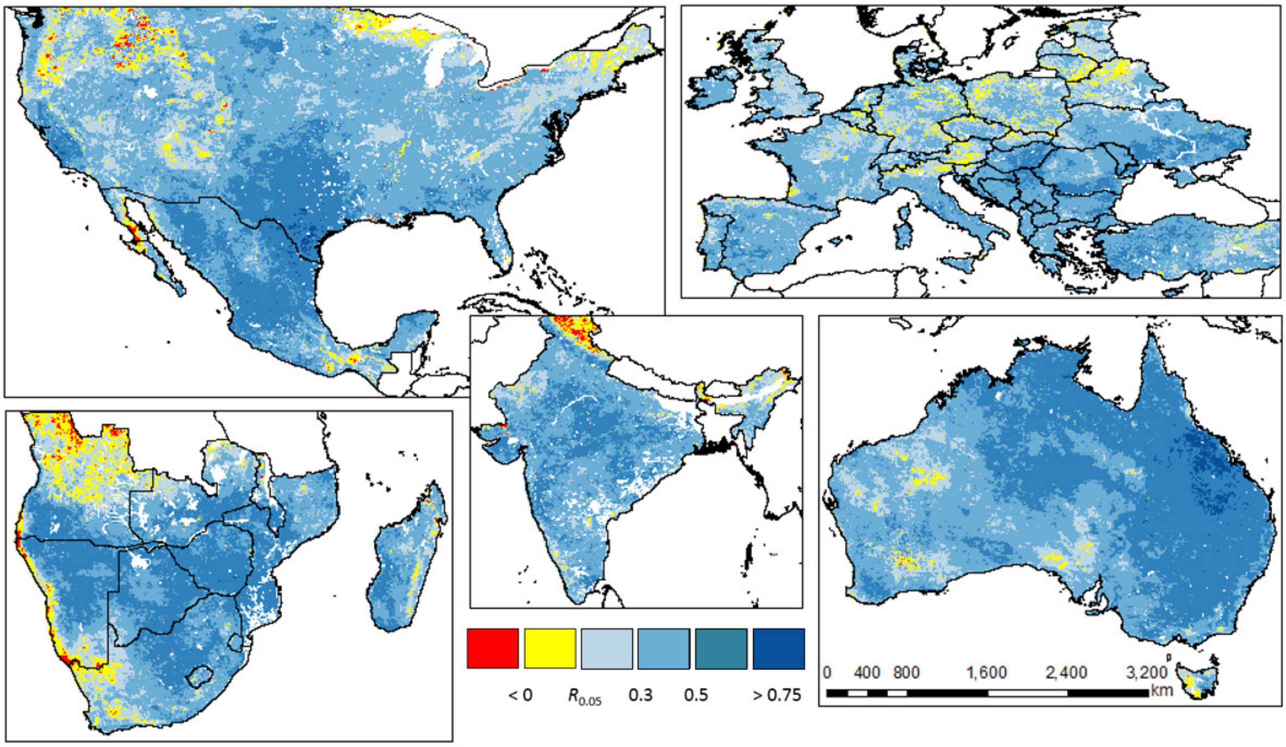

Fig. 2. Spatial distribution of the Pearson correlation coefficient (*R*) between Lisflood soil moisture anomalies (LIS) and land surface temperature anomalies (LST) over the five selected macro-regions. Values in red and yellow are negatively correlated or not significant at $p = 0.05$, respectively.

