SVM Selective Fusion (SELF) for Multi-Source Classification of Structurally Complex Tropical Rainforest

Robin Pouteau, Benoît Stoll

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***Abstract*—Accuracy of land cover classification is generally improved by inputting multi-sensory and GIS data since complex vegetation type identification benefits from synergism of complementary information. However, multi-source fusion can also deteriorate accuracy when some classes do not benefit from all sources. On the basis of this premise, we introduce a Selective Fusion (SELF) scheme based on Support Vector Machines (SVM) which use a single source for source-specific classes and fuse all sources for classes considered as "in difficulty". Our method yields better overall accuracy and Kappa than the classical systematic approach since it takes advantage of the accuracy achieved by SVM and its ability to weight numerous and heterogeneous sources without the drawback of being sensible to irrelevant data for source-specific classes. This operational method can be used efficiently to enhance accuracy when analyzing the wealth of information available from remote sensing products.**

***Index Terms*—Digital elevation model (DEM), ecosystems, image fusion, multispectral imaging, support vector machines (SVM), synthetic aperture radar (SAR), vegetation mapping.**

I. Introduction

An INCREASING number of sensors and GIS products of greater diversity is available to the remote sensing community. Such a variety of data has very useful complementary properties and multi-source fusion can therefore provide more accurate land cover classification than conventional mono-source approaches [1]–[10]. Besides, accuracy of these classifications is critical for an effective future use (biodiversity and forest management, species prediction modeling and other ecological applications, global change impact studies, etc.) to prevent error propagation.

A range of fusion algorithms and schemes have been proposed and compared over the past two decades which highlights that multi-source fusion is a key research topic with major stakes. They were introduced to integrate multi-sensor satellite or aerial imagery and GIS data. GIS data refers thereafter to Digital Elevation Models (DEM) extracted data, climate data, soil data or vector overlays such as roads, rivers, human population density or another mapped factor that affects the land cover distribution. To our knowledge, the first attempt is [1] where fusion of visible Landsat MSS (Multispectral Scanner) bands with infrared Landsat MSS bands is performed to map 11 classes in an agricultural landscape of New South Wales (Australia) using a probabilistic scheme that employs a global membership function and the Dempster's orthogonal sum combination rule. Optical Landsat MSS data and GIS data (elevation, slope and aspect) are fused in [2] to map 10 classes in a montane temperate forest of Colorado (USA) using the minimum Euclidean distance, the Maximum Likelihood Classifier (MLC) and the minimum Mahalanobis distance. This study shows that GIS data are individually less contributing to the classification success than optical data but the contribution of the three GIS data together faced to the Landsat MSS data seems significant since classification overall accuracy reaches 67.9% with the single Landsat MSS data and 78.0% with all the sources. The first comparative fusion of both optical and Synthetic Aperture Radar (SAR) data is probably [3] which used optical Daedalus 1268 Airborne Thematic Mapper data with "PLC-band, fully polarimetric NASA/JPL SAR sensor" data to map 6 classes in an agricultural landscape of Feltwell (UK) using various Artificial Neural Networks (ANN) approaches (structured- ANN and fully connected-ANN) and the k-nearest neighbors. Then, Benediktsson and Kanellopoulos [4] fused optical Landsat TM (Thematic Mapper) data with ERS-1 SAR data to map 12 classes in an anthropogenic area of Lisbon (Portugal) using MLC, ANN, the majority voting and the Logarithmic Opinion Pool (LOGP). In [5], optical Landsat TM data and ERS-1 SAR data are fused to map 16 classes in an agro-forest landscape of Gothenburg (Sweden) using MLC, ANN and the Sequential Maximum *A Posteriori* (SMAP). In 2002, Huang *et al.* [6] use Landsat TM and MODIS sensors to map 6 cover types across a landscape in Maryland (USA). They introduced Support Vector Machines (SVM) in multi-source comparative studies and compare it to MLC, ANN and Decision Trees (DT). Next, Song *et al.* [7] fused optical Landsat TM native bands with feature extracted from imagery, textural information from imagery and GIS data (elevation, slope, distance to water body and land cover/land use map) to map 14 classes in an agricultural landscape of Oklahoma (USA) using both C4.5 algorithm and SVM. Furthermore, the latter paper reveals that performance given by classifying multispectral satellite imagery along with GIS data is higher than by adding derived features from imagery

