USE OF INTRA-ANNUAL SATELLITE IMAGERY TIME-SERIES FOR LAND COVER CHARACTERISATION PURPOSE

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ABSTRACT

Automatic image classification often fails at separating a large number of land cover classes that punctually may present similar spectral reflectances. To improve the classification accuracy in such situations, multi-temporal satellite data has proven to be valuable auxiliary information. In this paper, we present a study exploring the usefulness of intra-annual satellite images time-series for automatic land cover classification. The reported work aims at producing a land cover classification of continental Portugal from multi-spectral and multi-temporal MODIS satellite images acquired at a spatial resolution of 500 metres for the year 2000. We started our study by performing a single date classification to define the month with the best score as a benchmark to compare with classification accuracies obtained with sets of images from various dates. Then, we considered various combinations of twelve intra-annual image observations (one per month) to quantify the gain when integrating temporal information in the classification process. Curiously, the results we obtained show that multi-temporal information does not significantly improve overall classification accuracy, but in particular it permits to better separate similar land cover classes even if those remain wrongly identified. Surprisingly also, we show that only few (typically 2) dates are sufficient to reach optimal performance of our multi-temporal classifier. In our study we used a Support Vector Machine learning approach.

Keywords: MODIS, intra-annual time-series, land cover, Support Vector Machine.

INTRODUCTION

Remotely sensed images of the Earth's surface have been widely used in the past decades for deriving land cover information by means of automatic classification. Commonly, land cover mapping involves single date image analyses. However, since maximum discrimination between different land cover classes occurs at different stages in the growth cycle of vegetation types, this approach has the drawback that not all differences are incorporated in the procedure (1). Thus, mapping of land cover often requires processing satellite images collected at different time periods and at many spectral wavelengths (2,3). Still, it is not clear yet which temporal observations are required to completely characterise land cover types, nor the specific effects of annual climatic anomalies on the selection of critical dates for land cover characterization (4). Nevertheless, multi-temporal satellite image datasets provide valuable information on the phenological characteristics of vegetation, thereby increasing the accuracy of cover type classifications compared to single date classifications (5,6). Remote sensors capable of providing surface information over large regions have usually a high temporal resolution but coarse spatial and spectral resolutions. Until recently, the *Advanced Very High Resolution Radiometer* (AVHRR), with 1.1 km spatial resolution and daily temporal resolution (7,8), was one of the few sensors on orbit with such properties. Thus, several available regional and global land cover classification studies and operational programs were based on AVHRR data, see e.g. (9) and (10), to cite but a few. In these situations, the multi-temporal spectral information provide a valuable substitute for the enhanced spectral and spatial characteristics of high resolution remote sensors (e.g., Landsat and SPOT), which have been mainly exploited for automatic land cover classification at national and local scales.

Nowadays, other Earth Observation (EO) sensors with high temporal resolutions, such as the *MEdium Resolution Imaging Spectrometer* (MERIS) and the *Moderate Resolution Imaging Spectroradiometer* (MODIS) are also available, featuring better spatial resolutions (up to 300 and 250 m, respectively) and superior standards of calibration, georeferencing and atmospheric correction, as well as detailed per pixel data quality information. As such, the EO community has started to explore images acquired by these two sensors for the land cover assessment at regional and global scales (e.g. 11,12,13,14,15,16,17,18). In particular, spectral, temporal, and spatial information acquired by these sensors are all included as part of the feature space exploited for land cover classification of wide regions (19). Imagery time-series analysis remains an essential approach for land cover cartography production at medium spatial scales, although high spectral resolution imagery allows for retrieving more detailed land cover features with single date information than before (3).

In this study we compare the accuracy of land cover classifications performed in Portugal with single date and intra-annual MODIS time-series acquired at a nominal resolution of 500 m. Specifically, we evaluate if classification accuracy is significantly improved with multi-temporal spectral information in opposition to single date spectral data. Land cover classification results were computed with Support Vector Machine (SVM), a recently proposed supervised classification system that is insensitive to space dimensionality (20).

