The Comparison Map Profile Method: A Strategy for Multiscale Comparison of Quantitative and Qualitative Images
Cédric Gaucherel, Samuel Alleaume, and Christelle Hély

Abstract—The comparison map profile (CMP) method compares two spatially explicit data sets (original images) at each point and through several spatial scales simultaneously. The CMP combines the moving window concept with similarity indices for quantitative or qualitative data to visualize and quantify outputs: Changes in mean similarity value and its variability through scales are reported on a profile, similarities between regions are estimated on monoscale maps, and their persistence through scales assessed on a mean multiscale map. The CMP method is first illustrated using two images with slight difference in the checkerboard pattern. Second, two sets of comparisons related to African vegetation are conducted using the CMP method. The first set deals with quantitative data of leaf area index (LAI): Remote-sensed LAI images extracted from the AVHRR-NVDI product are compared to simulated LAI output from a dynamic global vegetation model (DGVM) using the distance and the cross-correlational coefficient for quantitative comparison of values and structure patterns, respectively. The second set of images deals with qualitative data: the remote-sensed product of land cover type by IGBP-MODIS is compared to the DGVM classified LAI output into land cover types using the Kappa statistics as similarity index. Results show that taking spatial patterns into account using the CMP method decreases the mean correlation by 50%, and increases the distance by 50% as compared to the global pixel-to-pixel indices. Similarly, comparison of land cover maps costs only 35% of the global Kappa value. Equatorial gradients of vegetation from forests to grassland are the most persistent similar regions between both types of data sets. Potential limits and strengths of the CMP method are discussed.

Index Terms—Environmental factors, Image texture analysis, spatial data structure, vegetation mapping.

I. INTRODUCTION

The quantitative methods to assess the accuracy of spatial simulation model, for example, may be divided into one group applied to hard maps and data, and another applied to fuzzy maps and data [1], [2]. All these quantitative approaches give some global indices (i.e., defined here as a unique value for the whole spatial set) of the data accuracy and sensitivity. However, in any case, the accuracy is spatially explicit. This implies that errors cannot be located, shifts may be acceptable, but they will not be captured, and the error persistence through up-down scaling will not be detected. Visual task of comparison is often based on the evaluation of similarities between images represented in an appropriate feature space [3]. Image comparison is often performed by computing a correlation function, the root of the mean square error or measures of the signal-to-noise ratio, therefore summarizing the similarity between images within a unique value, thus loosing the local similarity information (in different regions within the image) and/or scaling information. Distance functions, combining global and structural information, seem to be more adequate to characterize low-level similarity of images. These distance-based approaches could be either metrics (Euclidian or Haganian) or nonmetrics when applied to object characterization [3]. Nevertheless, image comparison may be also performed using structural patterns (nonrandom spatial structure) not focused on object detection. In this case, no assumptions are made about the pattern properties and all parts of the images are similarly analyzed. This concerns for example the search for cross correlations using wavelets [4], [5], cokriging [6], and local correlation retrieval in radar interferometry [7]. Most of the previous methods are based on the use of a moving window or template over an image, each index being estimated within the window and the result being plotted at the center of it to reconstruct a new index image [8], [9].

Here, we present the comparison map profile (CMP) method, whose principle and originality lie on the use of the generic moving window method combined to a similarity index computation. Its aim is to propose a robust spatial tool that scans images and compares every kind of patterns (nonrandom spatial arrangement of data values and data structure) included in these images on the basis of classical similarity indices. Second, the moving window process is repeated several times through window size increase, this allowing retrieving pattern detections and their changes through scales.

Such methodology may be applied on quantitative or qualitative data types, but it requires that both images are of the same type and the same size. Images are similar when their data present the same patterns (both the same values and the same spatial structures). To compare two maps with quantitative
The objectives of this paper are twofold:

1) To present the CMP method using two generated images in a checkered pattern made of quantitative data and presenting a slight difference only (Figs. 1 and 2) with the monoscale and multiscale comparison maps (M), with a complementary comparison profile (P) and its confidence levels. While maps allow to rigorously quantify scale independent local similarities based on significant probabilities, the combination of such maps with the profile offers a simultaneous multiscale analysis.

2) To illustrate the efficiency of the CMP method applied on African data set images (remote sensed versus simulated by a vegetation model) for recovering vegetation patterns and comparing non a priori defined patterns between images through increasing spatial scales. In this example, such changes from local to regional patterns may provide insights on drivers affecting vegetation differently from remote-sensing and modeling activities points of view, as well as on the vegetation model strengths and limits.

