Validation of an empirical model, LAI~VI, to force a grass growth model on Reunion Island, France

Validation d'un modèle empirique LAI ~ IV pour le forçage d'un modèle de croissance à La Réunion, France

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Abstract: The Leaf Area Index (LAI) is a parameter of many growth models used to predict biomass. LAI was used, for instance, in the Mosicas (Martiné, 1999) and Gamede (Vayssières et al., 2009) growth models for sugarcane and grass respectively, on Reunion Island, France. Those models have exhibited some limitations and prediction error can be significant. The aim of our study was to estimate LAI from satellite imaging in order to force a grass growth model. Around 430 samples were obtained from nine experimental plots situated around Saint-Pierre and Plaine-des-Cafres (South-West of the island) from April to August 2015. The sample LAI values were averaged by plot and associated with average vegetation indices (VI), computed from Spot5take5 data. Due to the testing of different VI we observed a stronger correlation between NDVI (Normalized Difference Vegetation Index) and LAI compared to other VI. The relation was so great that we found correlation values of 0.87 and 0.92 for temperate and tropical grass, respectively.

Résumé: Pouvoir prédire la quantité de biomasse disponible représente un enjeu majeur pour l'agriculture réunionnaise. La pression foncière ainsi que les périodes de sécheresse plus fréquentes ces dernières années amènent au désire d'anticiper le manque de fourrage, mais aussi à celui de mieux le répartir sur le territoire. Le Leaf Area Index (LAI) est un paramètre de nombreux modèles de croissance utilisés pour prédire la biomasse. Le LAI est par exemple utilisé dans les modèles Mosicas (Martiné, 1999) et Gamede (Vayssières et al., 2009) pour prédire respectivement la biomasse de canne à sucre et d'herbe, à La Réunion. Ces modèles présentent certaines limites et l'erreur de prédiction peut être significative. Les conditions météorologiques étant très variées (22 microclimats sur l'île) et changeantes le modèle Mosicas a par exemple des difficultés à modéliser les pics de croissance des espèces tropicales. Le but de cette étude est d'estimer le LAI à partir d'images multispectrales afin de forcer un modèle de croissance de l'herbe. Le modèle corrigé régulièrement donnera une estimation plus précise de la biomasse disponible. Environ 430 échantillons ont été obtenus à partir de neuf parcelles expérimentales situées dans la région de Saint-Pierre et Plaine-des-Cafres (sud-ouest de l'île) d'avril à août 2015. Les valeurs de LAI de chaque échantillon ont été moyennées par parcelle et associées aux valeurs moyennes des indices de végétation (VI) calculés à partir d'images Spot5take5. Quatre indices de végétation ont été testés pour leurs caractéristiques différentes : NDWI (Normalized Difference Water Index), MSAVI2 (Modified Soil Adjusted Vegetation Index), RDVI (Renormalized Difference Vegetation Index), NDVI (Normalized Difference Vegetation Index). Nous avons observé une très forte corrélation entre le NDVI et le LAI par rapport à d'autres VI. Les résultats ont montré des corrélations de 0,94 et 0,92 respectivement pour les espèces tempérées et tropicales avec une RMSE à 0,35.

1. INTRODUCTION

Due to its insularity and constantly increasing population, Reunion Island is exposed to certain agricultural problems, such as land pressure and environmental issues. Livestock farming on the island is an agricultural sector undergoing continual change. The ruminant sector wishes to develop production and increase the self-sustainability of the island for meat and milk production, despite severe land availability constraints. More frequent drought periods have been seen in the last few years. To compensate for the lack of grass, farmers import luzerne and wheat straw, generating heavy costs for the farming economy. Today, the major issue is to be able to estimate forage availability, on a territory scale, in order to optimize forage distribution throughout the year, and anticipate the need for forage imports.

Available forage biomass (per unit area) can be predicted using grass growth models based on soil, plant and meteorological parameters. However, Reunion Island is an extremely complex territory due to its steep relief of volcanic origin and its different microclimates. While these models are correct, they are impacted by extreme and highly fluctuating meteorological conditions. In addition, they need field control measurements, such as grass samples, in order to calibrate the models according to different types of soils, grass species, etc. Such measurements are time-consuming and constraining.

