Efficiency of neural networks for consistent calibration of LAI products from input reflectance coming from several sensors: Application to CYCLOPES/VEGETATION and MODIS data

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Abstract

This paper evaluates the performance of a neural network approach to estimate LAI from MODIS and CYCLOPES reflectances and LAI products. A database was generated from downloading CYCLOPES and MODIS products over the BELMANIP sites and the 2001-2003 period. Data were aggregated at 3x3km², resampled at 1/16 days temporal frequency and filtered to reject outliers. It shows very consistent values of nadir normalized reflectances from both products lines in the red, near infrared and short wave infrared bands considered here. Neural networks were then trained over part of this data base for each of the 6 MODIS biome classes.

Results show very good performances of neural networks to estimate original LAI products from both MODIS and CYCLOPES normalized reflectances. Because MODIS algorithm is biome dependant, it was not possible to achieve similar good performances by training a single network over all the classes at the same time. More detailed analysis show that grasses and cereal crops and broadleaf crops are very consistent between CYCLOPES and MODIS. Conversely, other biomes including shrubs, savanna, needleleaf forest and broadleaf forest show significant discrepancies, mainly due to differences between LAI definitions used between CYCLOPES (closer to effective LAI) and MODIS (closer to true LAI). However, products derived from original CYCLOPES LAI products show a better agreement with both effective and true LAI ground measurements values. MODIS LAI products show more instability, in part because of the slightly shorter temporal resolution as compared to CYCLOPES.

These results confirm the interest and versatility of neural networks for operational algorithms. This approach could be extended to other products or sensors, and may constitute a step forward for the fusion of data from several sensors, hence contributing to develop ‘virtual constellation’.

Keywords: **Neural networks, LAI, CYCLOPES, MODIS, consistency of products**

1 Introduction

For the past decade, various medium resolution sensors are becoming operational and considerable improvements in the quality of terrestrial products derived from Earth-observation systems have been achieved. Leaf Area Index (LAI) is operationally estimated from remotely sensed optical imagery at global scale in the context of several international initiatives. NASA/MODIS (Knyazikhin et al., 1998) and FP5/CYCLOPES (Baret et al., 2007) LAI products are available freely to the users community. In addition, various products from different sensors are in development and will be soon available, such as ESA/GLOBCARBON (Plummer et al., 2006) or EUMETSAT/LSA SAF (Trigo et al., 2006) LAI products.

From the application side, scientific and institutional users need validated products that would be consistent between sensors and associated with a good and known accuracy (Morisette et al., 2006). According to GCOS (Global Climate Observation System) requirement documents (GCOS, 2006) the typical target accuracy for LAI is around 0.5 (15% in relative terms). However, recent validation studies have outlined significant discrepancies among several existing LAI products (e.g. Abuelgasim et al., 2006; Camacho-de Coca et al., 2006; Verger et al., 2006; Weiss et al., 2007). These results were used by the Committee for Earth Observation Satellite to state that none of the available LAI products are yet performing globally within threshold requirements (CEOS, 2006).
To fully exploit the potential of current Earth observation programs and take advantage of the several products available, efforts have to be directed towards improving their consistency and accuracy. This needs validation and inter-comparison studies that are still very scarce (Baret et al., 2006). Parallel development of new strategies for fusion of sensor measurements and derived products is also required. Among the several approaches suited to pair set of reflectances with the corresponding biophysical variables such as LAI, learning machine techniques such as neural networks (NNT) appear to be quite powerful and easy to implement operationally. They allow to adjusting and surface responses even when complex and non linear non-linear (Leshno et al., 1993; Krasnopolsky and Chevallier, 2003; Baret & Buis, 2007). This way, NNT could be the basis of a generic 'unified' LAI estimation algorithm allowing to cover operationally, with specific tuning, a large range of sensors. NNT are increasingly used for the interpretation of remotely sensed data and the estimation of LAI (e.g. Danson et al., 2003; Fang & Liang, 2005; Bacour et al., 2006; Baret et al., 2007, (Trombetti et al.)).

The objective of this paper is to evaluate the performances of neural networks when trained with the LAI product from one sensor and the reflectances from an other. More specifically, MODIS (collection 4) and CYCLOPES (version 3.2) normalized reflectances and LAI products were considered. The four combinations between reflectance and LAI products from MODIS and CYCLOPES were investigated and their performances evaluated with regards to their consistency and accuracy with regards those of the original MODIS and CYCLOPES LAI products.

In the first section, MODIS and CYCLOPES normalized reflectances and LAI products are first described along with neural networks description and issues related to the spatial, temporal and spectral sampling. After comparing original MODIS and CYCLOPES products, the NNTs are described with emphasis on the learning process and data base. Performances of the proposed approach is then evaluated based on direct and indirect validation, validation results are presented according to the methodology proposed by

Weiss et al. (2007) for the validation of global LAI products. And finally, main conclusions are given.

2 Data and methods

2.1 MODIS products

All MODIS products were downloaded from http://edcdaac.usgs.gov. They correspond to a 1km spatial resolution with a sinusoidal projection system.
MOD43B4 Nadir BRDF-Adjusted Reflectance Product provides atmospherically corrected, cloud-free, normalized reflectance values at 1 km spatial resolution for each of the MODIS land spectral bands (1-7, centered at 648 nm, 858 nm, 470 nm, 555 nm, 1240 nm, 1640 nm, and 2130 nm, respectively) at the mean solar zenith angle of each 16 day period (Schaaf, 2002). MODIS atmospheric correction scheme is described in Vermote et al. (1997). The Ross-Li BRDF model (Lucht, 2000) with model parameters provided by MOD43B1 product is used to compute MOD43B4 product. In addition to the spectral nadir normalized reflectance values, the MOD43B4 product also provides extensive quality information.

MODIS LAI product (MOD15A2)is composited every 8 days using a main retrieval algorithm based on a three dimensional radiative transfer model tuned for six main biome classes (Knyazikhin et al., 1998). A Look-Up-Table (LUT) is used to compare observed and modeled red and near infrared daily BRFs for a suite of canopy structures, leaf optical properties and soil patterns that represent an expected range of typical conditions for a given biome type. LAI is retrieved as the mean value from all possible solutions within a specific level of input satellite data and model uncertainties. If this algorithm fails, a back-up procedure is triggered to estimate LAI from biome specific NDVI based relationships (Myneni et al., 1997).

MOD12 global land cover, layer 3 (Friedl, 2002), is also used to provide the classification in six main biomes used in MOD15A2 LAI algorithm and includes: shrubs, savanna, grasses and cereal crops, broadleaf crops, needleleaf forest and broadleaf forest. Classification is derived from temporal profile features as observed during the year.

Numerous validation experiments support the reliability of MODIS MOD43 reflectance products (e.g. Jin et al., 2003), MOD12 landcover product (e.g. Cohen et al., 2006b) and MODIS LAI products (e.g. Wang et al., 2004; Tan et al.; 2005; Hummerich et al., 2005; Cohen et al., 2006b). A summary of published validation effort by multiple international teams is given in Yang et al. (2006).

2.2 CYCLOPES products

Version 3.2 of CYCLOPES products were used here. They are derived from VEGETATION sensor aboard SPOT4 and SPOT5 satellites (Henry, 1999). These products were downloaded from http://postel.mediasfrance.org. They correspond to 1/120° resolution (about 1km at the equator) and are projected in plate-carrée. Radiometric calibration process of VEGETATION data, the cloud screening algorithm, atmospheric correction, BRDF model inversion and LAI retrieval are described in Baret et al. (2007).
CYCLOPES normalized reflectances for a nadir viewing are calculated using Roujean et al. (1992) BRDF model for the median solar zenith angle during the compositing period. Successive inversions allow rejecting observations disturbed by residual clouds and/or

aerosols, as proposed by Hagolle et al. (2004).The temporal sampling interval is 10 days, and the temporal window over which reflectance are collected to adjust the BRDF model is 30 days, with gaussian weighing that puts more emphasis on observations close to the center of the window (Figure 1).
Nadir viewing top of canopy reflectance in red, near infrared and middle infrared bands from VEGETATION sensors are input to the LAI algorithm along with the sun zenith angle. LAI values are computed by inverting the PROSPECT+SAIL radiative transfer model (Jacquemoud and Baret, 1990; Verhoef, 1984) using neural networks. CYCLOPES LAI product corresponds therefore to some effective *LAI*. However clumping at the landscape level (mixed pixels) is accounted for: each pixel is supposed to be made of a fraction FVC of pure vegetation and (1-FVC) of pure bare soil (Baret et al., 2007). Large range of values for canopy structure, leaf optical properties and background reflectance were used to generate the training data base.
CYCLOPES LAI products were validated by Weiss et al. (2007) showing a better agreement with ground measurements than MODIS LAI products and better temporal consistency.