II. MATERIALS AND METHODS

A. Methodology

1) Index Definition: Similarities appear between two images (data mosaic) when values and/or variations in the studied parameter values are observed rigorously at the same place, whatever the scales are.

Dealing with quantitative continuous data types, we selected two indices to properly take into account both absolute values and spatial structures in the comparison process: the simple distance $D$ for absolute value comparisons

$$D = \text{abs}(\bar{x} - \bar{y})$$

with $\bar{x}$ and $\bar{y}$ being averages computed over pixels in both moving windows to be compared, and the CC [in (2) and (3)]
for spatial data structure comparisons. According to its definition, the CC coefficient uses standardized data, which cannot account for absolute values but rather CC tracks the normalized variances within both windows (each pair of moving windows) being compared

\[
CC = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} \frac{(x_{ij} - \bar{x}) \times (y_{ij} - \bar{y})}{\sigma_x \times \sigma_y} \tag{2}
\]

with \(\sigma_x^2 = \frac{1}{N^2-1} \sum_{i=1}^{N} \sum_{j=1}^{N} (x_{ij} - \bar{x})^2 \) \(\tag{3}\)

where \(x_{ij}\) (respectively \(y_{ij}\)) is the pixel value at line \(i\) and column \(j\) of the first (respectively second) moving window, each having \(N\) pixels. Here, every pixel is considered to have eight neighbors, and window shape is assumed to be symmetric and circular (approximately covering 78% of the corresponding square) to avoid directional biases.

Dealing with categorical data types, we selected the Kappa analysis because it is a standard statistics widely used in remote-sensed studies on classification accuracy assessment \([10], [11]\). This accuracy measurement is based on the difference between the actual agreement in the contingency matrix (i.e., the agreement between the simulation classification and the reference data indicated by the major diagonal) and the chance agreement that is indicated by the total of rows and columns (i.e., margins) \([12]\). The Kappa statistics is computed as

\[
\text{Kappa} = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \times x_{i+})}{N^2 - \sum_{i=1}^{r} (x_{i+} \times x_{i+})} \tag{4}
\]

where \(r\) is the number of rows in the matrix, \(x_{ii}\) is the number of observations in rows \(i\) and column \(i\), \(x_{i+}\) and \(x_{i+}\) are the marginal totals for rows \(i\) and column \(i\), respectively, and \(N\) is the number of observations \([12]\). The Kappa statistics mainly ranges from 0 to 1 but in some cases slightly negative values may appear, explaining the \((-1, 1)\) Kappa scale used in this paper. Associated to the Kappa coefficient, two complementary indices are available to enhance the classification accuracy assessment by analyzing the erroneous pixels: The omissions refer to the proportion of observed features on the reference data that are not classified correctly (underestimation), while the commission refer to features falsely classified as a specific class (overestimation).

2) Mapping Principle: Illustrated Presentation: We assumed two original images in a checkered pattern made of quantitative data and presenting a slight difference only \([Fig. 1(a) and (b)]\). To demonstrate the CMP method, we run both distance \((\text{Fig. 1})\) and cross correlation \((\text{Fig. 2})\) as complementary indices.

First, to quantify the spatial modulations of similarities at a given scale \(d\) related to the size of the moving window, we compute a map of similarity index \(S(d)\) (distance in \(\text{Fig. 1}\)) in three steps: 1) we compute the window similarity index \(S_W\) within a reduced window moving on the both whole original images \([\text{Fig. 1(a) and (b), blue circles}]; 2) we plot the resulting \(S_W\) value at the central pixel of the window on a new map \([\text{Fig. 1(d), blue circle}]; 3) we repeat this operation at each pixel of the image to create a new map (the monoscale map) with all the \(S_W\) values \([\text{Fig. 1(d) whole image}]. The overall similarity \(S(d)\) between the two images at that scale \(d\) is computed according to

\[
S(d) = \sum_{x=d}^{n_x-d} \sum_{y=d}^{n_y-d} S_W(\phi) \tag{5}
\]

and \(\phi = ([x, y], d)\) and \(d \in \left[1, \min(x, y) \right] \frac{3}{3} \tag{6}\)

with \(\Phi\) being the circular moving window defined by its centered pixel \((x, y)\) and its radius \(d\) (called the scale and representing the number of neighboring pixels near the central one), \(S_W(\Phi)\) being the local index computed within the moving window, and \(S(d)\) being the similarity measure of the total image at this scale \(d\). The 1/3 coefficient is an empirical estimate to limit the buffer size at the edge of the mosaics.