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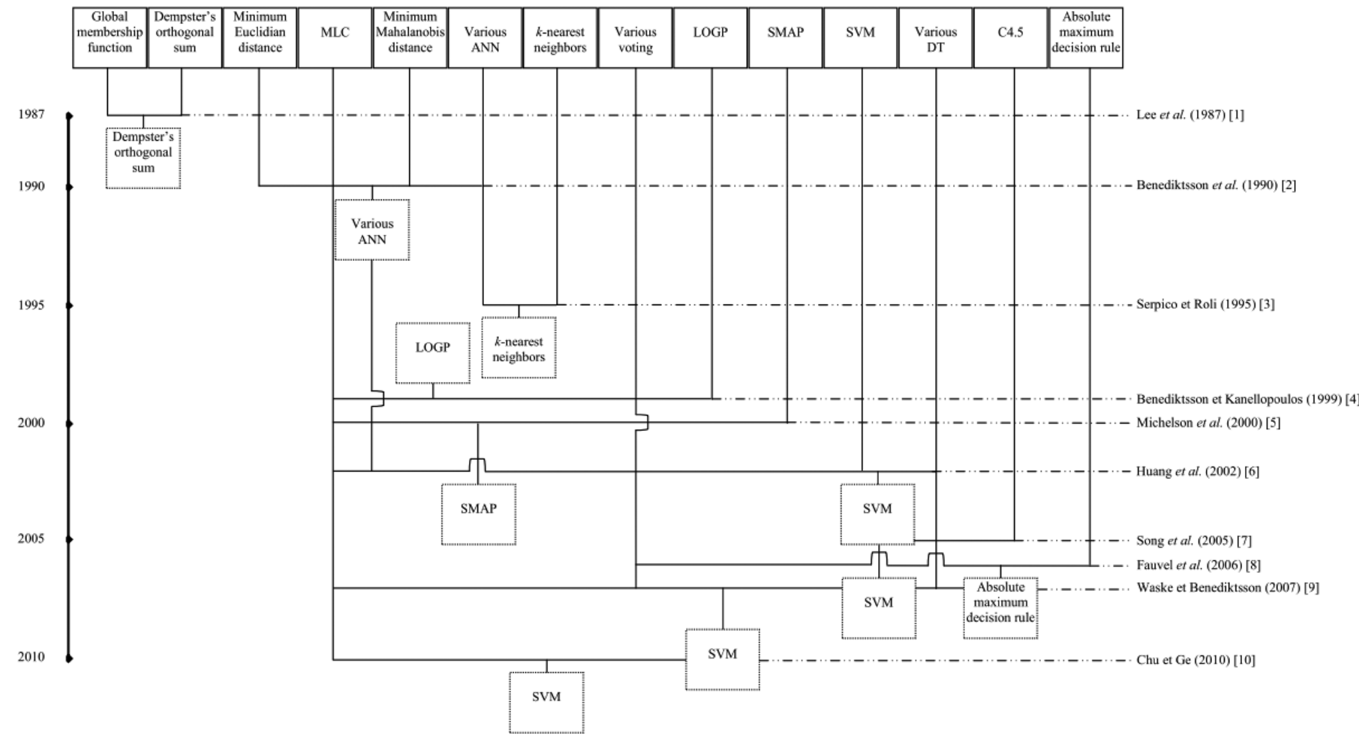


Fig. 1. Schematic representation of the results from studies comparing multi-source fusion algorithms for land cover classification (non-exhaustive list). SVM has been recently and successfully used for this purpose.

to the latter. This result suggests that classification accuracy decreases when data irrelevant for a range of classes are added. Two optical IKONOS images are merged in [8] to map 6 urban units in Reykjavik (Iceland) using ANN and a fuzzy decision rule. The ability of MLC, DT, "boosted-DT" and SVM to fuse optical Landsat-5 TM and SPOT-5 data with Envisat ASAR and ERS-2 data is compared in [9] over an agricultural landscape of Bonn (Germany) where 8 classes occur. More recently, Chu and Ge [10] fused optical SPOT-2 data with ALOS/PALSAR data to map 6 classes in an urban/peri-urban area of Hochiminh (Vietnam) using MLC and SVM.

The previous non-exhaustive list of studies comparing fusion algorithms mainly focuses on simple anthropogenic structures with few classes. According to the results of these comparisons, the best and the most recent fusion algorithm is arguably SVM (Fig. 1). SVM success in multi-source fusion is probably due to both its generally recognized performance in mono-source [11], [12] and the ability of machine learning algorithms to weight numerous and heterogeneous sources (different types, different units, mixing of continuous and categorical data) according to their relevance [2].

Although the classification scheme proposed by Waske and Benediktsson [9] is generic, quite simple to implement and adapted to classify data of different nature, its main drawback is that fusion is globally performed for all classes. Indeed, for some classes, multi-source fusion can also deteriorate accuracy found in mono-source when a non-relevant source is used [7]. This paper focusing on structurally complex montane tropical vegetation aims to assess an extension of this method: the Selective Fusion (SELF).

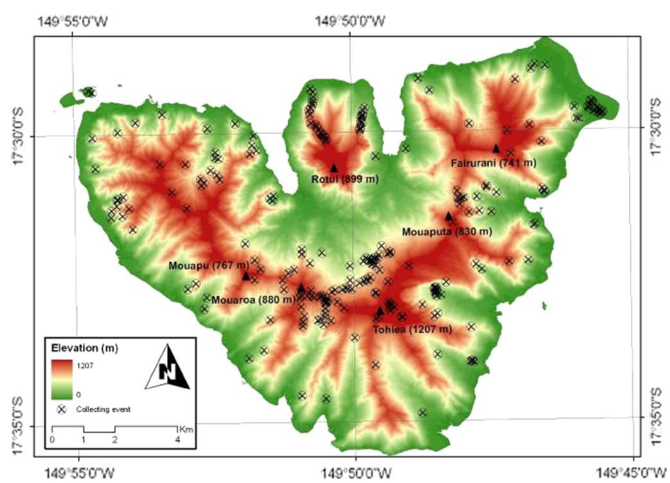


Fig. 2. Localization of the 255 collecting points on the DEM of Moorea.

II. Material and Methods

A. Study Site

This study deals with tropical rainforests which is a subject of great interest to scientists around the world. In witness thereof, United Nations General Assembly declares 2011 as the International Year of Forests.

The present study was conducted in French Polynesia (South Pacific) on the island of Moorea (140 km^2 with a highest summit reaching 1,207 m) located between $17°28'$ and $17°36'$ South and between $149°45'$ and $149°55'$ West (Fig. 2).

Structural complexity of this model is inherent to its high level of naturalness and lies in two scales: (i) at the image scale, the landscape of Moorea is made of numerous vegetation types (17) with spread and continuous ecotones (transition areas between two adjacent but different plant communities) where classification errors frequently occur [13] and rough topography causing a high spatial variation of vegetation types; and (ii) at the pixel scale, plant communities is made of species typically numerous in tropical rainforests and show a great intra-species spectral variability due to different growth and development stages, phenology, level of stress and topographical positions (ecotypes). The result is a great local variability of pixel gray-levels within each vegetation type.

B. *Ground Data Collection*

In this geographical context, where vegetation density and complex terrain with steep slopes are severe constraints for ground data collection, supervised classification is much appropriated because classification can be trained on few accessible areas and then extrapolated to the whole landscape. Relief is not a constraint to sample all vegetation types present across the landscape which are well known thanks to a range of past scientific works (e.g. [14], Moorea Biocode Project[1]) and a couple of years of field survey. Relief is in fact a constraint to reach sufficient training and validation areas, including vegetation of the steepest slopes and the highest summits.