2.3 Generation of a consistent data base

A data base of CYCLOPES and MODIS normalized reflectances and LAI need to be acquired over a globally representative ensemble of sites and over a time period long enough to show seasonal and interannual variability. The BELMANIP ensemble of sites was here used, including 397 sites aiming at providing a good sampling of biome types and conditions over the globe (Baret et al., 2006). A four year period was considered, starting in 2001 and ending in 2003.

The database should reflect high degree of consistency over the spatial, temporal, spectral and directional dimensions of the signal to allow cross learning and comparison.

For the spatial dimension, both CYCLOPES and MODIS products have approximately 1-km sampling interval while the projection systems used differ. To achieved a comparison of both products over the same support area the same projection system has to be used that should ideally keep the size of the sites independent from its location (Weiss et al., 2007). The MODIS sinusoidal projection system was selected because it ensures more consistency of the size between sites. CYCLOPES products were therefore reprojected into the MODIS projection using the bi-cubic resampling method (Reichenbach and Geng, 2003). To get about the same spatial resolution and minimize the influence of geo-location uncertainties and point spread function, 3×3 km^2 support area was considered for the analysis as recommended by Weiss et al. (2007). Only high quality level pixels were considered and the median value over the 3x3 pixels area was computed when at least 5 pixels were available for each product. Only MODIS LAI values retrieved with the main algorithm out of saturation conditions were included in the data base. Back-up algorithm retrievals have low quality and are not suitable for intercomparison and validation studies (Yang et al., 2006) as these products are generated from uncertain surface reflectances, mostly because of residual clouds and poor atmospheric correction (Wang et al., 2001). The dominant land cover class was assigned to each BELMANIP site from the yearly MOD12 product. To guarantee the homogeneity of the area, only those BELMANIP sites of the 397 data base were at least 5 pixels in the 3x3 km2 sites correspond to one class were considered in the analysis. Although sites could include pixels belonging to other surface types different to the dominant and some misclassification within MODIS land cover are also possible, this selection criteria provides more consistent analysis per classes.

For the temporal dimension, both resolution and sampling interval differ between MODIS, CYCLOPES LAI and normalized reflectance products. The lowest sampling frequency was selected as a reference, corresponding to the 16 days of MODIS normalized reflectance products. The 8 days original MODIS LAI products were composited to get about the same temporal resolution: the central 8 days value was averaged with the previous and the next ones, assigning a 0.5 weight to these borders observations within the central 16 days period corresponds to 81% of the whole temporal window that spans over 24 days (Figure 1). However, when one or two of the border observations were missing, the product was still computed. Conversely, when the centre observation was missing, no product was computed, corresponding to missing data. In case of CYCLOPES LAI and normalized reflectance products, they were interpolated at the 16 days of MODIS products dates. The contribution of the central 16 days period contributes on the average up to 61% of the whole temporal window (Figure 1) that spans over 40 days. However, when no product was available within ±15 days around the date considered, the corresponding data was discarded.

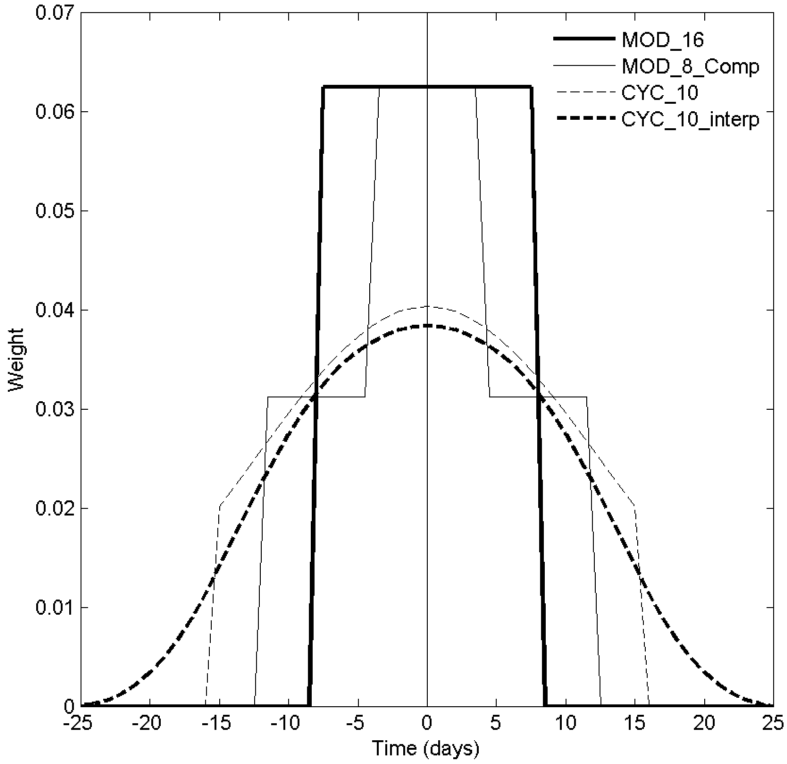

Figure 1. Temporal resolution corresponding to the several products investigated. The temporal window is centered at day=0. MOD_16 corresponds to MODIS normalized reflectance products. MOD_8_Comp corresponds to the compositing of three consecutive original 8 days MODIS LAI product to get a closer temporal resolution to that of MOD_16. CYC_10 is the original temporal resolution of CYCLOPES products. CYC_10_interp corresponds to the average temporal resolution when interpolating CYCLOPES products at MOD_16 dates.

From the 38112 observations potentially available at 16 days frequency for 4 years over the 397 sites, only 7572 matches i.e. 20% of the potential observations, were finally considered after the spatial and temporal resampling and filtering process. This corresponds to 994 acquisitions for shrubs, 1272 for savanna, 1829 for grasses and cereal crops, 817 for broadleaf crops, 1608 for needleleaf forest and 1052 for broadleaf forest).

For the directional dimension, despite differences in the BRDF model used for the normalization of CYCLOPES and MODIS reflectances, little differences are expected since time and geometry of observations are very close for both sensors. More effects are expected from the radiometric calibration, atmospheric and geometric corrections (Verger et al., 2005).

For the spectral dimension, a comparison between spectral response of both sensors for the three bands considered in this study shows that MODIS bands are "narrower" than those of VEGETATION, but are within the spectral range of variation of the VEGETATION ones. However, a particular simulation study (not shown here for sake of brevity) achieved at top of the atmosphere and encompassing a large range of vegetation types, atmospheric conditions and geometric configuration, demonstrated that despite these spectral differences, very good agreement without biases were expected between homologous pairs of bands.

Table 1. Comparison of VEGETATION/SPOT and MODIS/Terra spectral bands.

Spectral band	VEGETATION (nm)	MODIS (nm)
Red	B2 (610-680)	B1 (620-670)
NIR	B3 (780-890)	B2 (841-876)
SWIR	B4 (1580-1750)	B6 (1628-1652)

3 Comparing MODIS and CYCLOPES reflectance and LAI resampled original products

Pairs of homologous CYLOPES and MODIS products were compared over the whole data base of matches described previously. Linear rectangular regression between normalized reflectances of the two products for each of the three bands shows good agreement (Figure 2) although CYCLOPES is slightly but systematic lower than MODIS reflectances in the three bands. This was not expected from the simulation study related earlier related to the possible effects of the differences in spectral sensitivity between VEGETATION and MODIS sensors. These biases could be explained mainly by the combination of radiometric calibration uncertainties and inaccuracies of atmospheric correction although further investigations are required to better identify and quantify the sources of these differences.

The scatterplots for each band (Figure 2) shows some outliers that need to be eliminated to improve the consistency between products within this database. For each individual data (date*site), the sum of squared differences in the three bands between both sensors was computed. This criterion was used to reject data showing the largest discrepancies over the three bands. The 5%, 10%, 15% and 20% showing the larges discrepancies were tentatively rejected, and the corresponding regression performances were computed: when more outliers are rejected, the consistency between MODIS and CYCLOPES products obviously improves, resulting a higher correlation, a lower root m (Table 2). Reflectance consistency improves significantly for the first rejection fraction (5% and 10%) as observed both in Table 2 and Figure 2, while improvements vanished for larger rejection levels (15% and 20%). A similar number percentage of data were rejected among the several biome classes for 5% or 10% levels, while more differences across classes were found in the remaining data base when a more restrictive threshold was applied.

Comparison between CYCLOPES and MODIS LAI products shows a higher scattering as compared to reflectances (Figure 2). The systematic underestimation of CYCLOPES LAI compared to the MODIS one can be explained partly by the differences in product definitions. These results agree also with those of Weiss et al. (2006) who report an early saturation of CYCLOPES LAI product (values hardly go over LAI=4). Note that most outliers for LAI are eliminated when rejecting data showing inconsistencies between reflectances differing values of LAI between MODIS main product and CYCLOPES one were also filtered when applying a threshold of reflectance (Figure 2). although relative RMSE continues being higher 70%.