By repeating the similarity computation at each scale, the CMP method provides \(d\) monoscale similarity maps such as illustrated for four different scales \([\text{Fig. 1(d)–(g)}]\).

Second, all successive monoscale maps allow plotting the curve, namely the profile \([\text{Fig. 1(h)}]\), of the overall similarity value \(S(d)\) as a function of the scale \(d\) (from \(±1\) to \(±20\) pixels in this paper). It is built by averaging all \(S_W\) values reported on each monoscale map. A low similarity index value at a specific scale \(d\) means that spatial patterns between original images at that scale \(d\) are less (or not) similar. The profile can be roughly interpreted as a scalogram or a semivariogram \([13]\).

Finally, all monoscale maps can also be synthesized in one final multiscale similarity map \([\text{mean CMP map, Fig. 1(i)}]\). For each pixel, its \(S_W\) value over the 20-monoscale maps are averaged, and the result is reported on the multiscale map at the pixel location. Other combining operations than the average of monoscale maps, such as the product of the maps enhancing correlation gradients, could be used for the multiscale synthesis.

The multiscale CMP map synthesizes the similarity patterns of response across a range of scales, by highlighting the redundant structures over scales and by dimming distinct structures. This multiscale CMP map offers therefore the opportunity of an unbiased analysis relatively to the scales, as it is computed as the averaged map from all scales (on a pixel-to-pixel value basis), and it does not favor one or another.

Depending on the similarity index selected and its associated statistical rules, the CMP method uses significant probabilities in mono- and multiscale maps as well as confidence intervals through standard errors on the profile to allow robust comparisons and detection of significant similarities and their variability through scales \([9]\), which should be differentiated from similarities generated by random noises.

In addition to these calculations, some conventions are needed. By definition, two windows are not correlated if one and only one of them is perfectly homogeneous (presenting the same value at all pixels). In such case, CC is null and does not allow any comparison, while \(D\) between both windows is not null, except if both windows are homogeneous and present exactly the same pixel values. For this latter case, CC is set to one by convention. Such conventions facilitate the reading of
monoseasonal and multiscale similarity maps: at a given spatial scale. Both images are identical in regions where \( D \) is null and CC equals to one [see Figs. 1(d) and 2(d) for illustration], they are highly similar if \( D \) is small and/or significant CC close to one, and conversely they differ if \( D \) is high or significant CC low. All monoseasonal correlation maps only show the significant correlation values based on the degree of freedom computed from the pixel numbers in the window and a probability threshold of 0.05. The multiscale correlation map integrates and presents the mean correlation coefficient only for scales 4–20 [Fig. 2(i)] in order to remove the overestimation of nonsignificant relationships of very small windows (scales 1 to 3). Indeed, for \( d \) greater than 3 pixels, there are more than 50 pixels in each computation window and, therefore, the central-limit theorem guarantees that relations (significant correlations) between windows are correctly estimated.

The maximum scale and window size has been set here to \( d = \pm 20 \) pixels. This value has been empirically found to be a good optimization to get both broad scales global information [on the profile, Figs. 1(h) and 2(h)] and local information [on the multiscale map, Figs. 1(i) and 2(i)]. In order to avoid border-effects on image edges (or continent edges as for the African vegetation study case), pixels located at distance less than 20 pixels to these edges have been computed without the border (or ocean) pixels. The removal of these pixels prevent the user from overestimating the similarity for these moving windows, but it may introduce a bias due to the smaller number of pixels used for some \( S_m \) estimates, particularly for the smallest scales.

The simple difference (\( D \) computed pixel-to-pixel) between original images creates the global distance map [Fig. 1(c)]. Such map shows a pattern that is similar to the one obtained on the monoseasonal-1 map [Fig. 1(d)], the slight output difference resulting from the different number of pixels involved in the \( D \) calculation (pixel-to-pixel versus \( 3 \times 3 \) pixel window calculation). However, the CMP method allows reader to go further than the simple difference between original images in visualizing and quantifying the effects when changing spatial scale. The error (high \( D \) and low CC values), related to the difference between the two checkered patterns, affects neighboring regions that increase in size and in similarity values (lower \( D \) and higher CC) with increasing spatial scale. The profile minimum highlighted using the CMP method with correlation [Fig. 2(h)] points out the scale of the maximum effect of the missing square in the checkered pattern. To take into account the effect of spatial patterns in the data sets only costs 4.8% of the image of African LAI was computed using the 20-year averaged of total maximum LAI simulated by LPJ-DGVM. The image of African biome vegetation was derived from the MODIS/Terra Land Cover product (MOD12C1) based on the “International Geosphere Programme” (IGBP) global vegetation classification [17], modified by the University of Maryland to remove permanent wetlands, cropland mosaics, ice, and snow [18]. We aggregated at 0.5° the original NDVI image (0.25° spatial resolution) in order to fit the spatial resolution of the LPJ-DGVM outputs. We also aggregated several vegetation-type classes to obtain classes that may be compared with those from LPJ-DGVM (Table 1).