STUDY AREA AND DATA

The study area is the entire Portuguese mainland territory. Portugal is in a transition zone featuring diverse landscapes representing both Mediterranean and Atlantic climate environments. This landscape heterogeneity allows for the extrapolation of the developed methodologies to other regions of the world.

Our study relies on the MOD09A1 product, an 8 days composite of surface reflectance images, freely available from MODIS Data Product web site (http://modis.gsfc.nasa.gov). We considered a full year observation period, from February 2000 to January 2001 (12 cloud free images), of surface reflectances measured within seven disjoint spectral bands (VIS+SWIR+MIR) and imaged at a nominal spatial resolution of 500 metres. Moreover, two vegetation indices (i.e. Normalized Difference Vegetation Index (*NDVI*, Eq. 1); Enhanced Vegetation Index (*EVI*, Eq. 2)) were also calculated for each date and used as additional band information.

$$NDVI = (\rho_{nir} - \rho_{red}) / (\rho_{nir} + \rho_{red}) \quad (1)$$

$$EVI = 2.5 \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + 6\rho_{red} - 7.5\rho_{blue} + 1} \quad (2)$$

Where ρ_{nir}, ρ_{red} and ρ_{blue} represent the surface reflectance of near-infrared (B2), red (B1) and blue (B3) MOD09A1 bands, respectively.

The land cover classes used in this study are the following: Water Bodies (WB), Natural grassland (Ng), Broadleaved Closed Trees (BCT), Barren (B), Shrubland (S), Needleleaved Closed Trees (NCT), Irrigated Herbaceous Crops (IHC), Rain Fed Herbaceous Crops (RHC) and Continuous Artificial Areas (CAA).

METHODOLOGY

Sampling

In order to test the several classification approaches using the defined nomenclature, we selected a collection of representative sample units for the nine classes of the nomenclature for the year 2000. Each sample unit represents a specific land cover class covering a surface area of 500 m by 500 m (same as the nominal resolution of used satellite images) and the final set was acquired following a stratified random sampling design using the CORINE Land Cover 2000 (CLC2000) cartography (21) as strata. To recheck every sample unit collected for each land cover class and to take into account the generalisation procedure we used ancillary data (e.g. Landsat ETM+ images acquired during the year of 2000 and orthorectified colour infrared aerial photography of 1995). At the end of this process 354 sample units were uniformly collected all over the mainland territory and distributed among the classes as follows: WB (40), Ng (16), BCT (40), B (27), S (18), NCT (55), IHC (52), RHC (59), and CAA (47).

Classification

Land cover classification results were computed with Support Vector Machine (SVM). SVM are a new generation of supervised learning systems based on recent advances in statistical learning theory (22). Pioneered by the work on learning strategy by Vapnik and collaborators (23,24), they have rapidly and successfully been applied to numerous real-world classification problems. In short, SVM is a kernel-based classifier that uses a non-linear mapping to transpose the data initially lying in a non-linearly separable space, onto a (possibly infinite dimension) feature space. Due to the high complexity of this new representation, it is likely that the different classes become linearly separable. In our specific task, we used Gaussian kernels and a regularisation strategy that is often referred to as the ν-parameterisation in the SVM literature (25). The generalisation to multiple classes' problem was straightforward using a one-versus-the-rest strategy. See (11) and (13) for a complete and detailed description of the SVM learning system used in this study.

Twelve classifications with SVM, each one using a single-date image from a different month, were initially performed in order to compare the results of posterior multi-temporal images classifications against the best classification accuracy based on single date spectral information. In a second step, land cover classifications with SVM were performed with several combinatorial subsets of the twelve monthly images. We computed all possible classifications for subsets of two and three dates (66 and 220 combinations, respectively). A classification based on the set comprising all the twelve image dates was also performed. Other combinatorial subsets were discarded because we achieved the essential results with these arrangements.