Vegetation types were identified and geolocalized with a handheld Trimble GeoXH GPS on fifteen 125 m^2 circular regions of interest for each class. The sampled surface therefore represents 1/2,000 of the island surface which was identified as a good trade-off between SVM classification accuracy and collecting and processing time across another study site of French Polynesia in a previous study [15]. Half of this area was used for classification training and half for validation. Balance data sets were used in a bid to avoid under- or over-representation problems [16], [17]. Vegetation types were preferentially sampled in ecotones since they help to fit the optimal separating hyperplane by providing potential support vectors, typically characterized by a mixed spectral response [18], see [15] for a case in French Polynesia.

C. *Remotely Sensed Data*

Multi-source image fusion is critical for classifying complex structures since each complementary source can contribute to the classification success. Visible, infrared, SAR and DEM derived data can therefore be useful for species identification according to their physico-chemical, anatomical, structural and ecological properties respectively [19]. The use of data with various spatial resolutions also makes the study of vegetation on a multitude of scales and organization levels possible. All available remotely sensed data used thereafter were projected in the WGS 84-UTM 6 South coordinate system.

Physico-Chemical and Anatomical Properties of Canopy: Vegetation response in the optical region is a function of leaf tissue density and proportions, pigment composition and cell arrangement [19], [20]. We used a mosaic of five 0.60 m-resolution multispectral Quickbird scenes from 2006. Images were ortho-rectified using the cubic convolution approximation technique, more suitable than nearest neighbor and bilinear interpolation techniques according to Arif *et al.* [21]. Very high spatial resolution (VHR) is critical for plant species discrimination [22]–[24] using texture metrics for example.

[1]http://mooreabiocode.org/.

TABLE I
CHARACTERISTICS OF THE EIGHT TERRASAR-X©DLR (2010) SCENES

Date	Mode	Pass direction	Min. angle	Max. angle	Polarization
29 Apr. 2010	StripNear	Descending	31.97	33.31	Xvv-Xvh
1 Jun. 2010	StripFar	Descending	30.86	32.23	Xvv-Xvh
28 Aug. 2010	StripNear	Descending	31.97	33.31	Xhh-Xhv
31 Aug. 2010	StripFar	Ascending	33.05	34.36	Xvv-Xvh
19 Sep. 2010	StripFar	Descending	30.86	32.24	Xhh-Xhv
22 Sep. 2010	StripNear	Ascending	34.14	35.39	Xvv-Xvh
25 Oct. 2010	StripFar	Ascending	33.05	34.36	Xhh-Xhv
16 Nov. 2010	StripNear	Ascending	34.11	35.39	Xhh-Xhv

Eight gray-level co-occurrence matrix (GLCM) texture metrics were extracted from these data: mean, variance, homogeneity, contrast, dissimilarity, entropy, second moment and correlation [25]. Several papers (e.g. [26], [27]) show that extraction of texture metrics on multi-level window sizes can improve classification. Consequently our GLCM metrics were calculated on the 4 native bands and in 3 × 3, 9 × 9 and 15 × 15 pixels window sizes ($\mathrm{damping\ factor} = 1$). Since GLCM texture metrics have a strongly different nature from the spectral information, they were considered as a separated source as in [7]. The second source, namely textural information extracted from Quickbird imagery, is therefore made of 96 bands but SVM is not affected by data dimensionality [28]–[31].

Structural Properties of Forests: They can be extracted from SAR data [19]. In particular, the latter authors state that X-band (2.5–3.75 cm) interacts with surface of canopies giving information on surface roughness, C-band (3.75–7.5 cm) interacts with volume of forest canopies and gives information on leaf biomass and L-band (15–30 cm) offers a deeper penetration of canopies and gives information on woody biomass.

On the one hand, eight 2.75 m-resolution StripMap TerraSAR-X©DLR (2010) acquisitions were programmed over Moorea in vv-vh and hh-hv polarizations. Image characteristics are described in Table I whereas Fig. 3 briefly presents the employed mosaicking method.

On the other hand, we used a 5-m resolution JPL/AirSAR scene covering the whole island. These data include a Cvv channel (TOPSAR) and a L-band in full polarimetry (POLSAR). Supported by the work of Lardeux [32] in French Polynesia, we only used the linear intensities of the L-band, namely Lhh, Lhv and Lvv.