### C. Simulated Data From LPJ-DGVM

The images of simulated LAI and land cover types were computed using the LPJ-DGVM [14, 15] model for the African continent [19]. LPJ-DGVM is a coupled nonequilibrium biogeography–biogeochemistry model, based on explicit formulations of the dynamic processes in the soil–plant–atmosphere continuum including physiological, biophysical, and biogeochemical processes. Vegetation is taken into account through several plant functional types (PFTs), all of them undergoing plant population dynamic processes, competition, and disturbances [15]. PFT considered in this paper are tropical broad-leaved evergreen trees, tropical broad-leaved rainforest trees, temperate needle-leaved evergreen trees, temperate broad-leaved evergreen trees, temperate broad-leaved summergreen trees, C3 grasses/forbs, and C4 grasses.

The simulated LAI in each pixel of the image is the 20-year average of the annual maximum LAI simulated by LPJ-DGVM. This LAI value is the LAI sum of all present PFTs. Because less than 5% of African continent pixels presented LAI values higher than six, these pixel values were changed to six in order to apply the same maximum threshold as for remote sensed data.

The simulated land cover image was computed using a vegetation classification based on aforementioned maximum
Fig. 3. Comparison between two LAI images based on the absolute distance analysis through 20 spatial scales with (a) original LAI image from remote-sensing data computed from mean annual maximum LAI for the period 1981–2001, (b) original LAI image from LPJ-DGVM simulated data (using the same LAI scale as a), (c) global distance map based on pixel-to-pixel differences between a and b, (d) monoscale distance map for the smallest spatial scale (scale 1 representative of a 9-pixel window moving), (e) monoscale map for the intermediate spatial scale (scale 4 representative of a 81-pixel window moving), (f) monoscale map for the largest spatial scale (scale 20 representative of a 1681-pixel window moving), (g) multiscale distance map calculated from the 20 monoscale distance maps, and (h) distance profile (mean ±2 standard errors) through all spatial scales. All mono- and multiscale maps use the distance scale reported on (d). Illustration of moving-window pairs illustrated in (a), (b), (d), and (f) do not respect the effective window size from 1 to 20 pixels around the central one.

LAI simulated by LPJ-DGVM as well as on the proportion of dominant PFTs [19]. From this classification, we grouped all savannas together as well as deciduous and semideciduous forests together in order to fit both with the remote-sensed vegetation classes (five for vegetated areas including deserts, and one for water-bodies see Table I), and with their vegetation-type definitions.