There is little guidance in the literature on the criteria to be used in selecting the optimal kernel-specific parameters for SVM computation, so a number of trials were carried out with each dataset using different kernel-specific parameters, and taking into account classification accuracy as a measurement of their quality (20).

All classification results have been obtained using cross validation – a standard procedure used in longitudinal data analysis, e.g. land cover classification (26,27,28), that permits evaluating the first and second order statistics of the classifier. Cross validation permits evaluating the performance of a classifier from a single data set used for train and test purposes simultaneously. The data is split into *n* subsets of samples, and *n* classifications are performed using each subset as a hold-out set. The classifier accuracy is scored on the hold-out set of each classification. The average accuracy is taken as the estimated accuracy over the entire domain that is to be classified. We fixed to five the number of cross validation folds (26).

Analysis

In order to perform a systematic investigation of the relative gain from incorporating a temporal dimension into the land cover classification process, standard accuracy measures were derived from the classification results obtained with each combinatorial subset of the twelve monthly images. The measures used were: overall accuracy, producer's accuracy and user's accuracy (29).

Moreover, since the comparison of classifications was fundamental to the study, a statistically rigorous approach for asserting significant differences between our experimental setups was adopted (26). The goal was to evaluate $H_o : p_a = p_b$ versus $H_1 : p_a < p_b$, in which p_a and p_b indicate, respectively, the proportion of correctly classified pixels from *a* and *b* images datasets, and moreover card (*b*) > card (*a*). The hypothesis testing for the difference between two variables with binomial sampling distribution is based upon the standardised normal test statistic (30,31,32)

$$Z = \frac{\hat{p}_a - \hat{p}_b}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{m} + \frac{1}{n}\right)}} \xrightarrow{a} N(0,1) \tag{3}$$

in which $\hat{p}_a - \hat{p}_b$ is the sample estimate of $p_a - p_b$, $\hat{p} = (m\hat{p}_a + n\hat{p}_b)/(m+n)$, and *m* and *n* the number of samples used to derive $\hat{p}_a$ and $\hat{p}_b$, respectively. With this test, a significant increase in classification accuracy occurs at 95% level of confidence if $Z < -1.645$.

RESULTS AND DISCUSSION

In Figure 1 we present the overall 9-classes classification accuracy obtained with SVM applied to each of the monthly dates separately. The goal was to define the month yielding the best score and to use this as a benchmark to position the classification accuracies obtained with multi-temporal image sets.

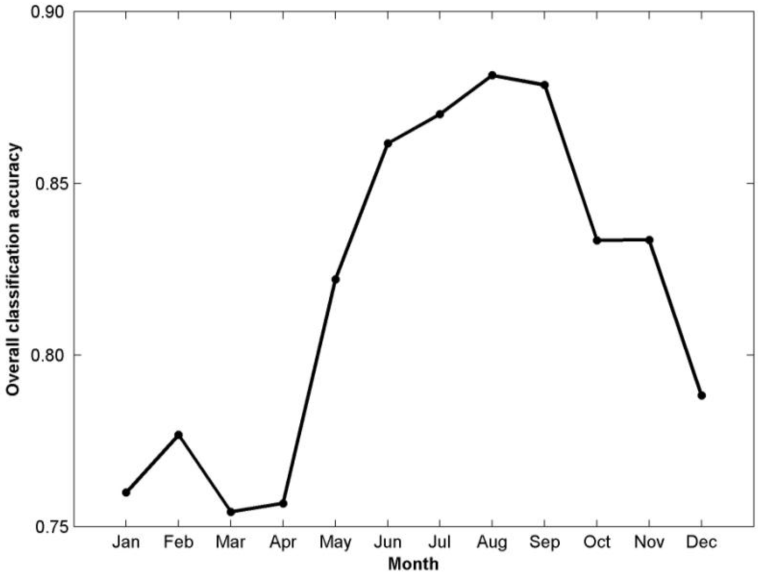

Figure 1. Overall classification accuracy as a function of time.