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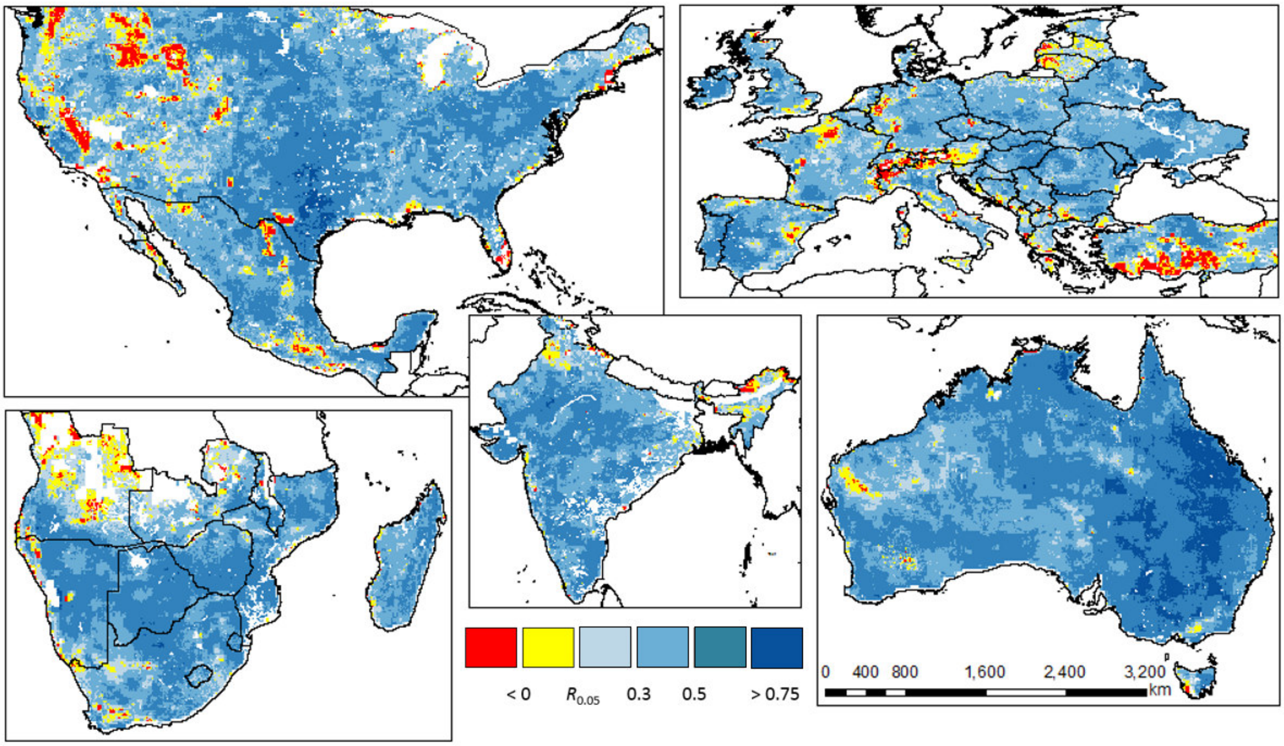


Fig. 3. Spatial distribution of the Pearson correlation coefficient (R) between Lisflood (LIS) and ESA Climate Change Initiative (CCI) soil moisture anomalies over the five selected macro-regions. Values in red and yellow are negatively correlated or not significant at $p = 0.05$, respectively.