III. APPLICATIONS

A. Distance and Correlation to Compare Two Images Based on Quantitative Data

The LAI Multiscale Distance map [Fig. 3(g)] shows that the mean CMP Distance between the original LAI images is twice higher (0.655) when taking into account the spatial patterns
Fig. 4. Comparison between two LAI images based on the CC analysis through 20 spatial scales with (a) original LAI image from remote-sensing data computed from mean annual maximum LAI for the period 1981–2001, (b) original LAI image from LPJ-DGVM simulation (using the same LAI scale as (a), (c) monoscale correlation map for the first spatial scale, (d) monoscale map for the intermediate spatial scale (scale 10), (e) monoscale map for the largest spatial scale (scale 20), (f) positive and negative correlation profiles (mean ±2 standard errors) through all spatial scales with corresponding percentage of significant pixels involved in the profile computation, and (g) multiscale correlation map as the average of the 20 monoscale maps. All mon- and multiscale maps use the correlation scale reported on (c). Illustration of moving-window pairs illustrated in (a), (b), (c), (d), and (e) do not respect the effective window size from 1 to 20 pixels around the central one. Global correlation between original images is equal to 0.747. The multiscale $D$ map reports four regions presenting slight higher $D$ than 0.655 (light blue). Some areas are similar at fine and large scales [Fig. 3(d)–(f), respectively] such as central part of equatorial region presenting a high similarity signal (low $D$) that is however dimmed through increasing scales, but still exists in the multiscale map. Conversely, the extreme north-western region as well as the transcontinental Sahelian regions and the African Horn in Ethiopia are the most different regions from both original LAI images, with high $D$ persisting through increasing scales, such differences being still visible in the multiscale $D$ map. The profile computed by the CMP method through all 20 spatial scales [Fig. 3(h)] synthesizes the transscale similarity information with the mean $D$ ranging from 0.95 for the finest scale (local patterns) to 0.45 for the largest scale (regional patterns). The significant monotonic decrease in average $D$ from small to large spatial scales is associated to a significant decrease in $D$ variability.
The multiscale correlation map [Fig. 4(g)] reports a mean CMP correlation between the original LAI maps of 0.137 when considering whole Africa and its spatial patterns through all scales. When considering only continental pixels that present significant correlation through all of the 4–20 spatial scales (38.2% of continental pixels), the mean CMP correlation increases to 0.359, which is still twice lower than the 0.747 global correlation computed pixel-to-pixel on both overall images. The multiscale correlation map highlights regions without significant similarity between original LAI images (e.g., Kalahari and northern Sahara desert regions) as well as few regions that present persisting structures or spatial patterns through scales (e.g., West Africa and northern and southern equatorial regions apart from the central equatorial rainforest).

The analysis of monoscale maps [Fig. 4(c)–(e)] shows for instance that central parts of Sahara and equatorial forest present similar spatial structures in both original images through homogeneous areas from nonvegetated areas with null LAI for Sahara, and maximum LAI for the equatorial rainforest. This homogeneity induces highly significant positive correlations for scale-1 [Fig. 4(c)]. However, with increasing scales, moving windows on simulated LAI image include both these homogeneous values with values being more heterogeneous (e.g., very low but not null LAI in desert), whereas the remote-sensed LAI image still records null LAI, this inducing a decreasing CC at intermediate scales. Above a certain window size, the covered region is very large and covers different regions with patterns that are globally more homogeneous between original images and, therefore, better correlated [Fig. 4(e)].

The CMP profile [Fig. 4(f)] highlights the fact that it is necessary to discriminate significant positive from significant negative correlations to prevent the user from misinterpretation of the mean signal. For instance, monoscale-1 map reports a mean correlation of 0.1, which is less informative than showing that only 18% of the continental pixels present significant correlations between LAI images for this finest monoscale map, which 3.6% presenting highly negative correlations (−0.790), whereas the other significant 15% present highly positive correlations (0.893). With increasing spatial scale, the percentage of pixels with significant correlations (both positive or negative) increases from 18% for scale-1 to 96% for scale-20, with most pixels referring to positive correlations (0.495 at scale-20). Moreover, the CMP method shows that the dominating positive correlation profile presents a minimum over scales 9 and 10, whereas the small number of pixels involved in negative correlations at larger scales does not allow concluding. The extracted monoscale-10 map allows the reader with partial interpretation of this minimum as compared to the finest and largest scales: The highly significant positive correlation in Sahara region reported at scale-1 have disappeared at scale-10, and the increased size window and its associated number of pixels as compared to scale-1 allows lower correlation values to be significant. As compared to largest scales for which the negative correlations have switched to positive and enhanced the mean correlation, the scale-10 still presents negative correlations that do not participate and, therefore, reduce the positive correlation profile. Finally, changes in correlation through increasing spatial scales are not related to change in standard error in the present application.

B. Kappa Statistics to Compare Two Images Based on Categorical Data

The multiscale Kappa map [Fig. 5(f)] shows that, when integrating all spatial scales, original land cover images only present some similarities (mean Kappa value of 0.221) mainly located in tropical regions. However, the global Kappa value is also quite low (0.344, see Fig. 5) without considering spatial pattern. Analysis of monoscale maps and profile shows that classification matching is relatively good at scale-1 [Fig. 5(c), mean Kappa 0.28], with several regions (e.g., northern Sahara, western seashore, and several regions of canopy cover gradient) presenting the perfect match between both original land cover images. Through increasing scales, the similar regions are less numerous and less similar, the equatorial vegetation cover gradients from central Africa to Sahel region being the only significant ones at scale-4 (minimum Kappa value on profile [Fig. 5(d) and (g)]). From this specific scale, increasing in window size increases back the Kappa value up to around 0.3 at scale-20, such value being mainly related to tropical gradients as seen before with vegetation cover decreasing from forests to savannas and grasslands.