A rejection level of 10% was finally selected because it provides a significant improvement of networks performances (see table 3) while not reducing too much the size of database and preserving the statistical distribution of acquisitions per classes.

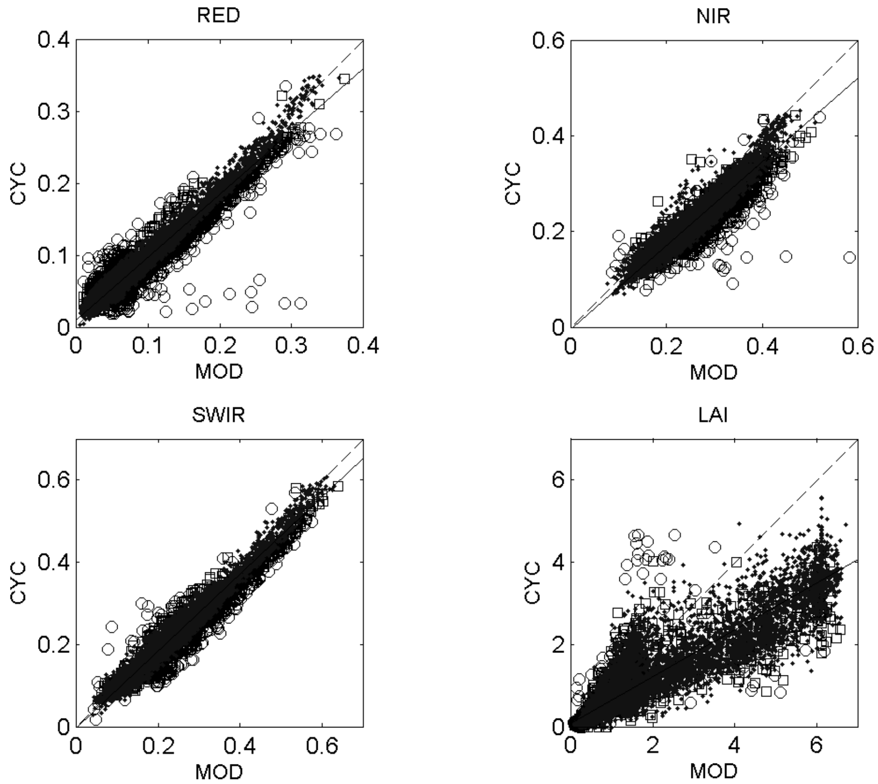

Figure 2. Scatter plots between CYLOPES and MODIS normalized reflectances and LAI products over BELMANIP sites during the 2001-2003 period. The 10% (20%) showing the largest reflectance discrepancies in the three bands are indicated with circle (square) symbols.

Table 2. Correlation coefficient (R^2), slope and offset of the rectangular linear regression. The root mean square error (RMSE) corresponds to the square root of the average squared difference between CYCLOPES and MODIS products. Comparison achieved over BELMANIP sites during the 2001-2003 period as a function of the rejection level. 0% rejection level corresponds to the original 7572 matches.

Product	Rejection Level	R^2	RMSE	Slope	Offset
Red reflectance	0%	0.956	0.021(24%)	0.875	0.010
	10%	0.985	0.012 (14%)	0.922	0.008
	20%	0.988	0.010 (13%)	0.935	0.007
Near infrared reflectance	0%	0.923	0.044 (19%)	0.874	0.004
	10%	0.950	0.038 (17%)	0.907	0.009
	20%	0.957	0.035 (16%)	0.926	0.012
Short wave infrared reflectance	0%	0.977	0.029 (13%)	0.936	0.003
	10%	0.983	0.025 (11%)	0.952	0.005
	20%	0.986	0.022 (10%)	0.961	0.005
LAI	0%	0.897	1.287 (77%)	0.569	0.088
	10%	0.909	1.295 (75%)	0.574	0.071
	20%	0.914	1.307 (74%)	0.578	0.055

4 Neural network training process

Because the type of inputs (reflectances in the red, near infrared and short wave infrared and the sun zenith angle) and outputs are the same (LAI) as in the case of the original CYCLOPES LAI products, similar neural networks will be used (Baret et al., 2007). They mainly consist in back-propagation networks made of one layer of five tangent-sigmoid and one layer linear transfer functions, resulting in 26 synaptic and 6 biases coefficients to be adjusted. The inputs and outputs were scaled by their minimum and maximum values. The Levenberg–Marquardt minimization algorithm was used in the learning process because of its convergence performances (Ngia and Sjoberg, 2000). To prevent hyper-specialization during the training process and test performance of the networks, the data base was split in two parts by randomly selecting cases. Two third of the cases were used to train the network (training database) and the last third to test the hyper-specialization during the training process and perform some validation (test database). Five networks were trained in parallel, each corresponding to independent random drawing of initial values of synaptic weights and bias. The one providing the best performances over the test database was selected.

In the original CYCLOPES approach, radiative transfer models were run to simulate actual VEGETATION observations from prior distribution of canopy characteristics. In the proposed approach, actual reflectances observed by VEGETATION (CYCLOPES) or MODIS are associated to the corresponding CYLOPES or MODIS LAI products in the learning process. Four combinations of reflectances and LAI will therefore be investigated (Table 3): CYCLOPES observed reflectance with CYCLOPES LAI products (CYCrhoCYClai) or MODIS LAI products (CYCrhoMODlai), or MODIS observed reflectances with CYCLOPES LAI product (MODrhoCYClai) or MODIS LAI products (MODrhoMODlai). These four combinations will yield specific results on the capacity of neural networks to learn a specific algorithm (case of MODrhoMODlai), or to cross learn a given product from observations coming from another sensor (cases of CYCrhoMODlai or MODrho CYClai). The case of CYCrhoCYClai will yield obviously only limited information since CYCLOPES algorithms was already based on a neural network. However, for which the distribution of vegetation types and observational conditions and uncertainties in this training database may be different from the characteristics used in the training database of the original CYCLOPES products. In addition, original CYCLOPES products were not biome dependant, while in the present approach specific learning will be applied to each of the six classes as in the case of the MODIS original algorithm. The same definition of the 6 biome types as in the original MODIS products will be therefore kept along this study. A comparison of the performances will be achieved between learning specifically for each class or learning across all classes.

Table 3. The four combinations of products investigated along with the RMSE values evaluated over the test data set. Numbers in parenthesis correspond to RMSE values when the learning is achieved across all classes.

	CYCLOPES reflectances	**MODIS reflectances**
CYCLOPES LAI	**CYCrhoCYClai** **0.119** (0.129)	**MODrhoCYClai** **0.297** (0.305)
MODIS LAI	**CYCrhoMODlai** **0.525** (0.609)	**MODrhoMODlai** **0.502** (0.558)

Results show that training networks per classes improves marginally the performances (Table 3 and Figure 3) as compared to training across classes for CYCLOPES LAI products (CYCrhoCYClai and MODrhoCYClai) because the original CYCLOPES LAI products were not dependant on classes. The slight improvement observed might be due to a more specific training achieved over more homogeneous learning database. Conversely, improvement is more significant for MODIS LAI products (CYCrhoMODlai and MODrhoMODlai) for which the original algorithm was biome dependent, However, the distribution of residuals between training per class and across classes (Figure 3) shows that the effect is small, with most of residuals within ±0.5 $m^2.m^{-2}$. Note also that the input reflectance data set (CYCLOPES or MODIS) has a second order influence on the performances, confirming the good consistency observed previously.