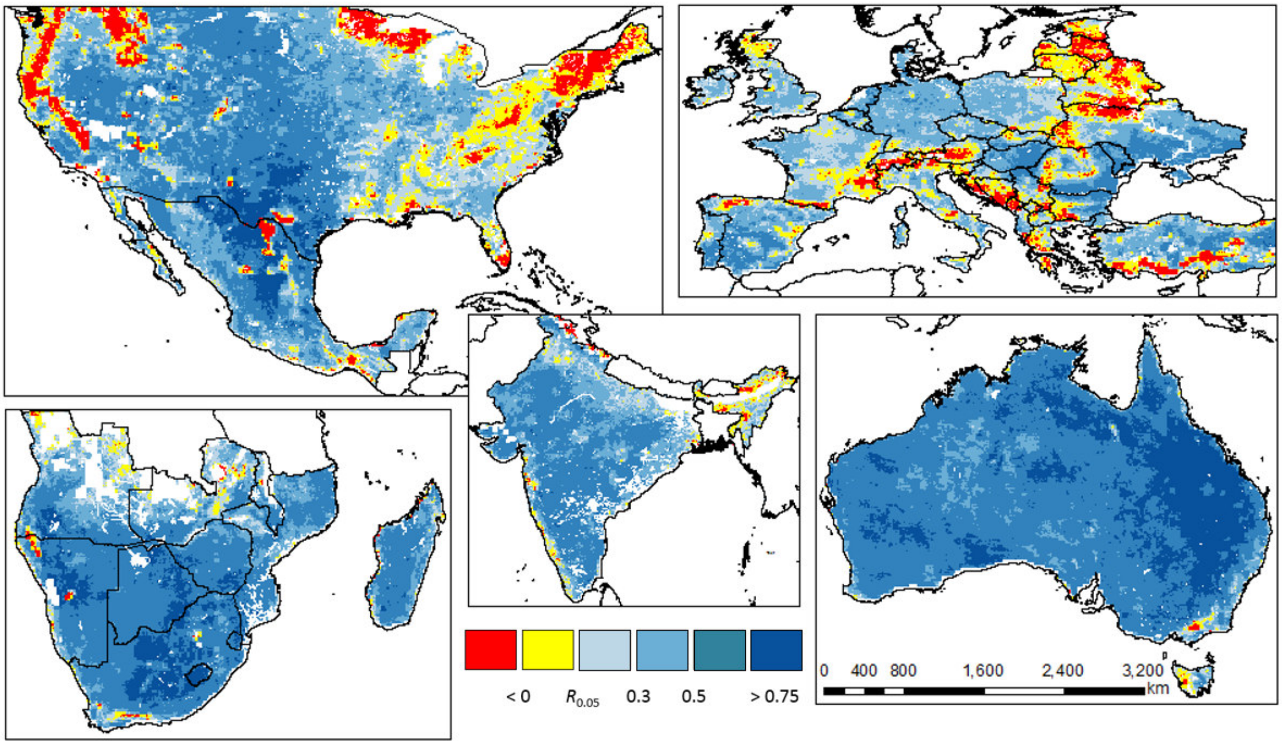
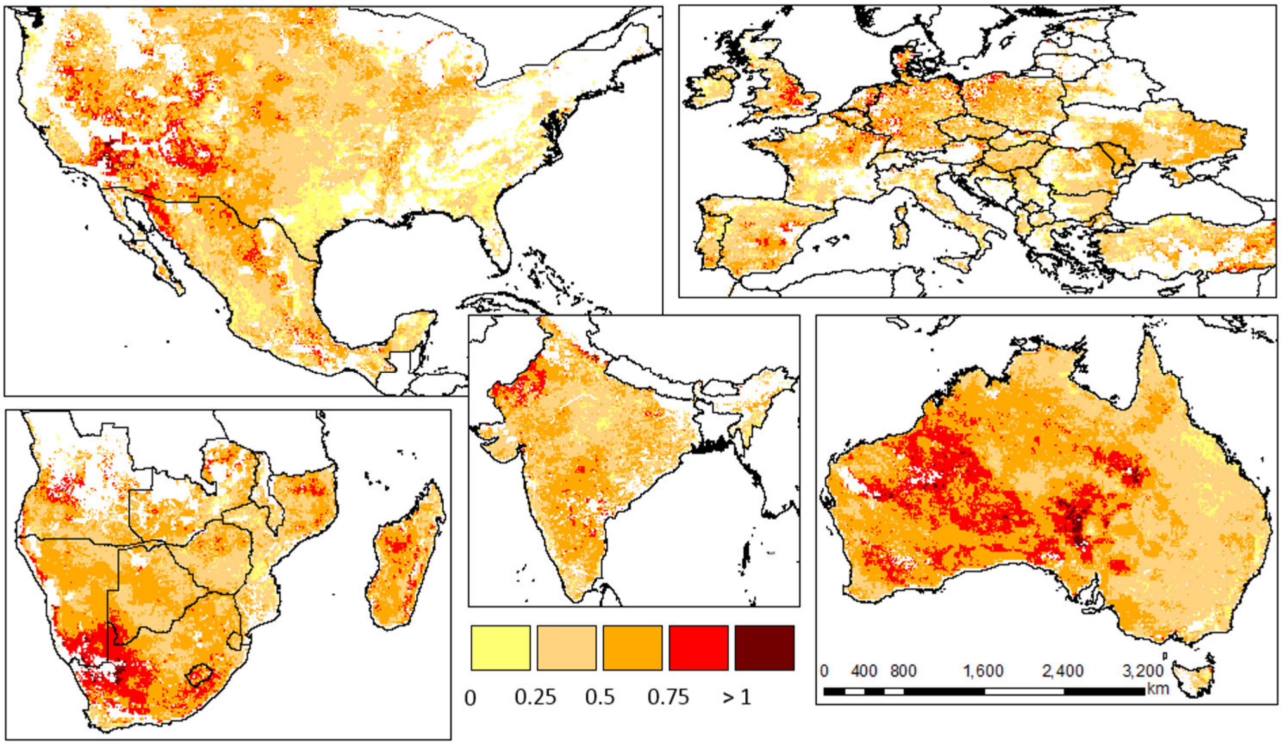