Satellite imagery is an essential tool for vegetation monitoring, on both local and global scales (Xie et al., 2008). Imagery for agriculture is very useful for biomass prediction goals. Most often, we find studies on a territory scale (region, country) with mid-spatial resolution, such as Modis or Landsat (Yunxiang et al., 2014, Zhao et al., 2014, Samimi et Kraus, 2004, Schino et al., 2003) or low resolution

(Wylie et al., 1995). Some studies can also be found on a plot scale for crop monitoring (Bacchini et Miguez, 2015). To estimate biomass, such studies use an empirical model between a vegetation index (VI) and biomass yield measurements. However, this leads to a loss of the functional aspect of the growth model which allows daily estimations, unlike high resolution satellite images taken at a lower time frequency.

Our study set out to combine these two methods in a hybrid approach, based on a growth model corrected by satellite image data where model prediction is replaced by satellite data. The first stage was to analyze the relationship between LAI computed from high spatial resolution SPOT5 imagery (10 m) and several VI, then compare different regression models able to predict biomass yield on plot and farm scales.

2. MATERIALS AND METHODS

2.1. Study area

The study was conducted on Reunion Island, located in the Indian Ocean, 800 km east of Madagascar (latitude 218060S, longitude 558320E, with a maximum elevation of 3,069 m asl). The island has diverse climatic and environmental conditions due to variations in altitude, rainfall, and agricultural activities. The coastal area is dominated by sugarcane production, whereas the upland central area is mainly used for cattle farming. Although the island is in the tropics, most forage crops are produced in upland areas, above an altitude of 400 m, with temperate, wet summers, from December to May, and cool, dry winters, from June to November. The heavy rainfall makes for quick forage growth. In winter, from June to September, the dry and cold climatic conditions considerably decrease forage growth rates. A wide variety of forage resources, both temperate and tropical grasses, is available depending on the altitude. *Chloris gayana* is a perennial tropical grass giving excellent productivity up to an altitude of 800 m. *Pennisetum clandestinum* (kikuyu) is a high-altitude tropical grass which is very hardy due to its creeping nature. It grows mainly between 600 and 1,600 m in altitude. Beyond 1,600 m, it is not resistant to low winter temperatures. Therefore, in the cool season, kikuyu is characterized by a vegetative pause. Temperate grass species (*Dactylis glomerata*, *Lolium perenne*, *Bromus catharticus*) are all mainly cultivated from an altitude of 800 m. All these species, other than *C. gayana*, can either be grazed or mowed. The sampling areas were multi-species grasslands, including up to four species in the same plot.

2.2. Satellite data

The satellite images used came from the SPOT5Take5 program simulating Sentinel-2. During the deorbiting of SPOT5, special programming was provided for Reunion Island allowing the reception of images up to September 2015. That programming offered two advantages: (i) the images were received every five days whereas they were only received every 15 days with SPOT5; (ii) the exact dates of satellite passes were known in advance, making it possible to match the sampling dates (field measurements) with image dates, thereby reducing the time gap (less than one day on average) between these two dates.

SPOT5 images offer four bands, Green (500-590 nm), Red (610-680 nm), NIR (780-890 nm) and MIR (1,580-1,750 nm) with a 10-m spatial resolution. In order to select an index providing a LAI prediction that was as accurate as possible, we calculated four VI from among the most widely used.

NDVI (Normalized Difference Vegetation Index) (Tucker, 1980) (equation 1) is the most widely used for vegetation monitoring (Collet and Caloz, 2001). It is found in many studies concerning LAI, giving good results on forage (Lim et al., 2015) and wheat (Kaur et al., 2015), both with 'R^2' correlation values of around 0.8.

$$NDVI = (PIR-R) / (PIR+R) \qquad (1)$$

NDWI (Normalized Difference Water Index) (Gao, 1996) (equation 2), which can be used to study water concentration, is used for vegetation monitoring (Psomas et al., 2011).

$$NDWI = (PIR-MIR) / (PIR+MIR) \qquad (2)$$

MSAVI2 (Modified Soil Adjusted Vegetation Index) (Qi et al., 1994) (equation 3) is a soil corrected index, effective for low covering vegetation. It provides a good estimation of LAI, as can be seen in Bal et al (2013) with wheat.