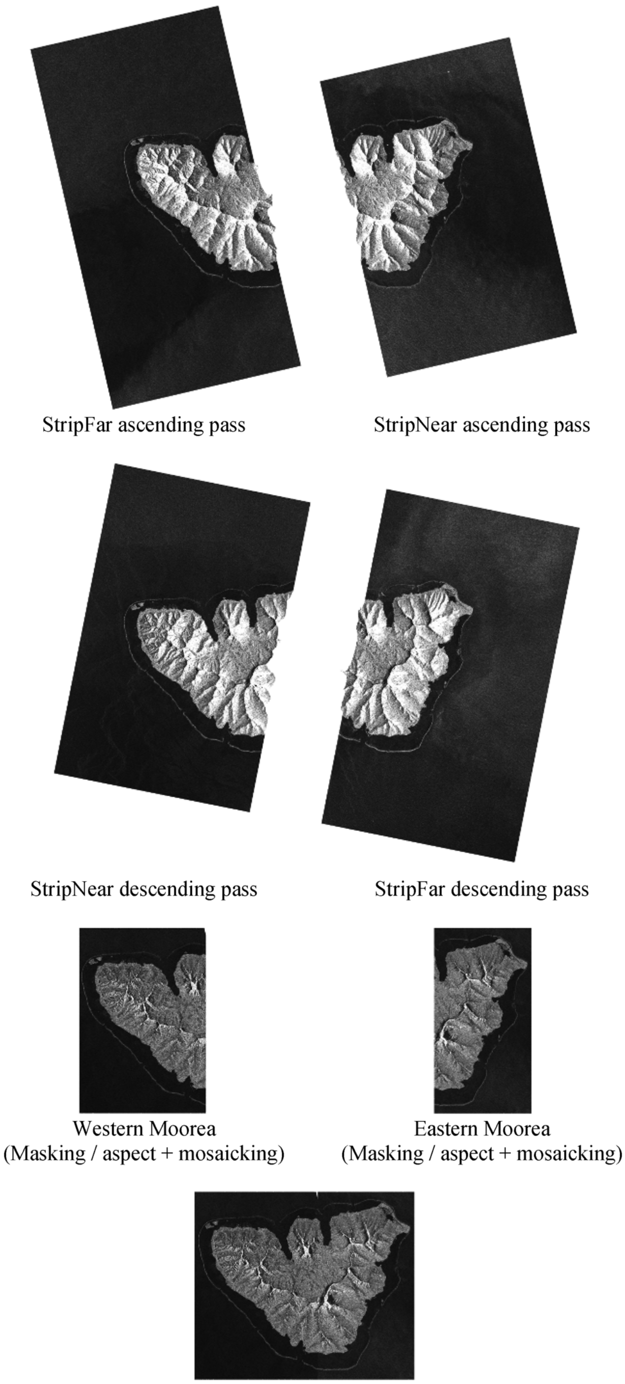


Fig. 3. Main stages of TerraSAR-X©DLR (2010) data preprocessing. By using complementary modes and pass directions with similar angles, masking based on aspect and mosaicking allow limiting relief shadow and overexposure areas.

For both TerraSAR-X and JPL/AirSAR data, we considered radar as monostatic and consequently that $\mathrm{hv} = \mathrm{vh}$ [33].

The scenes were geometrically corrected using a 5 m-resolution DEM. Speckle noise was reduced by using the Frost filter in a 5 $\times$ 5 pixels window, showing the best mean Jeffries-Matusita separability after several tests (in accordance with [34]). Separability may be an adapted metric when using SVM since they do not aim to describe classes as conventional approaches but to separate them [18].

Ecological Properties of Species: GIS data that can be used to model species distribution are presented in-depth in [35]. In the context of the high volcanic island of Moorea and its vegetation types, ecological data that appeared to us as the most contributing factors are of topographic nature.

The third data set was therefore a DEM provided by the *Sercice de l'Urbanisme* (Urbanism Department) of the French Polynesian Government. With a 5 m-resolution, it enables extraction of fine topographical descriptors impacting plant distribution in montane ecosystems [35]:

— elevation as a proxy of temperature;
— slope as a proxy of overland and subsurface flow velocity and runoff rate, effect of microtopography on precipitation, geomorphology and soil water content;
— aspect as a proxy of solar insolation and evapotranspiration;
— windwardness as a proxy of trade wind exposure;
— and a wetness index (WI) [36], [37]. The latter was used as an index of fluid drainage with low WI values representing convex positions like mountain crests and with high WI values representing concave positions like coves or hillslope bases. It is a function of the slope angle β (in radians) and the specific catchment area (As) expressed as m^2 per unit width orthogonal to the flow direction (1).

$$WI = \ln(As/\tan\beta) \tag{1}$$

D. Fusion of Support Vector Machines

SVM is introduced by Vapnik [38] and extensively described in [39]–[41]. It is arguably one of the most successful algorithms for multi-source fusion (Fig. 1). SVM consists in projecting vectors into a high dimension feature space by means of a kernel function then fitting an optimal hyperplane that separates classes using an optimization function.

According to [41] and supported by many others authors, the Gaussian Radial Basis Function (RBF) has both advantages (i) to be very successful since it works in an infinite dimensional feature space; and (ii) contrary to the other successful kernels (e.g. polynomial), RBF has a single parameter $\gamma > 0$.

SVM has been introduced for binary $(Q = 2)$ problems but a range of extensions has been developed to deal with $Q > 2$ classes problems. Among them, we chose the One-Against-One (OAO) algorithm consisting in the construction of $Q(Q-1)/2$ hyperplanes which separate each pair of classes.

The following two fusion schemes based on SVM were compared (Fig. 4):

(i) Systematic Fusion (proposed in [9]): a single SVM is trained on each source separately and an image containing the distance of each vector to the decision boundary of the SVM (rule image) is generated for each class. Rule images from all sensors are stacked and upscaled to the coarser resolution (5 m in our case) using the nearest neighbors resampling method, a more appropriate method than bilinear interpolation and cubic convolution to resample categorical data according to [42]. Then an addi-