The Kappa profile [Fig. 5(g)] synthesizes such information with mean Kappa values being very similar for scale-1 and scale-20, but they are associated to decreasing standard errors (half variability at the largest scale as compared to the local one). It also shows a minimum in the averaged Kappa values for scale-4, meaning that land cover patterns are poorly simulated, compared to remote sensed observations at this intermediate scale.

Fig. 6 illustrates the omission and commission calculations through spatial scales for the desert land cover class. From the multiscale maps point of view, except for the extreme southern African seashore, desert is not underestimated (bottom right panel). Conversely, it is underestimated over large northern African zones (bottom-left panel): At local scale, numerous omissions show that desert has been underestimated by LPJ-DGVM as compared to the remote sensed land cover image, mainly located in Sahara and Kalahari regions. Conversely, the commissions represent only few pixels for which the desert allocation is false and, therefore, overestimated. Larger spatial scales show that false classifications (omissions and commissions) are accentuated in area but reduced in values, and this in the direction where surrounding pixels belong to a different class: The latitudinal belt of omissions along the southern part of Sahara results from the misclassification as steppe (grass presence) in the simulated land cover map. At larger spatial scales, this initial omission belt presents decreasing omission values on its northern edge due to correctly classified desert pixels northwards. Conversely, the omission belt spreads southwards where neighboring pixels are representative of denser vegetation (steppes, savannas, and forests). This spreading through increasing spatial scales encompasses isolated misclassified pixels and overestimates their effects. The associated
IV. DISCUSSION

A. CMP Method

1) Main Features: In the process of comparing two images, the CMP method combines simple concepts such as resemblance indices and moving window to provide the user with information simultaneously for all points and all spatial scales. The comparison between original images through scales is concretely computed through the quantification and the visualization of a similarity index. The fact that almost any type of index may be used should be very convenient for all research fields involving image comparisons (remote sensing, image processing, biological and medical imagery, physical and environmental modeling). To our knowledge, the CMP method is the first attempt to efficiently assess such spatialized multiscale comparison. The CMP method has been developed to process either quantitative as well as qualitative data. It takes into account all

omission and commission profiles confirm these scaling trends (not shown).
likely spatial patterns from homogeneous to highly heterogeneous areas such as gradient, interfaces, and random heterogeneity and, thus, is quite generic. The CMP method is also an efficient statistical tool for analyzing temporal changes through spatial scales (translation, rotation, erosion, dilatation, etc.), the first date image being the reference image in such case. To propose a rigorous comparison between the CMP and other comparison methods would be relevant. We used the pixel-by-pixel difference map to highlight specificities of the CMP method maps. The closest comparison for profiles would involve a semivariogram, while this curve involves contrast distributions in successive directions. The CMP method is based on other indices and this comparison would be rather difficult to interpret.

All similarity maps provided with the CMP method allow identifying and focusing on specific areas that present similarities (or differences) between original images, as well as analyzing their changes or persistence through increasing spatial scales. Through the similarity profile, the CMP method...