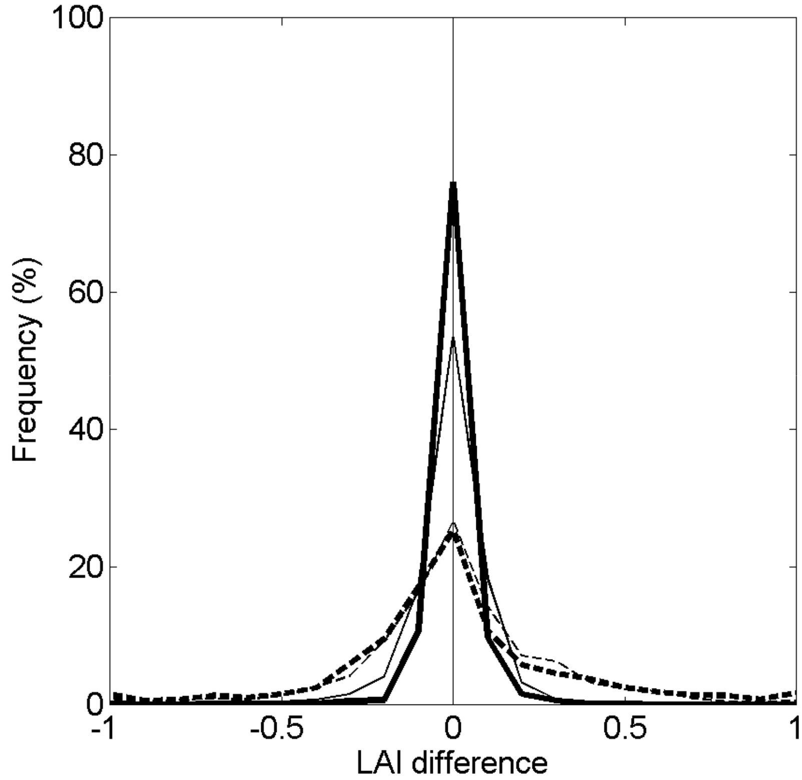

Figure 3. Histogram of LAI differences of NNT estimates on the test data base from a learning process per classes and across classes over CYLOPES (thick lines) and MODIS (thin lines) reflectances and CYLOPES (solid lines) and MODIS (dashed lines) LAI products

5 Evaluation of NNT performances

NNT performances are evaluated for the 4 combinations of reflectances and LAI. Indirect validation will first be achieved, consisting in analyzing the self consistency of products as well as the consistency between the several products and the original CYCLOPES and MODIS LAI products. Then, comparison with ground measurements (direct validation) will be presented

5.1 Indirect validation

The temporal consistency of NNT LAI estimates as compared to MODIS and CYCLOPES products is first investigated. Then, statistical distributions of the different biome classes are compared. Indirect validation was achieved over BELMANIP sites during the period 2001-2003 over the 7572 CYCLOPES and MODIS best reflectance matches as explained previously in section 3.

5.1.1 Temporal consistency

Temporal consistency was evaluated by the smoothness level of the temporal profiles. As a matter of fact, except in extreme situations such as fire, flooding, or change of land use, LAI results from incremental processes such as photosynthesis, assimilate allocation or senescence, producing relatively smooth variation time. This was evaluated as proposed by Weiss et al. (2007): the difference δ between $LAI(t)$ product value at date t and the mean value between the two bracketing dates: $\delta=(1/2(LAI(t+\Delta t)+ LAI(t-\Delta t)) - LAI(t)$, where Δt is the temporal sampling interval. Difference δ is computed only if the two bracketing *LAI* values at (t-Δt) and (t+Δt) exist. The smoother the temporal evolution, the smaller the δ difference should be. Histograms of δ (Figure 4) show that MODIS original products (MOD) are the most 'shaky', while temporal profiles of other products are smoother particularly when CYCLOPES reflectances are used. Obviously, these results could partly be explained by the actual temporal resolution of the products as already been outlined earlier in section 2.3: MODIS original LAI products are 8 days composite, as compared to the 24 days of MODrhoMODlai and MODrhoCYClai, 30 days of CYCLOPES (CYC) original products and 40 days of CYCrhoCYClai and CYCrhoMODlai products.

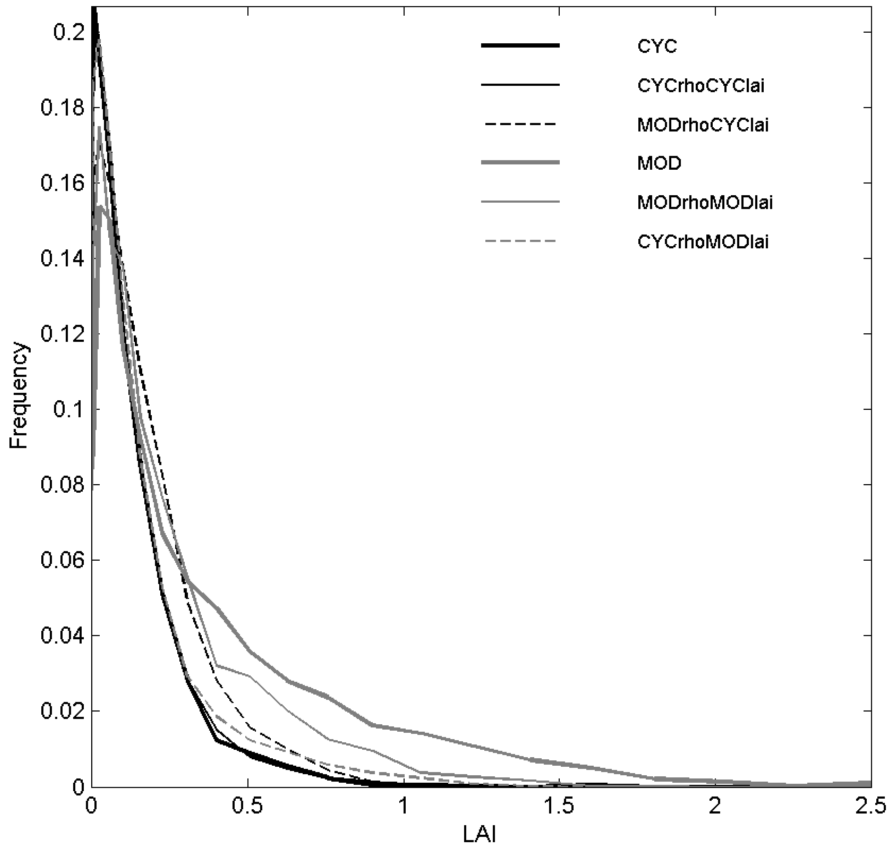

Figure 4. Histogram of the δ value for the 4 combinations of products developed and the original CYCLOPES (CYC) and MODIS (MOD) products.

To better document the temporal behaviour of each LAI product, time courses over a selection of sites will be described. In the following, results over sites corresponding to a range of vegetation types: Sky Oaks Biological Field Station (California, USA) classified as shrubs; Mongu a Savanna site located in western Zambia; Laprida (Argentina) classified as savanna by MODIS landcover but corresponding instead to grassland vegetation (www.avignon.inra.fr/valeri); Fundulea (Romania) crop site (www.avignon.inra.fr/valeri); Concepcion (Chile) corresponding to a mixed forest (www.avignon.inra.fr/valeri) classified as needleleaf forest by MODIS landcover; and Harvard (Massachusetts, USA) mixed forest classified as broadleaf forest by MODIS (BigFoot data (Cohen et al., 2006a)).

A relatively good agreement on the seasonality and its phasing is observed between original CYCLOPES and MODIS products and the four combinations NNT estimates (Figure 5). LAI magnitude show large discrepancies, except for the Fundulea agricultural site. Estimates from networks trained on CYCLOPES LAI data (CYCrhoCYClai and MODrhoCYClai networks) are very similar to CYCLOPES products. Conversely, LAI estimated from networks trained with MODIS LAI products (MODrhoMODlai and CYCrhoMODlai) are closer to original MODIS products. The best agreement was obviously found between the original LAI product and the NNT estimates based on LAI and normalized reflectances from the same source (either CYCLOPES or MODIS).

LAI estimated from MODIS reflectance (MODIS product, MODrhoMODlai and MODrhoCYClai estimates) shows a shakier time course than LAI estimated using CYCLOPES reflectances (CYCLOPES product, CYCrhoCYClai and CYCrhoMODlai estimates), confirming the previous findings (Figure 3).

Note that for the Laprida site, significant differences between original MODIS LAI and CYCrhoMODlai and MODrhoCYClai estimates were found. This feature can be explained in part as an influence of MODIS landcover misclassification as in other grassland sites classified as savanna the same tendency was observed.