Fig. 4. Spatial distribution of the Pearson correlation coefficient (*R*) between ESA Climate Change Initiative soil moisture anomalies (CCI) and land surface temperature anomalies (LST) over the five selected macro-regions. Values in red and yellow are negatively correlated or not significant at $p = 0.05$, respectively.



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542 **Fig. 5.** Spatial distribution of the error variance for the Lisflood (LIS) dataset over the five selected

543 macro-regions.

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Discussion started: 10 May 2017

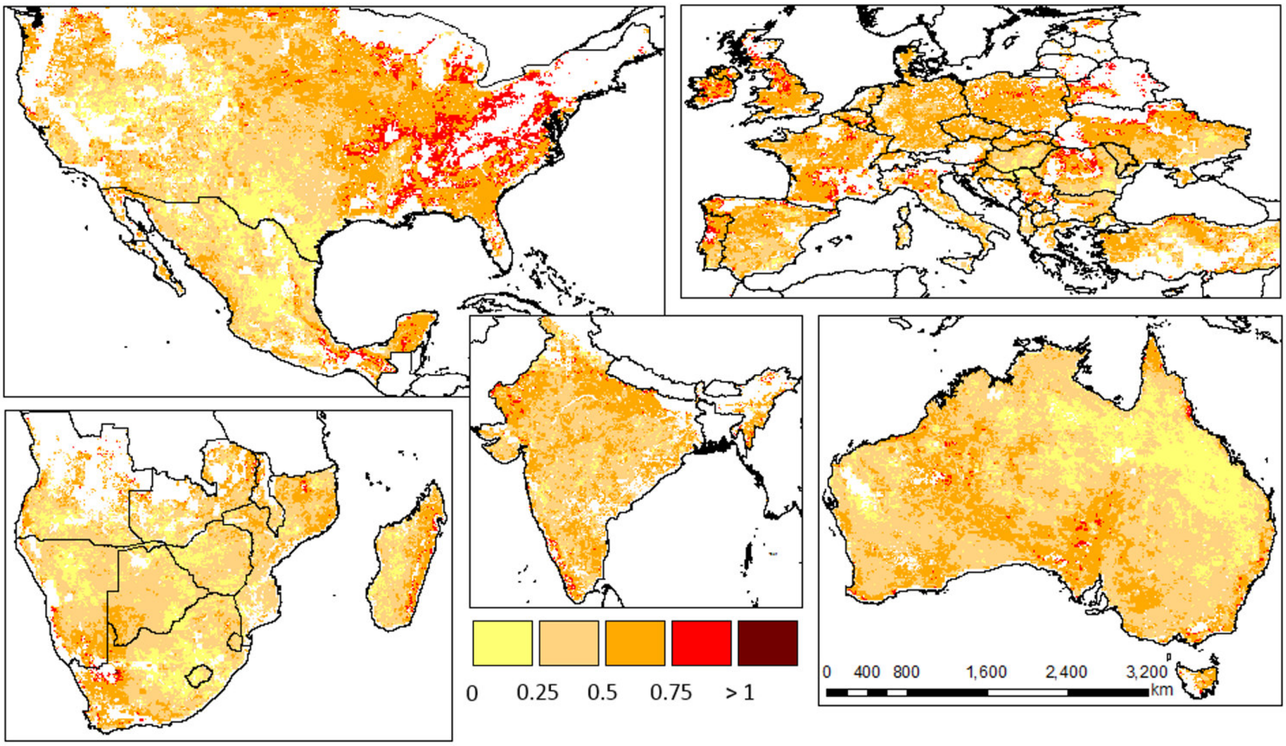

Fig. 6. Spatial distribution of the error variance for the land surface temperature (LST) dataset over the five selected macro-regions.

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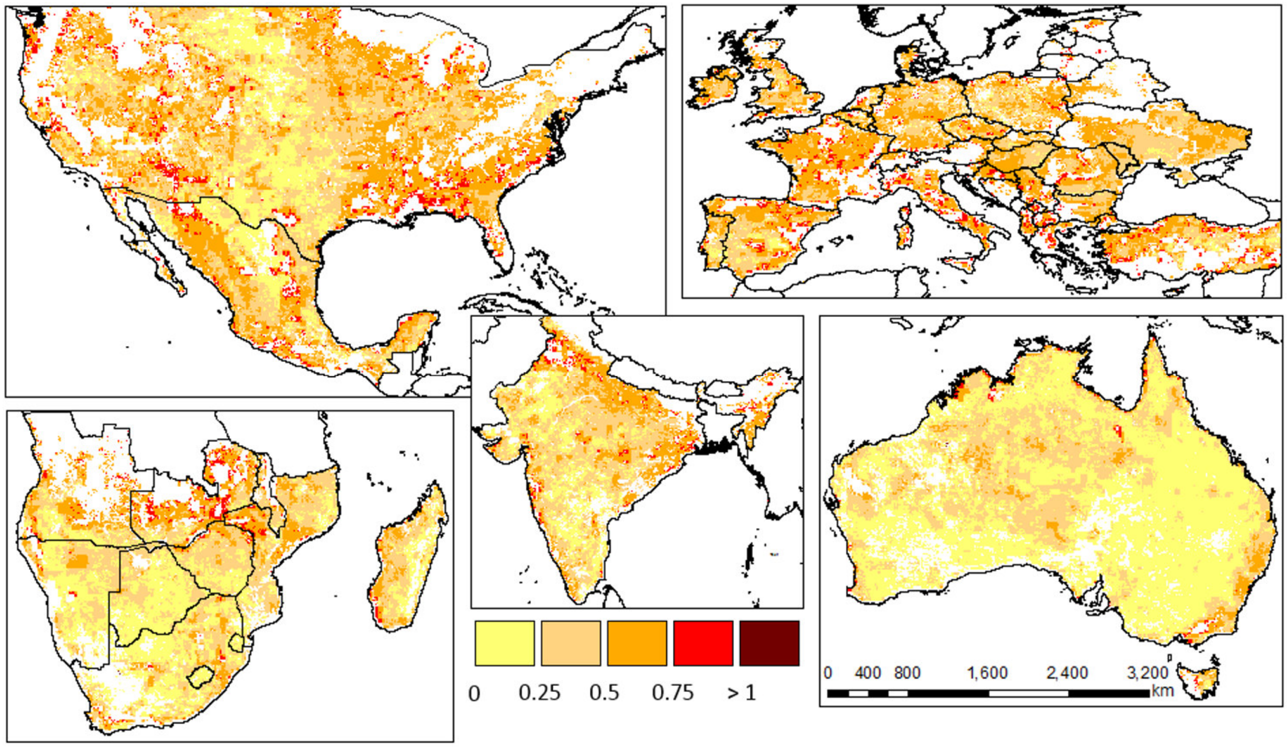