Fig. 6. Omissions and comissions (left and right panel, respectively) (top) for the desert classification for scale-1, (center-up) scale-4, (center-down) scale-20, and (bottom) multiscale average.
provides the user with both the mean comparison between
different images at all spatial scales, and its scale-dependent
associated variability (standard errors in this paper), which is
not available in the global computation methods. The difference
between the index value computed with the global method and
that computed with the CMP method for any given spatial scale
determines the importance of the spatial patterns involved in the
images at that focused scale, and the associated “cost” to take
them into account. Considering that the total covariance is the
sum of inner- and interwindows covariances across images, the
similarities of smallest and biggest scales converge to this total
covariance by either reducing the inner-window covariance
or the interwindow covariance, respectively. According to the
maximum window size selected and the corresponding maximum
number of spatial scales analyzed, the CMP mean index value
for the largest scale ($d = 20$) is almost never equal to
(although it converges to) the mean index value computed using
the global method. Minima, such as those illustrated in the
positive correlation and Kappa profiles and likely overlapping
several scales, highlight the scales for which the spatial patterns
within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
Within original images are the most different. In this paper,
LAI structures are the most different. In this paper,
LAI structures are the most difficult to simulate in moving windows.
maps as well as the multiple CMP correlation and Kappa maps. Conversely, the southern part of Sahara is representative of similar while different areas because it shows small distance values (Fig. 3) but no correlation between images (Fig. 4). This is explained by the fact that LPJ-DGVM simulates low but nonnull LAI over this region (LAI < 0.5), whereas remote-sensing product does not record the very sparse and temporary vegetation. It results in the nonnull standard deviation for LPJ-DGVM as compared to the null standard deviation from the remote-sensing product. The dense rainforest region presents the same shift from the core region (identical area) where both remote-sensing product and LPJ-DGVM present homogeneous maximum LAI, to the surroundings (similar but different). Here, the remote-sensing captor still saturates and, therefore, provides with a maximum homogeneous LAI value of six, when LPJ-DGVM simulates slightly lower and variable LAI values. In these regions, distances are null or very small, but correlations go from perfect to null. Kappa coefficient cannot be used to test similar while different areas, as it will provide the user with a null value if at least two pixels over the tested areas are not matching. Gradients are the third type of spatial patterns shared by both images. They exist through all spatial scales, and are correctly simulated as shown by the multiple correlation and Kappa maps [Figs. 4(g) and 5(f), respectively], but are mostly seen at intermediate spatial scales. North to the rainforest, LAI values decrease from six to zero, which correspond with a transition from closed-canopy rainforest toward open-canopy forest, savannas, grasslands, steppes, and desert. The detailed analysis of the LAI decrease in this Sahel region shows two gradients with opposite signs [positive (red) in the southern part versus negative (blue) to the north, Fig. 4(c)]. The positive gradient corresponds with the shift from the closed-canopy forest to the desert that occurs at the same locations in both original images (small distance and high correlation), whereas the negative gradient is representative of a northern latitudinal band with LAI increasing from three to five before to decrease again northwards toward the Sahara. This reverse shift only occurs in the simulated image from LPJ-DGVM, and it is responsible for some large distances [mismatch between desert area and open-canopy forest or savanna, Fig. 4(d)] as well. Other LAI or canopy openness gradients such as the southern rainforest shift toward savannas may be seen using the intermediate monoscale maps as well as the multiple CMP correlation and Kappa maps. Indeed, a similarity pattern centered over latitudinal gradients apart from the equatorial forest (30° N to 20° S) that are representative of several ecosystems whose spatial distribution lies along latitudinal bands from the equatorial tropical rainforest toward dry forest, savannas, grasslands, and desert northwards and southwards. The last spatial pattern is the heterogeneous areas such as the high-elevated and heterogeneous Ethiopian region, for which both images present significant positive correlations (Fig. 4), quite low distances (Fig. 3), and high but spread Kappa coefficients (Fig. 5).

Using the CMP method allowed us therefore to point out discrepancies between remote sensed and simulated vegetation likely based on technical limits of satellite captors: deserts (equatorial humid forests) being considered as absolute bare ground regions (homogeneous closed canopy forests) from satellite measurements whereas they may sustain sparse and light vegetation (dense but heterogeneous forest) from model point of view. The CMP method has also highlighted that LPJ-DGVM simulates a latitudinal band of savannas and open canopy forests, which does not exist in the remote-sensing data sets.

Image comparison using the global method shows that original images are closer (i.e., low global distance and good global correlation) than when compared with the CMP method. However, when spatial patterns are taken into account and compared using the CMP method, the original images are not as similar as the global method is showing. The CMP index integrates the spatial structures, i.e., the cost of simulating not only the values or categories but also of reproducing their patterns. Hence, it is generally much lower than the global associated index (mean CMP distance is 50% higher than the global distance value in Fig. 3, and the mean CMP correlation is 50% lower than the global correlation in Fig. 4). The qualitative comparison provides the same trends of reduced matching between land cover images when including spatial patterns, but this reduction represents only 36% less than the global Kappa (Fig. 5). The fact that the qualitative comparison provides the user with better results than quantitative data is likely because each land cover-type encompasses a range of LAI values. This kind of pixel aggregation reduces the mismatch between images.

As all current DGVM, LPJ-DGVM does not simulate spatial processes. The only spatial information comes from the input climate and soil data sets, while no neighboring pixel processes are explicitly simulated. This may explain why LPJ-DGVM simulations poorly reflect spatial patterns. Moreover, depending on the spatial scale we refer, spatial pattern origins may differ. Indeed, from small (local) to large (regional) spatial scales, several processes such as soil conditions, vegetation colonization, altitude, climate, large water bodies, and latitude effects may interact on vegetation composition and functioning analyzed here through land cover types and LAI, respectively. We think that overall human activities may be one of the most important factors explaining the differences found between the two data sets as satellite measurements take into account human activities impacts on vegetation, whereas LPJ-DGVM simulates potential natural vegetation without anthropogenic impacts.