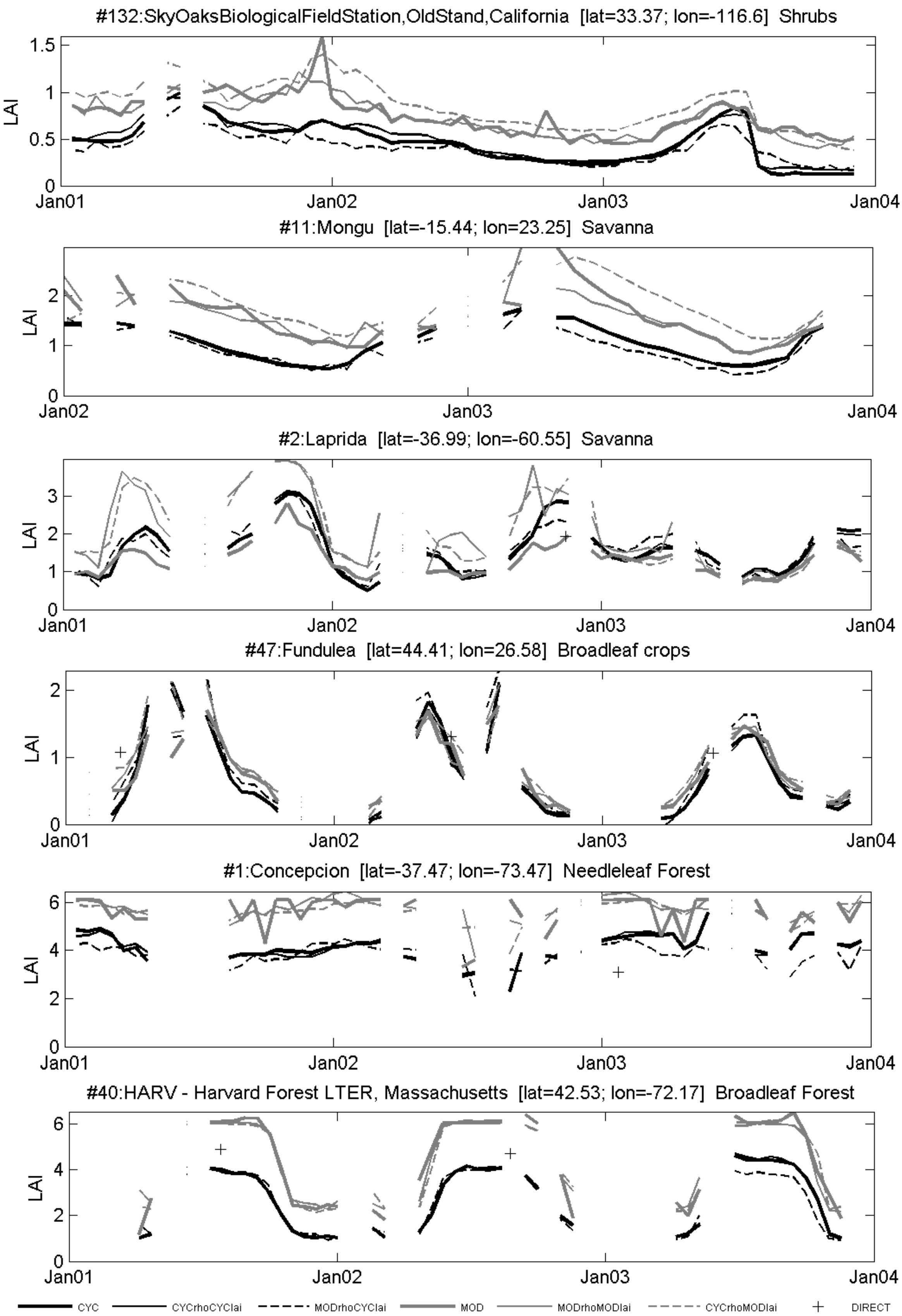

Figure 5. Temporal evolution of CYCLOPES, MODIS LAI products and NNT estimates for the period 2001-2003 over six 3x3 km^2 BELMANIP sites representing six MODIS biome classes.

5.1.2 Statistical distributions per biome type

Histograms of LAI values (Figure 6) show a general good agreement across all biomes between products derived from the same original LAI products: CYC, CYCrhoCYClai and MODrhoCYClai for CYCLOPES original LAI products, and MOD, MODrhoMODlai and CYCrhoMODlai for the original MODIS LAI products. While some similarities are observed between these two families of LAI products for shrubs, savanna, grasses and cereal crops, and broadleaf crops, larger discrepancies show off for forest canopies in agreement with previous validation studies (Weiss et al., 2007). An early saturation of LAI products derived from CYCLOPES (CYC, CYCrhoCYClai and MODrhoCYClai) appears, with maximum LAI values near 5. products derived from MODIS LAI show a broader distribution of values for forests with a narrow peak around 6 for broadleaf forests.

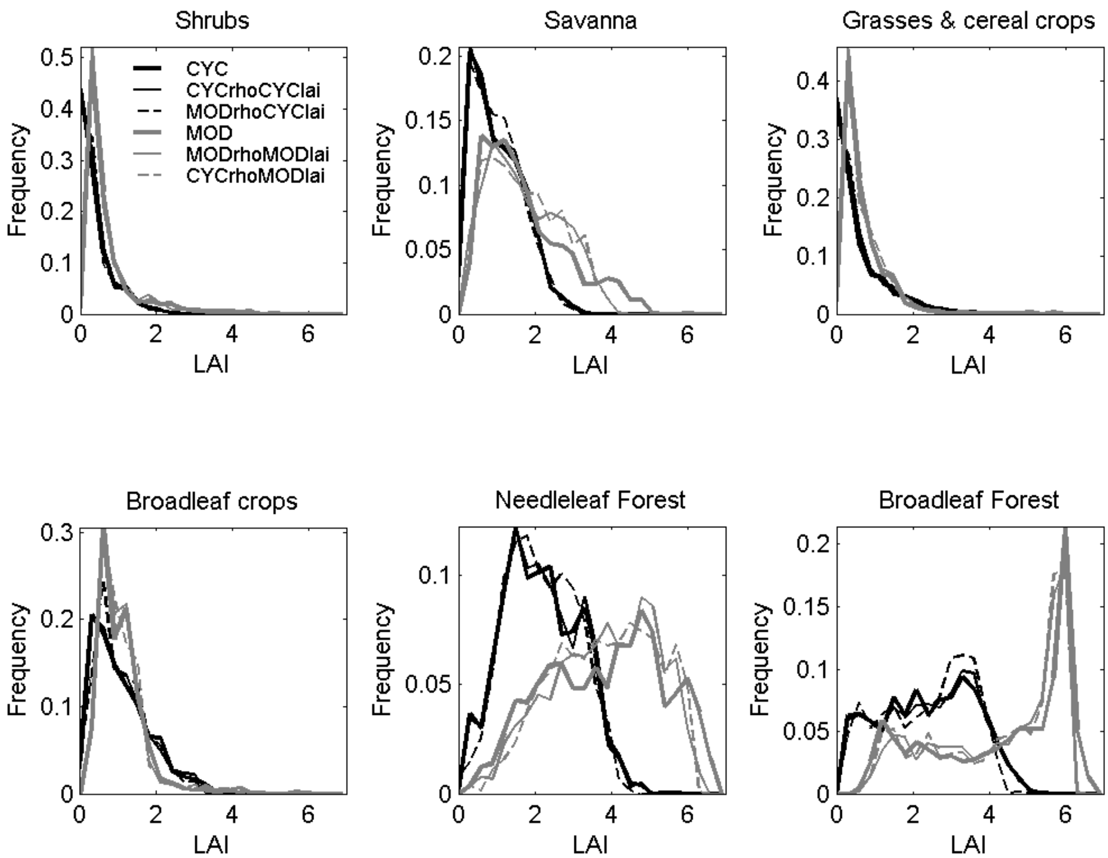

Figure 6. Distributions of CYCLOPES, MODIS LAI products and NNT estimates for six MODIS biome classes.

5.1.3 Scatterplots between the several products

Comparison between the four combinations of LAI products and the two original (resampled) LAI and CYCLOPES LAI products was achieved at the 16 days temporal frequency. Associated statistics including root mean square error (RMSE computed with the 1:1 line as a reference), correlation coefficient, slope and offset (the rectangular linear regression was selected for equal treatment of the two products to be compared) are presented in Table 4. These statistics were computed for each of the 6 biome types.

The capacity of neural networks to replace efficiently existing algorithms is here demonstrated. This was obviously not too difficult for CYCLOPES products that were already derived from a neural network approach (see top left graph of Figure 7). That was more questionable for the MODIS LAI algorithm which was based on other principles, but proved performing well (bottom left of Figure 7). Degradation of performances for MODIS as compared to CYCLOPES LAI products might be due to the larger instability observed within original MODIS products, partly due to the smaller compositing period, but also probably partly due to the way the solution is selected from the LUTs in the original MODIS algorithm. Further, errors in biome class assignment may also explain part of the degradation of performances.

The capacity of neural networks to estimate a product from reflectances coming from another sensor is also demonstrated (Table 4 and centre graphs in Figure 7). Very good agreement is observed when comparing the original CYCLOPES LAI product, with LAI estimates from MODIS reflectances. Reciprocally, good agreement is also observed between original MODIS products and NNT estimates from CYCLOPES reflectances. Again, the slight degradation in performances are probably due to the larger scattering associated to MODIS original products. No biases are observed over the whole range of variation as observed in Figure 7 and attested in Table 4 by the slopes (close to 1.0) and the offsets (close to 0.0), except for NNT estimates of MODIS products from both MODIS or CYCLOPES reflectances over Savanna, broadleaf crops and needleleaf forests. Note that NNT estimates of MODIS products from MODIS reflectances are very consistent with NNT estimates of MODIS products from CYCLOPES reflectances. The degradation of performances estimation in the case of MODIS over these biomes may be partly due to difficulties in the training process because of the instability of MODIS LAI products.