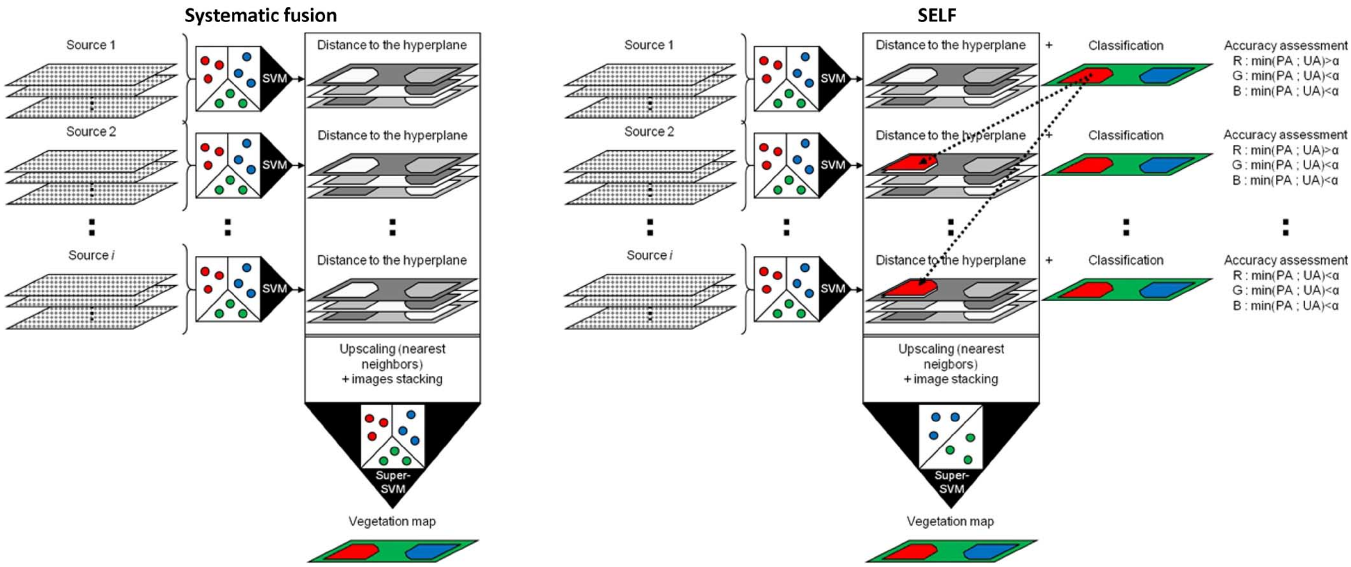


Fig. 4. Schematic diagrams of systematic fusion and SELF.

tional SVM is trained on all rule images to perform the fusion;

(ii) Selective Fusion (SELF): this fusion method aims to select the most relevant sources for vegetation type classification. It is a hybridization of mono- and multi-source SVM classification. The general principle is the same as for the systematic fusion but fusion is performed only when no single source is able to classify satisfactorily a class or a set of classes. A SVM is trained on each individual source to produce a rule image and a classification. On each classification, we calculate the $\min(PA_{\text{source } i}; UA_{\text{source } i})$, wherein $i \in [1, 4]$, PA denotes the Producer Accuracy and UA the User Accuracy. This metric takes into consideration classification accuracy from both the analyst and the user points of view. We consider that the source j ($j \in [1, 4]$) is the most successful if the condition (2) is fulfilled:

$$\min(PA_{\text{source } j}; UA_{\text{source } j}) = \max\left(\min(PA_{\text{source } i}; UA_{\text{source } i})\right) \quad (2)$$

Then we introduce a difficulty threshold α. As in the systematic fusion, an additional SVM is trained on all rule images to perform the fusion but only when:

$$\min(PA_{\text{source } j}; UA_{\text{source } j}) < \alpha \quad (3)$$

Should the opposite occurs, the class is not considered as "in difficulty", the spatial distribution of the considered class is the one from the source j and the class is expelled from fusion. If a pixel belongs to more than one class with this process, it is assigned with the class for which its vector is the nearest to the hyperplane.

III. Results

A. Source Contributions

After mono-source classifications illustrated by Fig. 5, texture extracted from Quickbird imagery produces the best accuracies (Table II) and the greatest contribution since it is the best source (source j) for 10 vegetation classes among the 17 occurring on Moorea (Table III). It is interesting to notice that texture extracted from Quickbird imagery is useful to distinguish low- to mid-elevation moist to wet vegetation types with the highest density and structural complexity (vegetation dominated by *Hibiscus tiliaceus*, *Neonauclea forsteri*, *Aleurites moluccana*, *Inocarpus fagifer* and *Spathodea campanulata*). DEM-extracted descriptors are the best source for 6 classes among 17 (Table III). These classes effectively occur in specific topographical positions as exposed in Fig. 6 based on the single elevation descriptor. Fig. 7 shows that elevation is the most contributing DEM-extracted descriptor based on the difference of accuracy with all DEM-extracted descriptors and without the regarded descriptor. Considering an environmental lapse rate of 0.58°C/100 m as observed in Hawaii [43], there is a shift of 7°C between sea-level and the highest summit, the mont Tohiea (1,207 m). Now, air temperature is one of the most important factors controlling vegetation zonation in mountain ecosystems [44]. The second most contributing descriptor is windwardness since trade wind exposure is the cause of a humidity asymmetry across the island with frequent orographic precipitations in the windward coast of Moorea and dry down-slope foehn winds in the leeward coast. In decreasing order, elevation and windwardness are followed by aspect, slope and WI. All DEM-extracted descriptors have a positive contribution. Quickbird bands are the best source for a single class (vegetation dominated by *Miscanthus floridulus*) (Table III) which is easily discernible from a simple NDVI image since this grassy to shrubby vegetation type is characterized by a low vegetation density due to frequent fire events.