The best classification rates are attained in summer times (between June and September), with August being the month with the maximum overall classification accuracy. These results are similar to the ones obtained by (13), confirming that this is the best period to discriminate between core cover types in Portugal.

A closer view at the user's and producer's accuracies per class (Table 1), based on the classification results derived with the reflectances and vegetation indices measured in the August image, shows that "Natural grassland" (Ng) is definitely the least distinguishable land cover class, frequently confounded with "Shrubland" (S), "Barren" (B) and "Rain Fed Herbaceous Crops" (RHC). Similarly, "Shrubland" (S) is often confounded with several land cover classes, but mainly with "Natural Grassland" (Ng).

Looking at Figure 2 we perceive that the core class averaged EVI time series corresponding to “Barren” (B) and “Natural grassland” (Ng) overlap in the entire summer period. Furthermore, the “Natural grassland” (Ng) profile is up to a scale factor, very similar to the “Rain Fed Herbaceous Crops” (RHC) response. Similar results were observed with NDVI and spectral bands. For these reasons, it is not surprising that classification results computed with a single summer image reveal a mixture between these cover types. However, and given the different phenology of these classes, it is reasonably expectable that adding more temporal information in the feature space, selected at phenologically critical times (e.g. February or November), should improve their particular classification performances (6). The complexity is to define which summer and winter dates should be combined to increase land cover classes discrimination.

Table 1: User’s and Producer’s accuracies per class. This repartition corresponds to the SVM classification based on reflectances and vegetation indices obtained at a single date (August, 2000).

	WB	Ng	BCT	B	S	NCT	IHC	RHC	CAA	User's accuracy
WB	40	0	0	0	1	0	0	0	0	0.98
Ng	0	5	0	1	4	0	0	2	0	0.42
BCT	0	0	40	0	2	2	0	0	0	0.91
B	0	4	0	18	2	0	1	0	1	0.69
S	0	3	0	2	6	0	1	0	0	0.50
NCT	0	0	0	0	2	53	0	0	0	0.96
IHC	0	0	0	0	1	0	50	0	0	0.98
RHC	0	4	0	1	0	0	0	56	0	0.92
CAA	0	0	0	5	0	0	0	1	46	0.88
Producer's accuracy	1.00	0.31	1.00	0.67	0.33	0.96	0.96	0.95	0.98	-

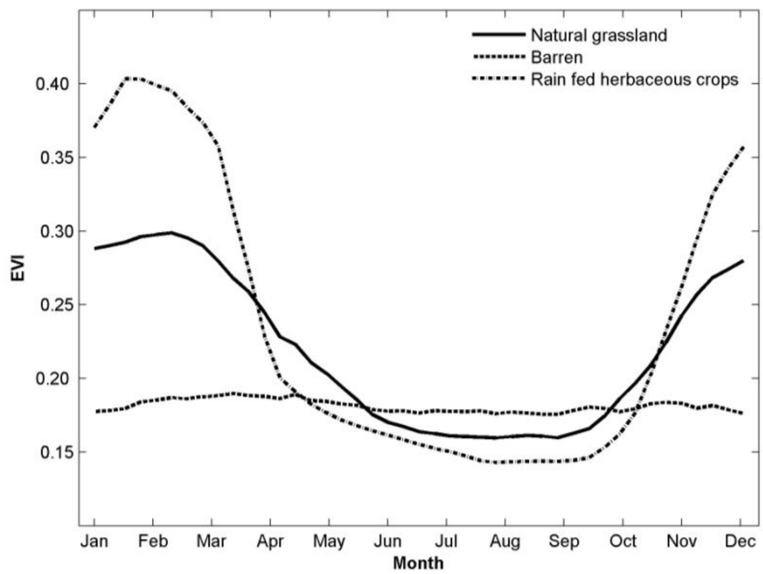

Figure 2: Mean EVI values as function of time for “Natural grassland” (Ng), “Barren” (B), and “Rain Fed Herbaceous Crops” (RHC). See (33) for further details on mean profiles calculation.