MSAVI2 = (2*PIR+1-√((2*PIR+1)²-8*(PIR-R))) / 2 (3)

RDVI (Renormalized Difference Vegetation Index) (equation 4)was defined by Roujean et al (1995) as the combination of two VI: DVI (Difference Vegetation Index) (Tucker, 1980) and NDVI. RDVI inherits from these two indices the ability to provide information for low and dense covers, respectively.

RDVI = (PIR-R) / √(PIR-R) (4)

2.3. Field measurements

The great diversity of forage systems on Reunion Island led us to take measurements on a wide altitudinal gradient. Nine plots were selected from the coastal zone to the highlands (from 600 to 1,600 m). Five of the plots were cultivated with tropical forage species, and the others with temperate species. The Leaf Area Index (LAI) is defined by half of the total green leaf area per unit of ground area (Watson, 1947) and is used in several grass growth models (Martiné, 1999, Vayssières et al., 2009, Johnson et Thornley, 2006, Brisson et al., 2003) because of its decisive role in photosynthesis, growth, and senescence. LAI was measured with an AccuPAR LP-80. This monitoring tool enabled the measurement of PAR (Photosynthetically Active Radiation) on and under the canopy. With this measurement we were able to estimate LAI by inversion (equation 5) of a simplified equation of Norman (1979).

$$LAI = \frac{\left[\left(1-\frac{1}{2K}\right)f_b-1\right]ln\tau}{A(1-0.47f_b)} \quad (5)$$

Where τ is the ratio of PAR measured below the canopy to PAR above the canopy, K the extinction coefficient for the canopy, f_b the fraction of incident PAR which is beamed, A = 0.283+0.785a-0.159a² (a is leaf absorptivity in the PAR band)

One of the main issues for remotely sensed observation of vegetation is the scale difference between the size of the study sites and the resolution of the remote sensing data (Eisfelder et al. 2012). To limit the potential error between field measurements and remote sensing data it is common to sample in a homogenous area (Frisson et al., 1998, Sannier et al., 2002, Wessels et al., 2006) or to increase the number of sampling units in one pixel (Baccini et al., 2008). The latter option is known to be more appropriate for low or mid-resolution satellite data. As we used high resolution data we chose to increase the number of sampling units within the plots.

According to the SPOT5 spatial resolution, each measurement was taken at more than 15 m from the plot boundaries, to avoid an edge effect due to trees, hedges and roads which might interfere with the spectral signal. Each sampling unit within a plot was more than 10 to 15 m away from the others and positioned at the center of a homogenous biomass area with a radius of 5 m. For each unit, four LAI measurements were taken in line with the four cardinal points, and then averaged.

2.4. Treatments and data analyses

LAI measurements were averaged by plot and linked to the average of the VI within a plot, while respecting as short as possible a time gap between the image and the measurement dates. Sampling was carried out within three days of the image being received. If the sampling sites were cloud covered on the images, they were excluded from the analysis.

Two types of models were used in similar studies, the linear model and the exponential model. The linear model is commonly used in arid areas (Ren et Feng, 2015, Schaffrath et al., 2011). Moreover, the most widely used model is the exponential model (Meneses-Tovar, 2011, Ji et Peters, 2007). The empirical relationship between LAI and VI led us to select an exponential model (equation 6):

$$Y = a.\exp(b.x) \qquad (6)$$

The natural log transformation of the dependent variable y led to a linear model, which could be fitted with a standard regression analysis (equation 7).

$$Ln(y) = \ln(a)+b.x \qquad (7)$$

The diagnosis of the model was based on the correlation coefficient $\hat{\sigma}$ and the Sum of Squared Error (SSE) as follows (equation 8):

$$\hat{\sigma}=\sqrt{(SSE/(n-2))} \quad (8)$$

All statistical analyses were performed using R software (R Official Site 2017).

3. RESULTS

The sampling campaign from April to August 2015 resulted in 429 samples of which only 315 were usable (not affected by clouds, not abnormal). All the samples averaged by plot gave a base of 34 usable values (Table 1).