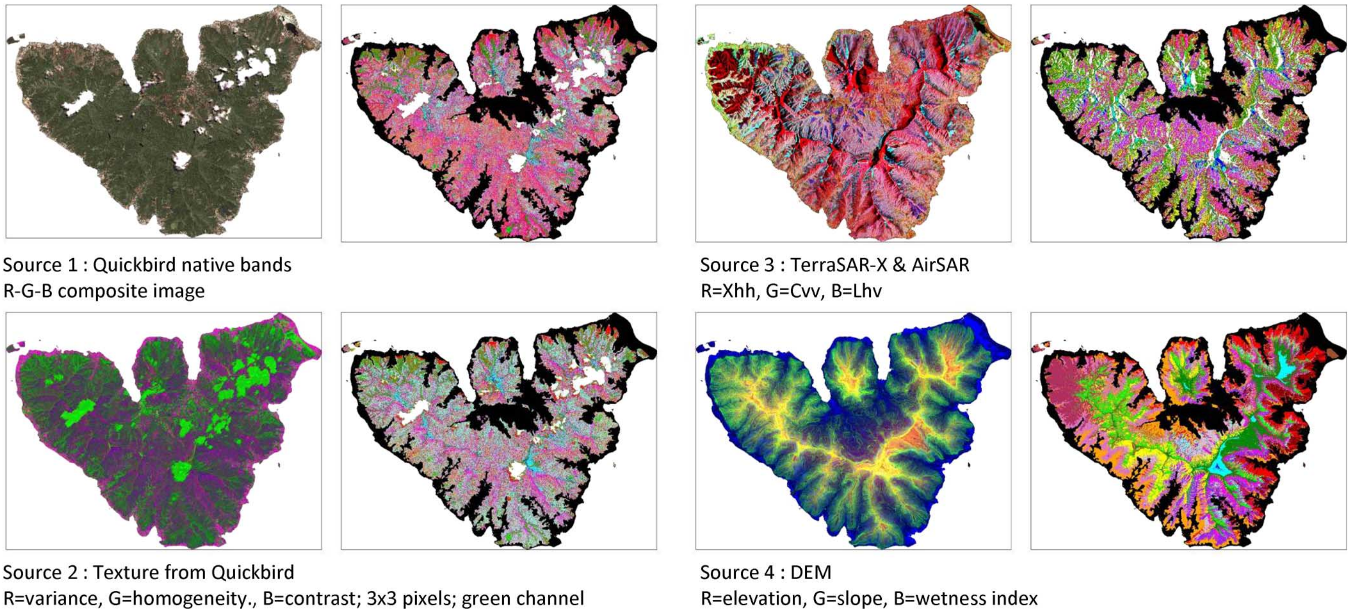


Fig. 5. The 4 sources (left) and the corresponding mono-source SVM classifications (right). Color set is given in Fig. 10 (white represents "no data").

TABLE II
ACCURACIES ACHIEVED BY SVM USING DIFFERENT SOURCES

Sources	# bands	OA	Kappa
1. Quickbird native bands	4	0.627	0.606
2. Texture from Quickbird	96	0.831	0.821
3. SAR data	7	0.633	0.610
4. DEM-extracted data	5	0.642	0.620
Systematic fusion	-	0.882	0.877
SELF	-	0.907	0.904

Finally, no class is specific to the SAR source since structure is typically different among plantations, valley high forests, steep slope and ridge low forests and high-elevation wet vegetation but structure is not relevant to identify accurately species. However its contribution is not nil. Indeed, systematic fusion without SAR data yields an overall accuracy (OA, based on the mean of accuracy of each class) of 0.851 (data not shown) whereas the OA is 0.882 when SAR data are added (Table II). SAR data therefore play a complementary function. We can assume that their contribution should increase when the canopy is partially or totally invaded by wines such as the invasive *Merremia peltata* and to fill "no data" due to cloud caps on optical imagery.

B. Fusion Scheme Comparison

As shown by Fig. 8, SELF outperforms systematic fusion since only two classes are integrated into the fusion (namely vegetation dominated by *Syzygium cumini* and *Neonauclea forsteri*). In this case, the difficulty threshold $\alpha = 0.615$ and the SELF OA reaches 0.895. Logically, when $\alpha = 1$, OA provided by systematic fusion and SELF is the same (0.882). In the optimal configuration i.e. when $0.845 < \alpha < 0.860$, SELF integrates 8 classes including 4 of the 5 classes belonging to the dense and complex low- to mid-elevation moist to wet forests.

IV. DISCUSSION

By providing good analytical results, SVM is substantially able to deal with the structural complexity of tropical rainforests. The fact that the hyperplane solely lies on the most discriminative vectors (the support vectors) [18] may make SVM less sensible to noisy or non-representative pixels (typically found on VHR imagery representing structurally complex landscapes) than conventional classifiers. Moreover, the use of the RBF kernel which allows fitting the decision boundary in an infinite dimensional feature space may be an adapted tool to deal with this complexity.

Results from this study confirm the assumption that if identification of the most structurally complex vegetation types can benefit from complementary information, multi-source fusion can also deteriorate classification accuracy of source-specific vegetation types (i.e. vegetation types for which other sources provide no valuable information) (see Fig. 8 when $\alpha > 0.860$). These results also highlight that if machine learning algorithms such as SVM are able to weight different relevant sources as stated by [2], they are also unable to totally exclude irrelevant data. This is one of the reasons of the SELF success.

Another probable explanation comes from the fact that a smaller number of classes are inputted in the additional SVM with the SELF than with the systematic fusion. Andréfouët *et al.* [45] now demonstrate that the smaller the number of classes, the better is the classification accuracy.

The use of multi-source remotely sensed data is dramatically useful for tropical rainforest mapping. Spatial pattern of multi-organization level tree constituents such as leaves, branches and trunks is well assessed by multi-scale texture metrics extracted

TABLE III
VEGETATION TYPES OCCURRING ON MOOREA (LABELED ACCORDING TO THE DOMINATING SPECIES) WITH MONO-SOURCE AND SELF (WITH OPTIMIZED DIFFICULTY THRESHOLD α) CLASSIFICATION RESULTS

Vegetation types	Source *j*	Source in SELF	SELF PA	SELF UA
Plantations				
Cocos nucifera	4	All	0.951	1.000
Falcataria moluccana	2	All	0.897	0.933
Pinus caribaea	2	2	0.964	0.978
Coastal vegetation				
Typha domingensis	4	4	1.000	1.000
Low- to mid-elevation mesic to moist vegetation				
Casuarina equisetifolia	2	2	0.966	0.993
Dicranopteris linearis	2	2	0.954	0.959
Leucaena leucocephala	2	2	0.960	0.951
Metrosideros collina	4	All	0.911	0.973
Miscanthus floridulus	1	1	0.860	0.884
Syzygium cumini	4	All	0.773	0.580
Low- to mid-elevation moist to wet vegetation				
Aleurites moluccana	2	2	0.988	0.933
Hibiscus tiliaceus	2	All	0.766	0.756
Inocarpus fagifer	2	All	0.873	0.784
Neonauclea forsteri	2	All	0.899	0.855
Spathodea campanulata	2	All	0.737	0.800
High-elevation wet vegetation				
Montane cloud forest	4	4	0.953	0.964
Summit shrubland	4	4	0.971	0.962