In Table 2 we present the results of the classifications performed with combinatorial subsets of two dates. In all cases, a SVM is trained and optimized on reflectance from all spectral bands and vegetation indices. In Figure 3 we present, for each month m_i (i=1,…,12), a box plot with the overall classification accuracy distribution (median, quartile, extremes and outliers) obtained for all pair-wise combinations of m_i with each of the remaining eleven months (Table 2).

Table 2: Overall land cover classification accuracies obtained with combinatorial subsets of two dates.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	-	0.84	0.84	0.85	0.88	0.88	0.89	0.89	0.88	0.86	0.85	0.84
Feb	0.84	-	0.81	0.85	0.86	0.87	0.87	0.88	0.87	0.86	0.86	0.85
Mar	0.84	0.81	-	0.81	0.86	0.87	0.88	0.88	0.88	0.87	0.86	0.85
Apr	0.85	0.85	0.81	-	0.87	0.87	0.87	0.88	0.87	0.87	0.87	0.86
May	0.88	0.86	0.86	0.87	-	0.86	0.87	0.87	0.88	0.87	0.87	0.87
Jun	0.88	0.87	0.87	0.87	0.86	-	0.86	0.88	0.87	0.89	0.89	0.88
Jul	0.89	0.87	0.88	0.87	0.87	0.86	-	0.87	0.88	0.89	0.90	0.89
Aug	0.89	0.88	0.88	0.88	0.87	0.88	0.87	-	0.87	0.88	0.90	0.89
Sep	0.88	0.87	0.88	0.87	0.88	0.87	0.88	0.87	-	0.87	0.88	0.88
Oct	0.86	0.86	0.87	0.87	0.87	0.89	0.89	0.88	0.87	-	0.86	0.87
Nov	0.85	0.86	0.86	0.87	0.87	0.89	0.90	0.90	0.88	0.86	-	0.85
Dec	0.84	0.85	0.85	0.86	0.87	0.88	0.89	0.89	0.88	0.87	0.85	-

The most important remarks when comparing these results with those from Figure 1 is that the best median pair-wise classifications are achieved considering at least one image from summer time, and overall classification accuracies with summer images are those that have the smallest intervals of variation (Figure 3). These outcomes confirm, once again, that spectral information from summer is necessary for a superior discrimination of land cover classes in Portugal. Specifically, the maximum overall classification accuracy was obtained by combining August and November images (the same value was achieved with the subset containing July and November dates), and the median values of the classifications achieved by combining August with all other months proved to be greater than the combinatorial sets of all other dates.