Four VI were sufficient to obtain models with a reliable correlation coefficient and residual standard error (Table 2). NDWI, which seemed to be the least appropriate in its description for estimating LAI, was logically less efficient with a lower correlation coefficient than the other indices. RDVI, described as an index reliable for low and high coverage was particularly efficient for the tropical species. However this index was less efficient for the temperate species. Two indices emerged: MSAVI2 and NDVI. These two indices gave similar results for LAI estimation. Nevertheless, the estimation by NDVI was better with a correlation coefficient from 0.92 to 0.94 ($p<0.0001$).

We observed a saturation of NDVI for high LAI values. This saturation was reflected in the increase in difference between LAI and was predicted making growth the standard error. Figure 2 shows an under-estimation of LAI when LAI is high.

4. DISCUSSION

The relationship between VI calculated from SPOT5 images and the LAI was very strong. Other studies which may have used different methods to estimate LAI from satellite images have been undertaken. They gave similar results in terms of the significance of the results. Aboelghar et al (2010) dealt with rice along the Nile. The data used (Spot4) had the same resolution as SPOT5 images and the coverage was homogenous with a mono-species study area. The correlation between VI and LAI reached a maximum of 0.82 with NDVI. When comparing with our study we found that we had better results with an area that was more complex to sample because of the multi-species plots. Pontailler et al (2003) obtained a maximum correlation of 0.95 between LAI and estimated LAI. However, in that study, NDVI was not calculated from satellite images but from a laboratory sensor. Also, the number of measurements was much smaller (7) compared to our study. White et al (1997) also obtained similar results, but with a very heterogeneous population from grass to conifers.

Given that the vegetation index MSAVI2 is a soil adjusted index, we expected a better estimation of LAI than with the other indices. Theoretically this index can limit the soil effect in the VI. It is not necessarily the case, as experienced by Ren et al (2015) in Mongolia's arid and semi-arid zones, where the soil is rather more visible than on Reunion Island.

While the results allowed us to estimate LAI with great precision, it is still necessary to understand the possible sources of error. As in other studies (Menesses-Tovar, 2011, Moges et al., 2005) we found a saturation of VI for the estimation of vegetation cover characteristics. To explain this phenomenon, we had to look at the shape of the plant. There is densification of grass during the grass growth period. Thus, a certain share of the vegetation under the canopy is not visible from above, overshadowed by the upper part of the cover. While the VI provides information about the upper part of the vegetation, the grass continues to grow with a limited effect on the spectral signal Steltzer et Welker, 2006).

Another cause of error may be due to the sampling procedure. Some species are more or less adapted to the season and take over from others, changing the composition of the prairie during the year. This phenomenon generates heavy heterogeneity in plots. Improving the number of samples could be a solution to correct this error, but it is certainly a time consuming method.

5. CONCLUSIONS

The livestock sector is playing a growing role in Reunion Island agriculture. At the present time, limited by the amount of forage available, imports are essential. The dependence of this overseas territory is heightened by strong urbanization on agricultural lands. A monitoring tool able to estimate forage quantities in order to manage stocks and anticipate import costs is crucial. Our study highlights a strong relationship between LAI and VI for both tropical herbaceous cover and temperate herbaceous cover.

NDVI proved to be the best index for estimating this parameter out of the several indices tested. We obtained strong correlations with a value of 0.93 and 0.94 for tropical and temperate grasses, respectively. This estimation accuracy would not have been possible without the improvement in satellite imagery. The SPOT5take5 program was in fact a major factor in these results with regular image dates at 10 m. It enabled quick sampling, closest to the image dates. It should be noted that this program prefigured Sentinel2 which will allow free images every 5 days (with Sentinel-2 A and B). Estimations every five days will enable frequent data production to be fed into a grass growth model.

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Table 1. Data description with the number of usable values, gap in days between image shoot and sampling date, minimum and maximum values, average and standard deviation of measured LAI.

Table 2. Correlation index and equation order by VI and species.

Figure 1. Location of the nine study sites, South Reunion Island

Figure 2. Distribution of sampled plots for the NDVI~LAI relation and comparison of estimated LAI vs measured LAI.