ACKNOWLEDGMENT
The authors would like to thank the Climate Research Unit for providing the climate data, Y. Gally for computer assistance, and M.-J. Fortin for her constructive review about this manuscript.

REFERENCES
differential Doppler compensation using the continuous wavelet trans-

to a plane turbulent jet,” ISME Int. J. Sec. B Fluids Therm. Eng., vol. 40,

cokriging with limited field soil observations,” Soil Sci. Soc. Amer. J.,

J.-M. Nicolas, P. Bolon, I. Petillot, A. Julea, L. Valet, J. Chanussot, and
M. Koehl, “Combining airborne photographs and spaceborne SAR data

“Conceptual and mathematical relationships among methods for spatial


variograms for characterizing landscape spatial structures from remote

[14] B. Smith, I. C. Prentice, and M. T. Sykes, “Representation of vege-
tation dynamics in the modelling of terrestrial ecosystems: Comparing
two contrasting approaches within European climate space,” Glob. Ecol.

of ecosystem dynamics, plant geography and terrestrial carbon

global leaf area index and absorbed par using radiative transfer mod-
1997.

fication logic based on remote sensing for use in global biogeochemical

[18] M. C. Hansen, R. S. Defries, J. R. Townshend, and R. Sohlberg,
“Global land cover classification at 1 km spatial resolution using a clas-
sification tree approach,” Int. J. Remote Sens., vol. 21, no. 67, pp. 1331–
1364, Apr. 2000.

[19] C. Hély, L. Bremond, S. Alleaume, B. Smith, M. T. Sykes et al., “Sensi-
tivity of African biomes to changes in the precipitation regime,” Glob.

with the Kappa statistic,” Ecol. Model., vol. 62, no. 4, pp. 275–293,


GAUCHEREL et al.: CMP METHOD: STRATEGY FOR COMPARISON OF QUANTITATIVE AND QUALITATIVE IMAGES 2719

Cédric Gaucherel received the French B.S. degree in physics from the University of Grenoble, Grenoble, France, in 1990, and the M.S. degree in astrophysics, the Ph.D. degree in astrophysics, and the D.Sc. degree in ecology from the University of Orsay, Paris, France, in 1992, 1997, and 2006, respectively.

Since 2006, he has been a Research Scientist with the French National Center of Agricultural Research (INRA, AMAP Laboratory). His background is in physics and remote sensing, allowing him to transfer skills in modeling and spatial analyses into environmental topics. He has developed mechanistic models of various ecosystem components such as vegetation distribution, animal population, human influence, and climatologic variable, with the ultimate aim to merge them into an integrated view of ecosystem complexity.

Samuel Alleaume received the French B.S. degree in biology from the University of Rennes I, Rennes Cedex, France, in 1992, the first M.S. degree (specialty remote sensing) in geography from the University of Rennes II, Rennes, France, in 1994, and the second one (specialty geographic information system) from the University of Quebec in Montreal, QC, Canada, in 1999.

From 1999 to 2006, he was with several international projects such as the SAFARI 2000 Project at the University of Virginia, the European SO&P Project at the University of Aix-Marseille, the European FireParadox Project at CEMAGREF. Since 2007, he has been Engineer in GIS, remote sensing, and databases in hydrobiology and environmental studies at CEMAGREF (HYAX unit). His research interests are in the areas of spatial analysis, habitat changes, and ecosystem disturbances.

Christelle Hély received the French B.S. and M.S. degrees in biology from the University of Rennes I, Rennes Cedex, France, in 1992 and 1994, respectively, and the Ph.D. degree in environmental sciences from the University of Quebec, Montreal, QC, Canada, in 2000.

From 2000 to 2004, she worked as a Postdoc for the international project SAFARI 2000 at the University of Virginia, and for the French National Center for Scientific Research (CNRS, laboratory CEREGE). Since 2004, she has been a CNRS Research Scientist with the University of Aix-Marseille, Aix-en-Provence, France. Her research interests are in the areas of ecosystem dynamics and disturbances such as wildfires (from boreal to tropical ecosystems), vegetation modeling, and climate change.