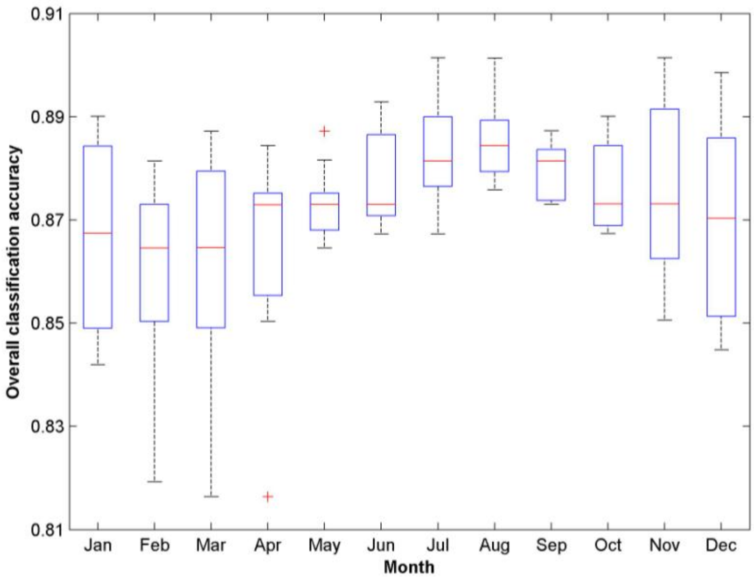

Figure 3: Overall classification accuracy per combinatorial subsets of two dates. Each box plot represents the lower quartile, median, and upper quartile of classification accuracy obtained for all pair-wise combinations of each month with each of the remaining eleven months images. Classification values that are considered as outliers are represented by "+".

This result suggests that it is most likely to obtain an overall maximum classification value if spectral information from August is in the dataset used for land cover classification. Moreover, looking closer at the results from Figure 2, we also perceive that November and December are some of the winter dates that maximize the distance between the mean profiles of cover types that mix up in summer (e.g. Ng and B). For that reason, it is expected that the classification accuracies of these classes could be increased by using these dates together with the summer dates as input features for classification. Classification results with two dates proved that the previous analysis of EVI mean profiles of Figure 2 is sensitive, and that the overall classification accuracy can be increased by using spectral features from different seasons (summer and winter) in the classification process (Table 3).

A similar classification approach with combinatorial subsets of three dates was also performed. Figure 4 compares the best overall classification accuracies obtained when training a SVM (i.e. optimizing its parameters) on observations from month m_i, from the pair (m_i, m_j), and from the triplet (m_i, m_j, m_k). For each m_i - combination, only the best classification accuracy is displayed.

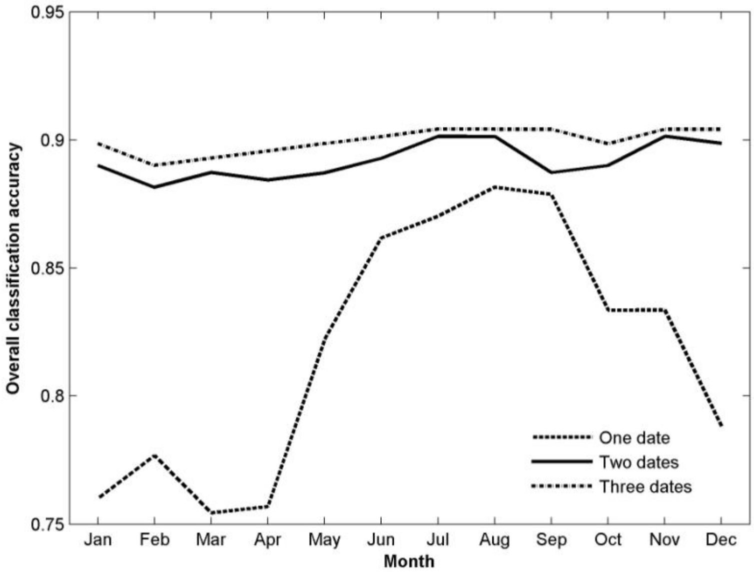

Figure 4: Overall classification accuracy obtained with observations from a single date and from combinatorial sets of two and three dates. For each month, only the best overall classification accuracies obtained by combining it with one and two other dates are displayed.

This figure shows that increasing the temporal spectral features for classification maximizes the monthly overall classification accuracy achievable with single date information. However, this is mostly evident for months out of the summer period, which are the ones that clearly benefit from those combinations, whereas it is not so important for the classification results achieved with a single date in summer. This is an important result showing that the best classification accuracy attained with single date information is quite similar to those attained with two and three dates.

Classification accuracies for the nine land cover classes using single-date, two-dates, three-dates and twelve-dates spectral information and vegetation indices as input features for the classification with SVM are presented in Table 3. Notice that for two and three dates, only the combinatorial set with the best overall classification accuracy in each case is presented.