Table 4. Statistics of a per classes comparison between CYCLOPES, MODIS LAI products and NNT estimates over BELMANIP filtered data base during the period 2001-2003 for each of the six biome types: root mean square error (RMSE), correlation coefficient (R^2), slope and offset of the rectangular linear regression (y=slope x+offset with x corresponds to the lines in the table and y to the columns).

	RMSE / R^2	CYC	CYCrhoCYClai	MODrhoCYClai	MOD	MODrhoMODla	CYCrhoMODlai
Srubs N=844	CYC		0.04	0.10	0.50	0.47	0.46
	CYCrhoCYClai	1.00		0.11	0.52	0.49	0.47
	MODrhoCYClai	0.97	0.97		0.50	0.46	0.48
	MOD	0.93	0.93	0.94		0.20	0.19
	MODrhoMODlai	0.94	0.93	0.97	0.96		0.19
	CYCrhoMODlai	0.96	0.96	0.95	0.97	0.96	
Savanna N=1145	CYC		0.05	0.20	0.99	0.85	0.81
	CYCrhoCYClai	1.00		0.19	1.00	0.85	0.81
	MODrhoCYClai	0.95	0.96		1.00	0.83	0.84
	MOD	0.81	0.80	0.81		0.54	0.57
	MODrhoMODlai	0.88	0.88	0.92	0.87		0.35
	CYCrhoMODlai	0.94	0.94	0.91	0.85	0.93	
Grasses and cereal crops N=1539	CYC		0.13	0.21	0.43	0.32	0.32
	CYCrhoCYClai	0.98		0.20	0.42	0.30	0.30
	MODrhoCYClai	0.95	0.95		0.44	0.27	0.37
	MOD	0.84	0.85	0.83		0.33	0.31
	MODrhoMODlai	0.91	0.92	0.94	0.89		0.26
	CYCrhoMODlai	0.92	0.93	0.88	0.91	0.92	
Broadleaf crops N=717	CYC		0.16	0.29	0.40	0.41	0.30
	CYCrhoCYClai	0.98		0.25	0.39	0.38	0.27
	MODrhoCYClai	0.92	0.94		0.37	0.29	0.32
	MOD	0.84	0.84	0.85		0.29	0.30
	MODrhoMODlai	0.83	0.84	0.90	0.90		0.30
	CYCrhoMODlai	0.92	0.93	0.87	0.89	0.88	
Needleleaf forest N=1548	CYC		0.10	0.40	1.87	1.78	1.73
	CYCrhoCYClai	1.00		0.39	1.87	1.78	1.73
	MODrhoCYClai	0.92	0.92		1.86	1.73	1.77
	MOD	0.83	0.84	0.86		0.72	0.76
	MODrhoMODlai	0.89	0.89	0.97	0.88		0.53
	CYCrhoMODlai	0.95	0.95	0.91	0.87	0.92	
Broadleaf forest N=971	CYC		0.19	0.40	2.09	2.00	1.97
	CYCrhoCYClai	0.99		0.37	2.05	1.97	1.93
	MODrhoCYClai	0.95	0.95		2.08	1.98	1.98
	MOD	0.89	0.89	0.92		0.61	0.61
	MODrhoMODlai	0.92	0.93	0.97	0.94		0.39
	CYCrhoMODlai	0.94	0.95	0.95	0.94	0.97	

	Offset / Slope	CYC	CYCrhoCYClai	MODrhoCYClai	MOD	MODrhoMODla	CYCrhoMODlai
Srubs N=844	CYC		0.01	0.01	0.03	0.05	0.06
	CYCrhoCYClai	1.03		0.00	0.01	0.04	0.05
	MODrhoCYClai	1.03	1.00		0.01	0.04	0.04
	MOD	0.56	0.54	0.54		0.02	0.03
	MODrhoMODlai	0.58	0.56	0.58	1.04		0.01
	CYCrhoMODlai	0.59	0.57	0.57	1.05	1.00	
Savanna N=1145	CYC		0.00	0.05	-0.13	0.18	0.25
	CYCrhoCYClai	1.00		0.05	-0.14	0.17	0.25
	MODrhoCYClai	1.05	1.05		-0.24	0.12	0.15
	MOD	0.55	0.54	0.52		0.22	0.27
	MODrhoMODlai	0.66	0.66	0.64	1.16		0.04
	CYCrhoMODlai	0.69	0.69	0.65	1.19	1.02	
Grasses and cereal crops N=1539	CYC		0.01	0.03	0.12	0.20	0.18
	CYCrhoCYClai	1.04		0.02	0.10	0.18	0.16
	MODrhoCYClai	1.06	1.02		0.08	0.17	0.15
	MOD	0.93	0.90	0.88		0.10	0.07
	MODrhoMODlai	1.08	1.04	1.02	1.16		-0.03
	CYCrhoMODlai	1.03	0.99	0.97	1.10	0.95	
Broadleaf crops N=717	CYC		0.03	0.11	0.14	0.19	0.23
	CYCrhoCYClai	1.03		0.08	0.11	0.16	0.20
	MODrhoCYClai	1.12	1.08		0.02	0.07	0.14
	MOD	1.13	1.09	1.00		0.06	0.12
	MODrhoMODlai	1.25	1.20	1.10	1.09		0.06
	CYCrhoMODlai	1.27	1.22	1.14	1.13	1.04	
Needleleaf forest N=1548	CYC		0.01	0.20	0.16	0.73	0.83
	CYCrhoCYClai	1.01		0.18	0.14	0.71	0.81
	MODrhoCYClai	1.10	1.09		-0.16	0.53	0.49
	MOD	0.60	0.59	0.55		0.51	0.55
	MODrhoMODlai	0.70	0.70	0.66	1.15		0.04
	CYCrhoMODlai	0.72	0.72	0.65	1.16	1.01	
Broadleaf forest N=971	CYC		0.04	0.15	0.63	0.99	0.92
	CYCrhoCYClai	1.00		0.11	0.59	0.95	0.88
	MODrhoCYClai	1.07	1.07		0.44	0.84	0.72
	MOD	0.66	0.66	0.62		0.36	0.25
	MODrhoMODlai	0.73	0.73	0.69	1.09		-0.12
	CYCrhoMODlai	0.72	0.72	0.67	1.07	0.98	

However, NNTs could not reconcile discrepancies between the original CYCLOPES and MODIS products as observed by Weiss et al. (2007) Table 4 and Figure 2. Comparison between products derived from CYCLOPES original LAI products and those derived from MODIS ones show large scattering (Table 4 and graphs on the right of Figure 7). A closer inspection of the performances per biome classes (Figure 8) shows that good agreement is observed for Grasses and cereal crops and broadleaf crops biome classes. As a matter of fact, they correspond to canopies with very limited leaf clumping. Conversely, differences between the effective CYCLOPES LAI and MODIS ‘true’ LAI definitions show off for the other biomes, with on the average slopes close to 0.6 between CYCLOPES and MODIS LAI values (Table 4). In addition, some saturation of CYCLOPES LAI is observed for broadleaf forest, for values larger than 4 (Figure 7 and Figure 8).

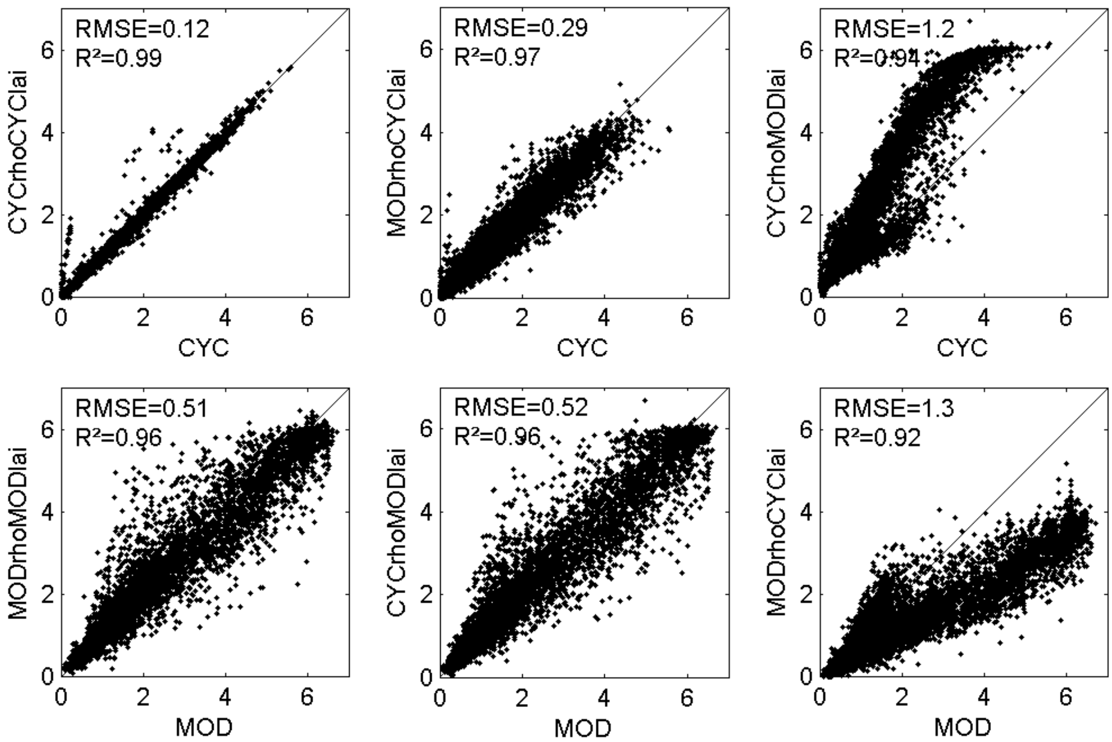

Figure 7. Comparison between several LAI products over the whole dataset.