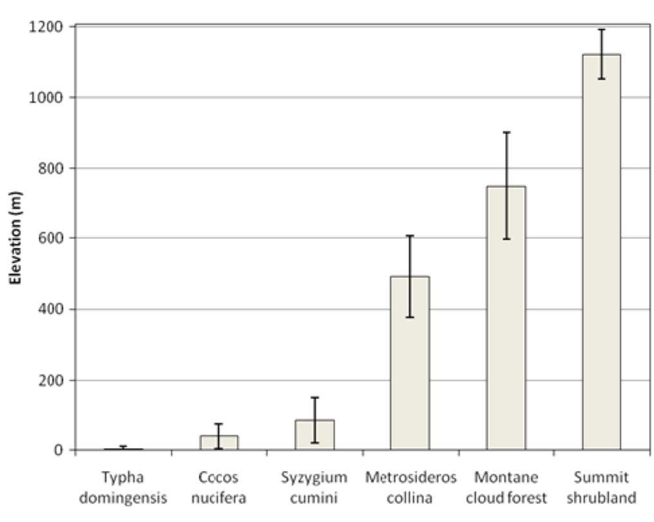


Fig. 6. Elevation range of the 6 DEM-specific classes extracted from the SELF classification. Elevation is a good discrimination factor.

from VHR imagery and critical for identifying species with high structural complexity such as the ones found in the low-

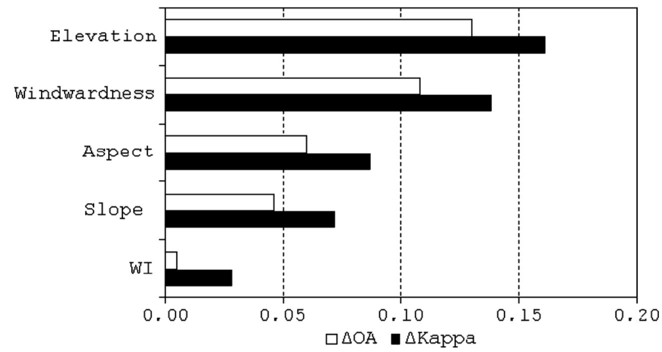


Fig. 7. Relative contribution of DEM-extracted descriptors based on the difference of accuracy (Δ) achieved with all descriptors and without the regarded descriptor.

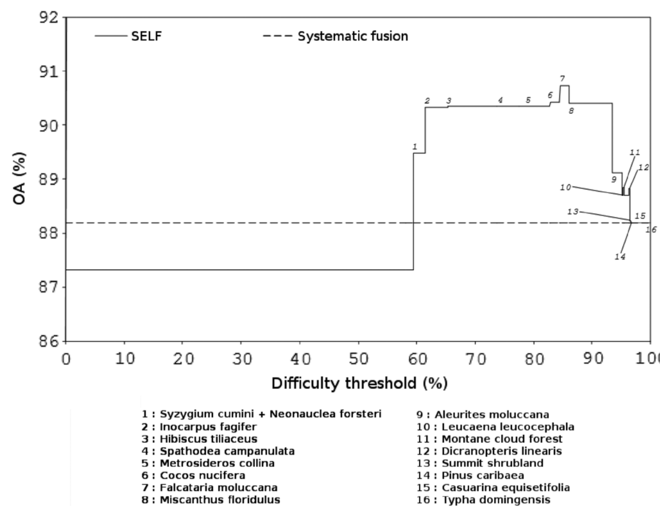
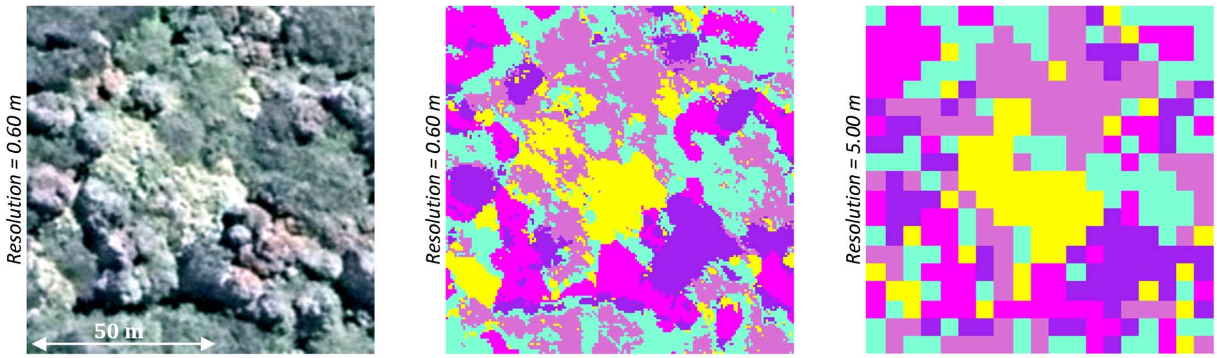


Fig. 8. Comparison of OA provided by systematic and SELF according to the difficulty threshold α.

to mid-elevation moist to wet forests of Moorea (Fig. 9). The success of the use of multi-scale textural data is also made possible by the use of SVM to integrate them since it is not affected by data dimensionality [28]–[31]. In this study, we chose to extract GLCM metrics which are the most usual method but further metrics might be used [45]–[48]. Ecological information also plays a substantial role in our context for modeling vegetation types with pronounced topographical preferences unlike ubiquitous species (with a wide ecological spectrum) (Fig. 9). According to our results, native bands of VHR imagery seem not very discriminative at the species scale excepted for early successional stages after fires. Structural properties of forests are also not on their own sufficient to identify species but provide significant complementary information.