Looking at the results of this table we perceive that overall and particular classification accuracies obtained with one or more dates are quite similar. The classification results showed that embedding information available for all dates simultaneously had to face the problem of insufficient training data, which modestly degraded the classification scores previously obtained for some classes with only two and three dates. Also, the sparseness of available samples adds to the classification difficulty. However, we notice that using spectral data and vegetation indices from August and November images as input features for classification, the overall accuracy was improved, as well as the producer's accuracies of "Shrubland" (S), "Barren" (B) and agricultural (IHC, RHC) classes. This is the most important result proving that multi-temporal data, may be redundant regarding the overall classification task, but can turn out to be useful at separating two specific classes (which does not necessarily mean that individually those classes will be correctly identified in a multi-class classification context).

Table 3. Overall classification accuracies from the best single date classification, from the best two and three-dates combinatorial sets and from the twelve-dates association. The table shows the individual classification accuracy for each class (producer's accuracy) and overall accuracy.

	Number of input dates for classification			
Land cover class	1 August	2 August + November	3 August + November + July	12 Dates
Water Bodies (WB)	1.00	1.00	1.00	1.00
Natural grassland (Ng)	0.31	0.31	0.31	0.38
Broadleaved Closed Trees (BCT)	1.00	0.98	0.95	0.95
Barren (B)	0.67	0.70	0.74	0.67
Shrubland (S)	0.33	0.44	0.39	0.33
Needleleaved Closed Trees (NCT)	0.96	0.96	0.96	0.96
Irrigated Herbaceous Crops (IHC)	0.96	0.98	1.00	0.98
Rain Fed Herbaceous Crops (RHC)	0.95	0.98	1.00	0.98
Continuous Artificial Areas (CAA)	0.98	0.98	0.98	1.00
Overall accuracy	0.89	0.90	0.90	0.90

Table 4 provides the *Z* values calculated in order to check how significant the improvements in overall classification accuracy are when we take into account more than one single-date spectral features and vegetation indices for classification. *Z* values were computed considering the proportion of correctly classified sample units per combinatorial subset presented in Table 3. If the calculated *Z* value is smaller than -1.645, the difference between the overall classification accuracies obtained with two different imagery time sets can be interpreted as a significant increase in classification accuracy at a 95% confidence level.

Table 4: Z values to appraise the significance of the difference between classification accuracies from the best single date classification, from the best two and three-dates combinatorial sets and from the twelve-dates association.

Number of input dates for classification	1	2	3	12
1	-	-0.61	-0.74	-0.36
2	-0.61	-	-0.13	0.25
3	-0.74	-0.13	-	0.38
12	-0.36	0.25	0.38	-

The results introduced in Table 4 show that there is no significant improvement between the performances of SVM using spectral data from one, two, three or even twelve dates as input features for classification (all calculated *Z* values are superior to -1.645). It can be concluded that for this land cover sample set, all combinations of time features are equivalent for classification with SVM. This result was not surprising, since it has been previously shown in (3) that the temporal domain was not relevant for land cover classification with MODIS data in Arizona. Still, it is important to note that overall classification accuracy results always benefit from the addition of multi-temporal information, as observed in Table 3.

CONCLUSIONS

The results we obtained show that combining intra-annual monthly spectral information for land cover classes' discrimination in Portugal does not significantly improve the best overall classification attained with single date information. Spectral data from summer dates proved to be indispensable for most land cover classes' discrimination, but pair-wise classes discrimination benefit from the inclusion of spectral data of at least one winter date. Thus, we should remark that the use of multi-temporal imagery data for the discrimination between particular land cover classes proved to be important, although overall accuracy did not significantly benefit from it. However, since spectral profiles of vegetation classes are in general smooth slowly varying functions, it is expectable that few temporal spectral features are sufficient to assemble most of the discriminant information.

From a methodological viewpoint, SVM proved to be insensitive to the dimensionality of input data, given that similar overall land cover classification accuracy results were obtained with one and twelve monthly imagery spectral data.

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