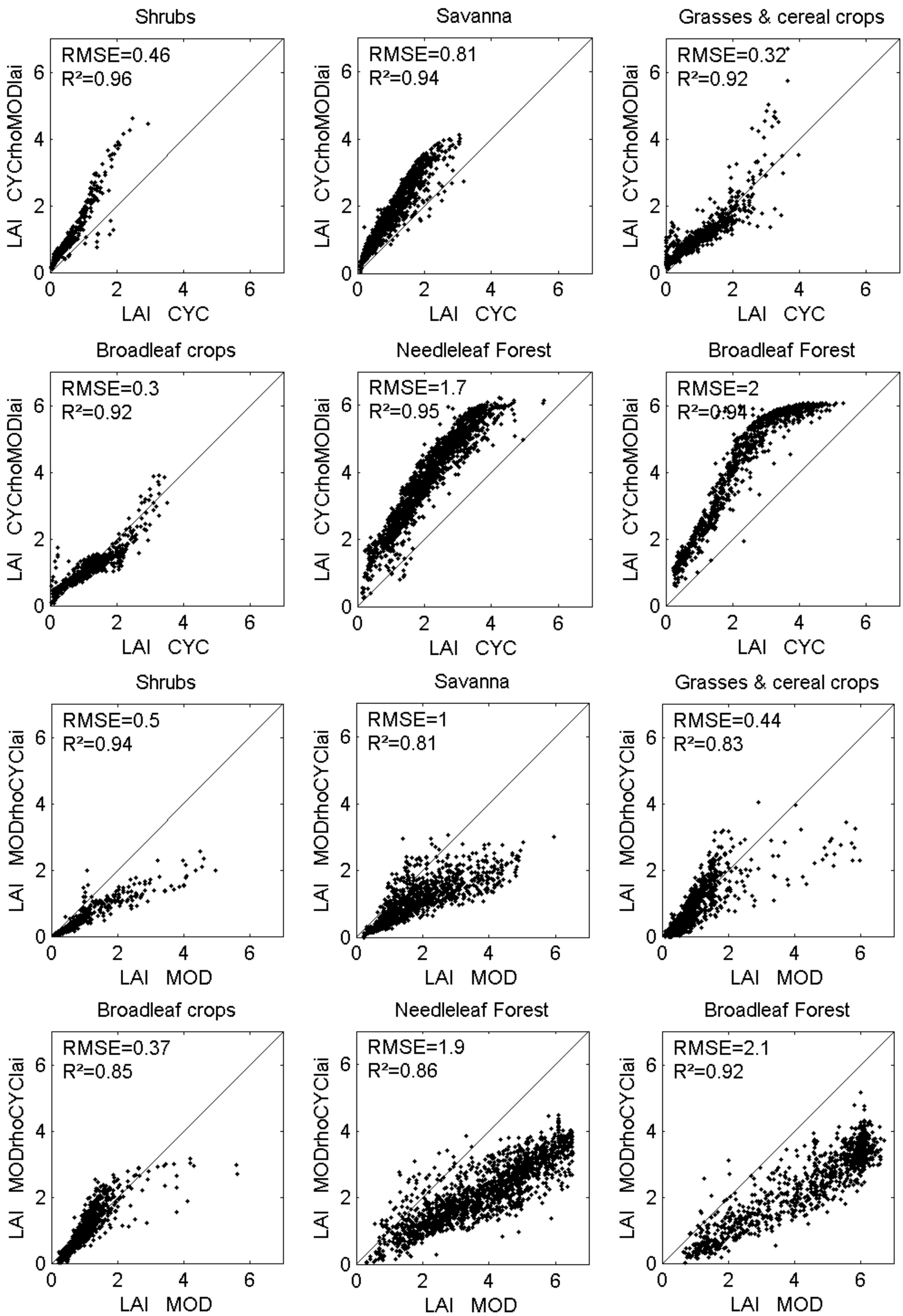

Figure 8. Comparison between CYCLOPES and MODIS products for each of the 6 biomes

5.2 Direct validation

Original MODIS and CYCLOPES LAI products and NNT estimates were compared with direct ground measurements of effective and true LAI (Figure 9). These measurements result from several international field campaigns and are available for about 40 sites widely distributed both in location and surface type. The methods used to scale up local ground measurements to the site level are described in (Morisette et al., 2006). Note that ground measurements could be derived from several devices and interpretation techniques, and may provide estimates of effective LAI values (assuming the canopy as a turbid medium) or true Lai values when leaf clumping is accounted for. In this study, 18 sites (Table 5) were matching our CYCLOPES and MODIS observations, some of the sites being sampled several times.

Results (Figure 9 and Table 6) show that products derived from the original LAI CYCLOPES products perform the best both for the effective and true LAI values, scoring the lowest RMSE values. Little differences are observed depending on the type of reflectance inputs used. Products derived from the original MODIS LAI products show larger RMSE values both for effective LAI as expected, but also for true LAI. Part of this feature could be explained by the instability in the algorithm, but also some over estimation is observed for needleleaf forests and in a lesser degree for Savanna, while LAI for the other biomes show some underestimation.

Because of the low number of data points, it is difficult to draw firm conclusions. As a matter of fact, there are not enough sites available for the larger LAI values, where maximum differences between CYCLOPES and MODIS show off. Additionally, ground measurements are associated to errors and biases that are difficult to estimate. Assuming that these ground measurements uncertainties are normal distributed with relative error of 15% (relative), and that products are associate to an intrinsic 0.5 (absolute) error as expected by users, then, a simple Monte Carlo simulation applied over the 17 available effective LAI ground measurements shows that direct validation statistics would be RMSE=0.59±0.10, R^2=0.93±0.03, slope=0.97±0.12 and offset=0.05±0.19. These numbers are not too far from our best performances for LAI products.

Table 5. Sites used for the Direct validation. Data sources are mainly Big-Foot (Cohen et al., 2006 a and b) and VALERI (www.avignon.inra.fr/valeri)

Site Name	Meas. date	Biome Class	Lat. (°)	Long. (°)	LAIeff	LAItrue	Source
Concepcion	23/01/2003	Broadleaf Forest	-37.47	-73.47	3.0		Valeri
Laprida	13/11/2002	Savanna	-36.99	-60.55	1.9	2.7	Valeri
Turco	29/08/2002	Shrubs	-18.24	-68.19	0.0	0.0	Valeri
Haouz	25/03/2003	Shrubs	31.66	-7.60	1.6		Valeri
Sevilleta	26/07/2002	Grasses & cereal crops	34.35	-106.69		0.1	Big-Foot
Sevilleta	22/08/2002	Grasses & cereal crops	34.35	-106.69		0.3	Big-Foot
Sevilleta	09/09/2002	Grasses & cereal crops	34.35	-106.69		0.4	Big-Foot
Sevilleta	15/11/2002	Grasses & cereal crops	34.35	-106.69		0.3	Big-Foot
Sevilleta	23/06/2003	Grasses & cereal crops	34.35	-106.69		0.6	Big-Foot
Sevilleta	28/07/2003	Grasses & cereal crops	34.35	-106.69		0.5	Big-Foot
Sevilleta	15/09/2003	Grasses & cereal crops	34.35	-106.69		0.5	Big-Foot
Sevilleta	21/11/2003	Grasses & cereal crops	34.35	-106.69		1.0	Big-Foot
Konza prairie	16/08/2001	Grasses & cereal crops	39.09	-96.57		2.9	Big-Foot
Harvard forest	26/07/2001	Broadleaf Forest	42.53	-72.17	4.9		Big-Foot
Harvard forest	24/08/2002	Broadleaf Forest	42.53	-72.17	4.7		Big-Foot
Sud_Ouest	20/07/2002	Broadleaf crops	43.51	1.24	1.2	1.9	Valeri
Alpilles	20/07/2002	Broadleaf crops	43.81	4.74	1.0	1.7	Valeri
Larzac	12/07/2002	Savanna	43.94	3.12	0.6	0.8	Valeri
Metl Oregon	24/09/2002	Needleleaf Forest	44.45	-121.57	1.9		Big-Foot
Fundulea	17/03/2001	Grasses & cereal crops	44.41	26.59	1.1		Valeri
Fundulea	09/06/2002	Grasses & cereal crops	44.41	26.59	1.3	1.6	Valeri
Fundulea	31/05/2003	Grasses & cereal crops	44.41	26.59	1.1		Valeri
Larose	19/08/2003	Needleleaf Forest	45.38	-75.22	3.5	5.6	Valeri
Thompson	15/07/2001	Needleleaf Forest	56.05	-98.16		1.6	Big-Foot
NOBS-BOREAS	14/07/2001	Needleleaf Forest	55.89	-98.48		3.5	Big-Foot
NOBS-BOREAS	14/07/2002	Needleleaf Forest	55.89	-98.48		3.2	Big-Foot
Jarvselja	27/06/2003	Needleleaf Forest	58.30	27.26	4.2		Valeri
Hirsikangas	02/08/2003	Needleleaf Forest	62.64	27.01	2.5		Valeri
Flakaliden	20/08/2002	Needleleaf Forest	64.11	19.47	2.5		Valeri