Fig. 7. Spatial distribution of the error variance for the ESA Climate Change Initiative (CCI) dataset over the five selected macro-regions.

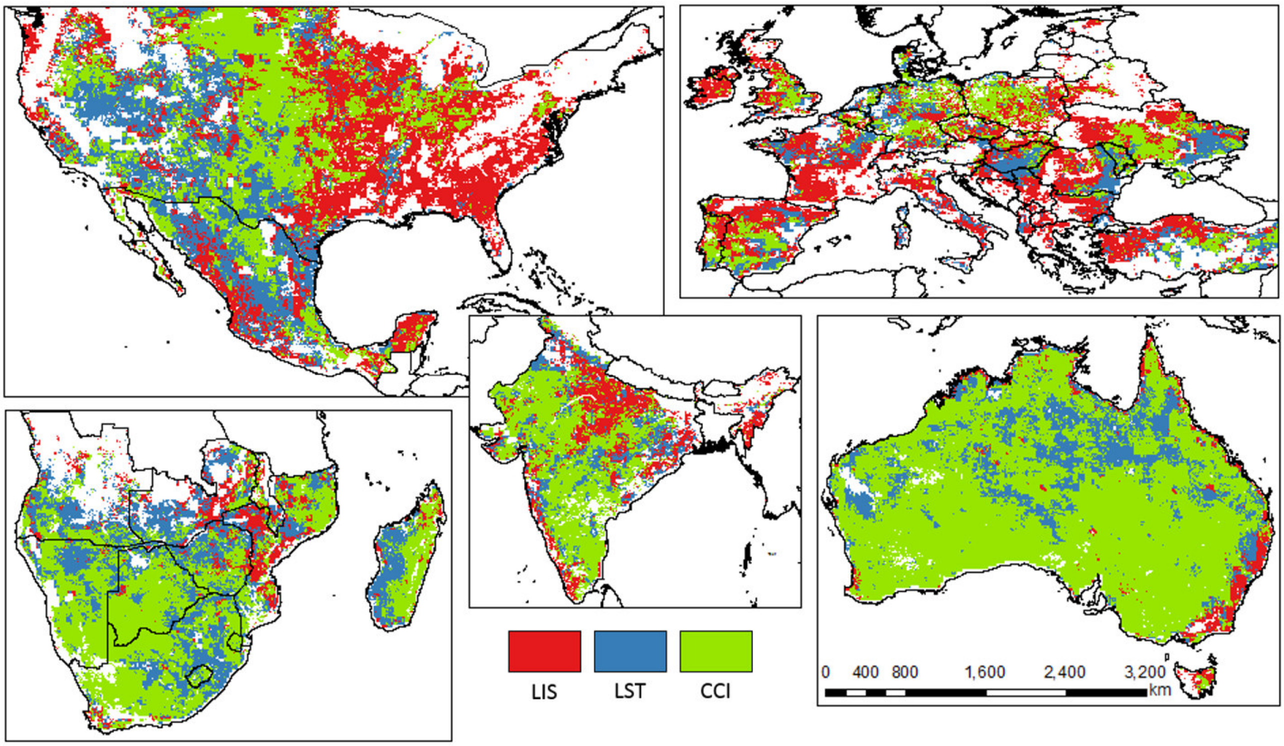

Fig. 8. Maps representing the best performing (lowest error variance) dataset for each cell according to the TC analysis.