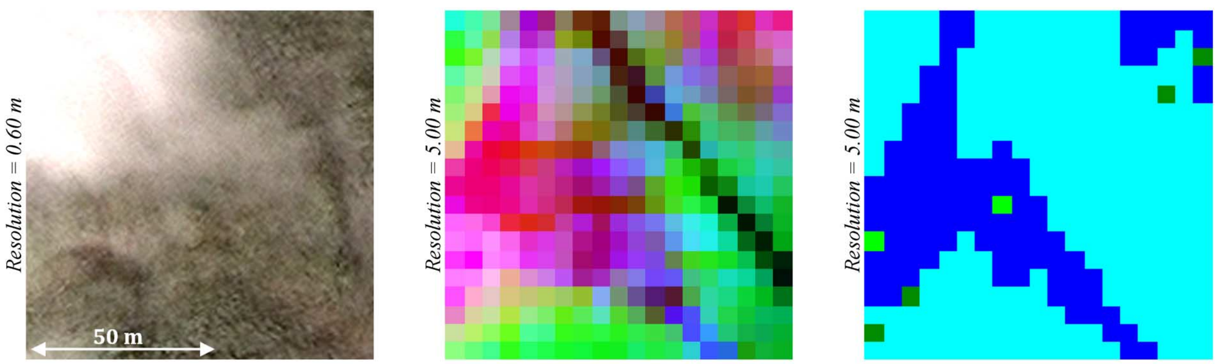
Sources complementarities have also the advantage to fill "no data" area due to cloud caps (generally persistent in tropical environments) and relief shadows (frequent in montane environments) (Figs. 9 and 10). Concerning this aspect, SELF is more limited than systematic fusion because "no data" are filled with classes inputted in the additional SVM only. However, the analyst can get around this limit by forcing certain classes to be integrated in the SELF by voluntarily collecting ground data under



RGB composite Quickbird image representing a low- to mid-elevation moist to wet forest

Mono-source SVM classification based on GLCM texture metrics extracted from Quickbird imagery

SELF output – Texture extracted from Quickbird imagery is predominant to discriminate species in dense and structurally complex vegetation



RGB composite Quickbird image representing the cloudy mont Tohiea, the summit of Moorea

Three of the corresponding DEM-extracted variables: R = Elevation (1128-1207 m), G = Slope (0-66°) and B = Wetness Index (0.43-6.44)

SELF output – For both classes "cloud forest" and "summit shrubland", SELF solely lies on DEM-extracted data which allow to fill "no data" due to the cloud cap

Fig. 9. The individual contribution of each source depends on the nature of each class. Color set is given in Fig. 10.

"no data" (as a result, $\min(PA_{\text{source } j}; UA_{\text{source } j})$ will yield low values).

The SELF scheme we introduce in this paper consists either to use jointly all source or to use a single source. In a future work, an extended scheme permitting to integrate intermediate combinations of sources (two or three sources for example) should be implemented to be more generic.

V. Conclusion

Fundamental research in the field of land cover classification often focuses on structurally simple landscapes (e.g. urban areas, croplands, managed monospecific temperate forests, etc.). But Earth observation methods also must be able to be applied on the most complex structures such as tropical rainforests (6% of the terrestrial world's surface and 80% of the world's known biodiversity) and at the finest scales (e.g. the species scale).

Integration of multi-sensory and GIS data which are sensible to complementary properties of forests is a unique opportunity to this end. In this way, a range of algorithms and classification schemes have been introduced. One of the most recently used and probably the most successful algorithms is support vector machines (SVM). However, SVM-based systematic classification schemes proposed in the past are not optimal since they deteriorate accuracy when sources irrelevant for certain classes are used. So, we introduced a classification scheme based on SVM that hybridize mono-source classification when vegetation types are source-specific and multi-source fusion when vegetation types are unable to be satisfactorily classified with a single source.

Regarding our results, this operational Selective Fusion (SELF) scheme makes a good trade-off by taking advantage of the very good accuracy achieved by SVM without the drawback of being sensible to irrelevant data for source-specific vegetation types.

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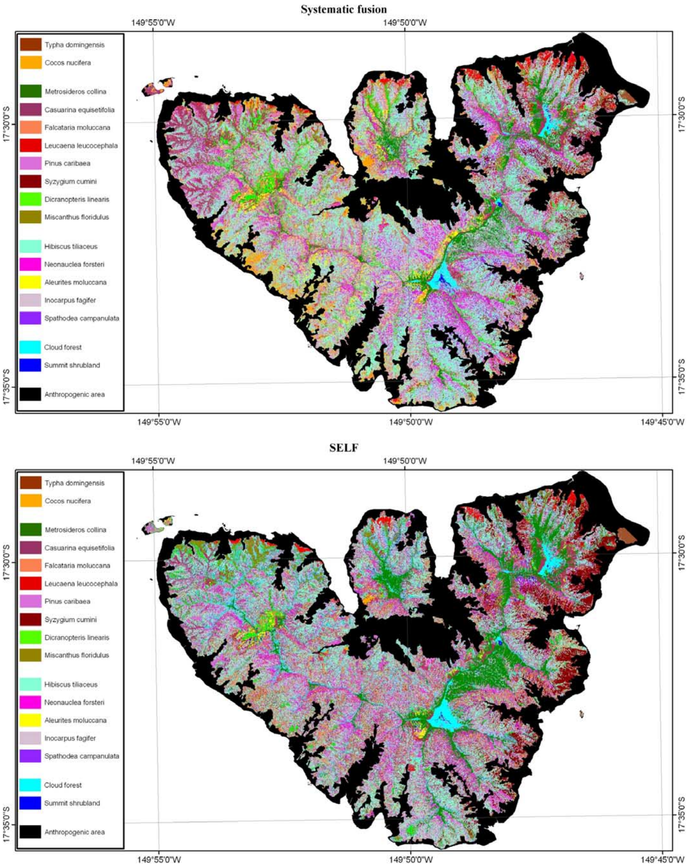

Fig. 10. Comparison of mapping results yielded on Moorea by both methods: the systematic fusion (above) and the SELF (below).

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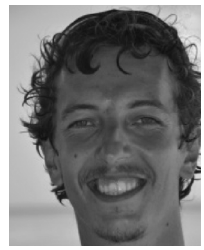

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