Table 6. Statistics of the direct validation for LAI eff (17 points) and LAI true (19 points). RMSE corresponds to the quadratic distance to the 1:1 line (and not the best regression).

	LAIeff				LAItrue			
	RMSE	R^2	slope	offset	RMSE	R^2	slope	offset
CYC	0.68	0.88	0.83	0.47	0.71	0.91	0.75	0.04
CYCrhoCYClai	0.68	0.88	0.85	0.42	0.70	0.91	0.75	0.04
MODrhoCYClai	0.57	0.92	0.80	0.45	0.73	0.91	0.72	0.05
MOD	1.3	0.93	1.4	0.07	0.92	0.86	1.10	0.02
MODrhoMODlai	1.4	0.93	1.4	0.06	0.86	0.89	1.10	-0.03
CYCrhoMODlai	1.5	0.91	1.3	0.34	1.00	0.84	1.00	0.14

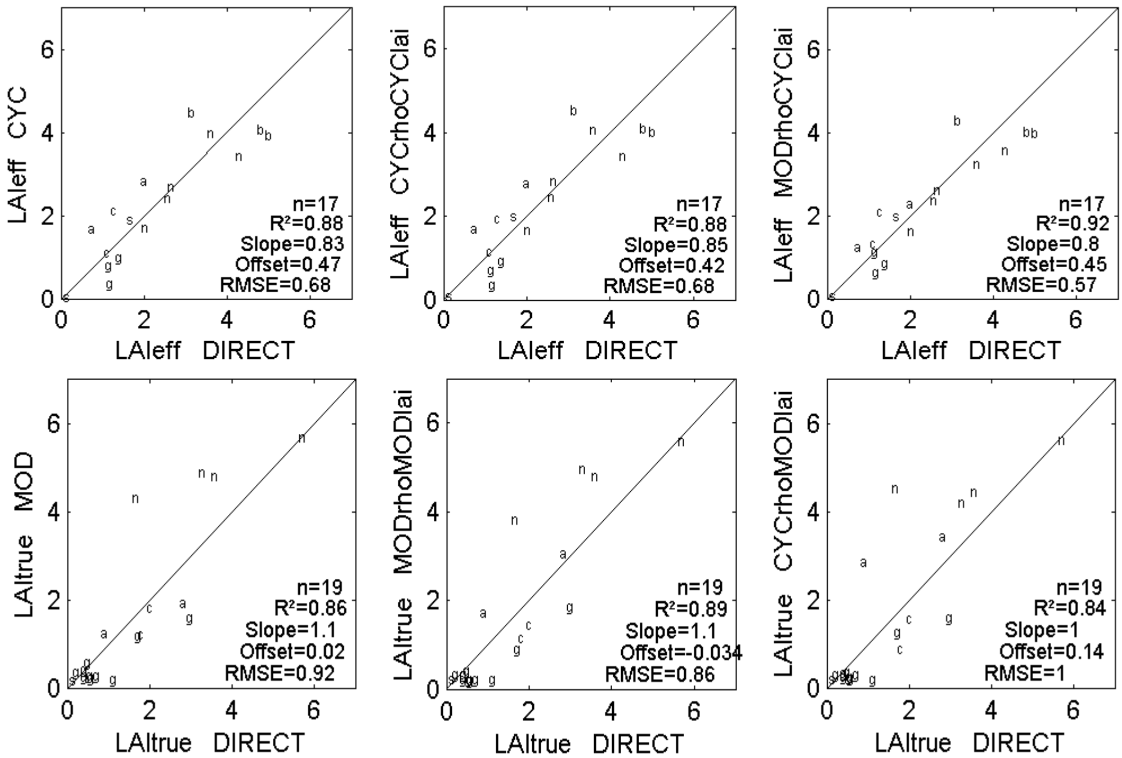

Figure 9. Comparison of CYCLOPES, MODIS LAI products and NNT estimates with direct ground measurements of effective LAI (17 points) and true LAI (19 points). Letter markers correspond to different biome classes: shrubs (s), savanna (a), grasses and cereal crops (g), broadleaf crops (b), needleleaf forest (n) and broadleaf forest (b). slope and offset values were calculated with the ordinary least squere linear regression.

6 Conclusion

Results presented in this paper demonstrate the versatility and performances of neural networks approach to learn several LAI products from several reflectance products. NNT trained with the same LAI products and different input reflectance products showed very consistent. This was also a consequence of the very good consistency observed between reflectance products of the two sensors considered: VEGETATION (CYCLOPES) and MODIS. Note that the approach does not need a very accurate absolute calibration of reflectance products: the main requirement here is a very high degree of spatial and temporal consistency of reflectances in each band.

Comparison between MODIS original products and NNT estimates both from MODIS or CYCLOPES reflectances show that MODIS algorithm has some instability that makes more shaky temporal profiles. Part of these instabilities may be attributed to the shorter temporal resolution of the original MODIS LAI products considered here. However, there might be some intrinsic effects associated to the size of the LUTs used, the way solutions are selected, or error in biome classification. NNT trained over MODIS original products seem to smooth out efficiently these instabilities. MODIS reflectance products show also a slightly noisier than CYCLOPES reflectance products, probably a consequence of the compositing period: only 61% of the signal collected in CYCLOPES compositing time window is content in the 16 days MODIS compositing window.

The main differences between LAI products considered in this study are driven by the differences between the original MODIS and CYCLOPES LAI products. Although CYCLOPES includes some clumping at the landscape level, its definition is closer to an effective LAI obtained with a turbid medium canopy assumption. Conversely, MODIS includes some clumping at the plant level that makes its products closer to the true LAI. Note that for CYCLOPES LAI products, training without distinction between classes does not provide significant improvement as compared to training for each individual biome class. Conversely, significant differences show off for MODIS for which the original LAI products were tuned for each biome class independently. For Grasses and cereal crops and broadleaf crops, because leaf clumping is actually very limited, MODIS and CYCLOPES LAI products agree very well. For the other biomes, and particularly forests, both products show still relatively good consistency, with however a systematic bias corresponding probably to leaf clumping.

Direct validation showed that NNT estimates using CYCLOPES LAI products perform the best when compared to effective LAI measurements. Performances are close to the theoretical ones when assuming 15% relative uncertainties in ground measurements and 0.5 target absolute uncertainty for LAI product. This would indicate that with small improvements in both ground measurements and algorithms, target product performances requirements would be soon reached at least for the effective LAI. True LAI is much more complex, and presumably need additional information on leaf clumping which is probably not accessible using only the spectral dimension of remote sensing observations.

Because of constraints coming from the original products considered, results have been obtained at a degraded spatial resolution of $3\times3km^2$. Similarly, the temporal resolution was not very thin, from 16 to 40 days. However, the principles developed in this study should also apply to better spatial and temporal resolution products, providing that there is good consistency in the training database between output LAI products and input reflectance. It could be also applied to any other products providing that a strong link exist with remote sensing signals. The quality of the training data base, mainly driven by the number, distribution and consistency of the inputs (radiometric signals) and outputs (the products) is critical in the success of the approach. In this study, the database was relatively limited but sufficient for a good training. However, it was not possible to get fully independent training and evaluation processes except in the case of the direct validation exercise. This aspect should certainly be improved when going from demonstration (this study) to more operational applications.

This study opens avenues for the development of consistent multi-sensor operational products. Training networks over the same LAI data base with input reflectances coming from several sensors would allow easily fusing the products for improved continuity and performances. This would provide a possible way to build ‘virtual constellations’ from different sensors, and exploit them in synergy. This issue will be addressed in depth in a forthcoming study.

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