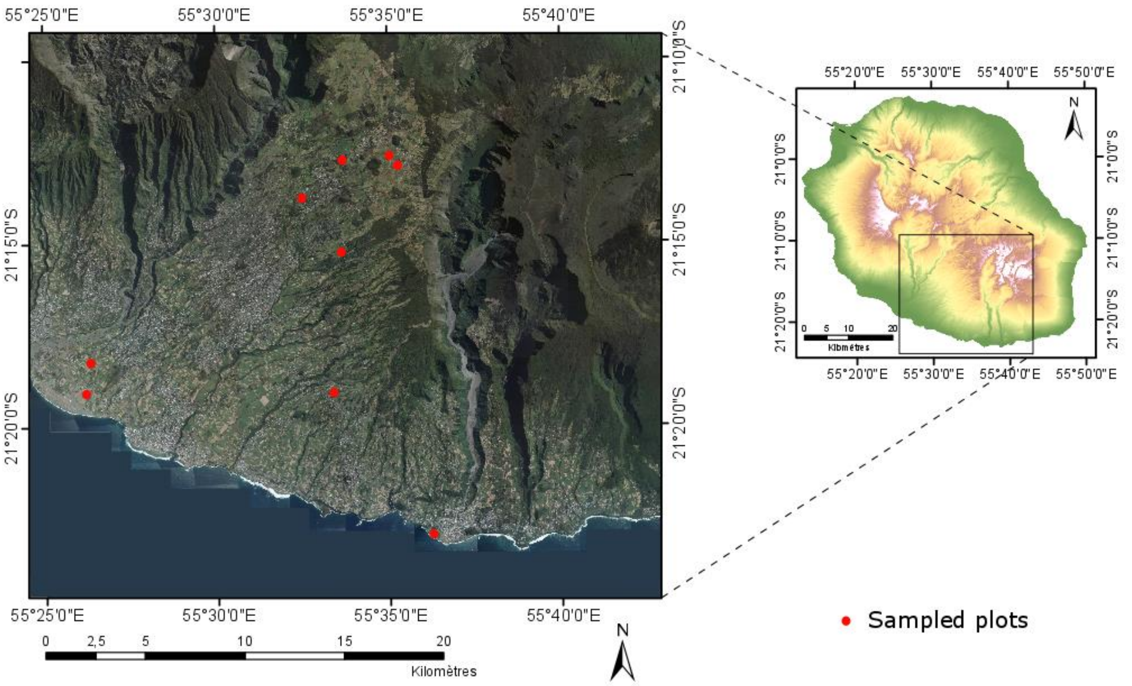
Table 1

Species	N	Measurement –image gap (days)	Min LAI	Max LAI	Avg LAI	Std-Dev LAI
Tropical	21	0.33	0.06	3.3	1.34	1.19
Temperate	13	0.54	0.08	3.9	2.20	1.29
All	34	0.41	0.06	3.9	1.67	1.29

Table 2

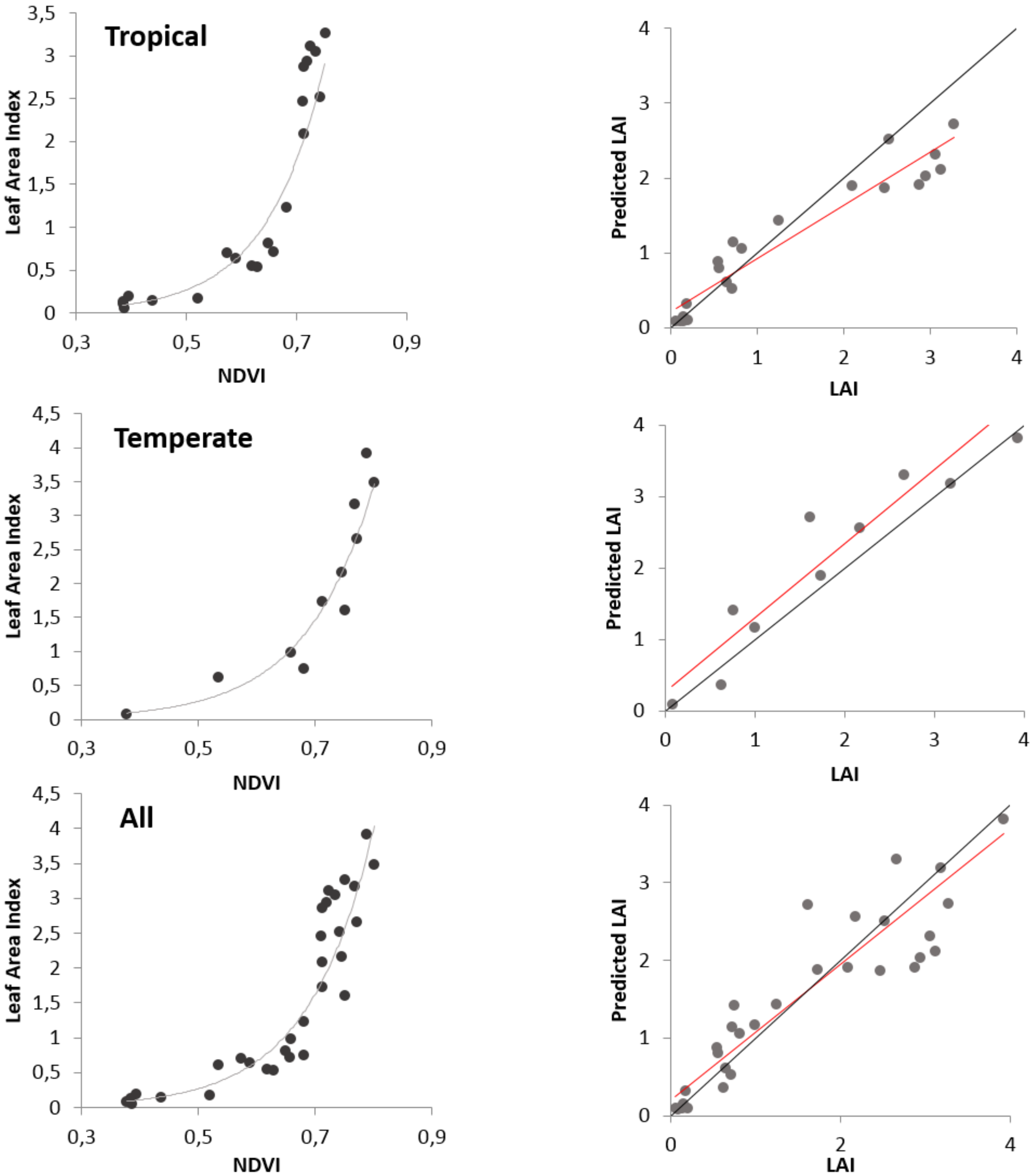
Indices	Species	R^2	Std-Err	Equation	P-value
NDVI	Tropical	0.9244	0.3711	0.0023*exp(9.4835*NDVI)	4.16E-12
	Temperate	0.9366	0.3007	0.0037*exp(8.5314*NDVI)	1.08E-06
	All	0.9258	0.352	0.003*exp(9.0022*NDVI)	< 2.2e-16
NDWI	Tropical	0.8947	0.438	0.0835*exp(8.6737*NDWI)	9.839E-11
	Temperate	0.8526	0.4585	0.0927*exp(7.3046*NDWI)	5.008E-05
	All	0.877	0.4533	0.0878*exp(7.9919*NDWI)	3.426E-15
MSAVI2	Tropical	0.9052	0.4154	0.0001*exp(11.1642*MSAVI2)	3.585E-11
	Temperate	0.9297	0.3166	0.0002*exp(10.6418*MSAVI2)	1.726E-06
	All	0.915	0.3768	0.0002*exp(10.8978 *MSAVI2)	< 2.2E-16
RDVI	Tropical	0.9319	0.3523	0.0056 *exp(0.4009*RDVI)	1.543E-12
	Temperate	0.8911	0.3941	0.22 *exp(0.2802*RDVI)	1.258E-05
	All	0.8912	0.4264	0.0111*exp(0.3376 *RDVI)	5.422E-16

Figure 1



55°25'0"E
55°30'0"E
55°35'0"E
55°40'0"E
21°10'0"S
21°15'0"S
21°20'0"S
0
2,5
5
10
15
20
Kilomètres
N
55°20'0"E
55°30'0"E
55°40'0"E
55°50'0"E
21°0'0"S
21°10'0"S
21°20'0"S
Sampled plots

Figure 2


Tropical
Temperate
All
Leaf Area Index
NDVI
Predicted LAI
LAI