Impact of Internal Parameterization on the Performance of Support Vector Machines for Crop Mapping Sentinel-2 NDVI Time Series

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Abstract: The Support Vector Machines classifiers has been increasingly used to derive land-cover/ land-use information from satellite imagery. As software implemented classifiers, SVM give satisfactory but imperfect results, when performed at first using the default set of parameters. Thus, obtaining the best results requires a basic understanding of the theory behind their workings and how their accuracy can be parametrically influenced. In this paper, we report the result of an investigation of the SVM's different parameters, applied to satellite data for crop mapping, in order to develop some guides for parameterizing this classification technique. The internal parameters considered in this study include the Kernel function, Pyramid Level, Penalty parameter, Gamma parameter, the Bias and the Degree. A set of 21 NDVI time-series layer-stack, extracted from Sentinel-2 (S2) images, were used. The results showed that the Kernel function choice, and the four internal parameters, namely, Penalty parameter, Gamma parameter, the Bias and the Degree, can improve the classification accuracy. The best overall accuracy reached 94.50% using the polynomial function.

1 INTRODUCTION

With the contribution of remote sensing latest high spatio-temporal resolution imagery (HSTRI), land-cover classification and crop mapping have become essential tools in agricultural management by regularly assessing the vegetation status using various technics in different parts of the globe (Anderson, Allen, Morse, et al 2012; Mulla, D. J. 2013; McDowell, Nate G., et al. 2015; Lawley, V., et al. 2016; Khanal, S., et al 2017). Nowadays, the available and free S2 data, is the most popular source of HSTRI used by researchers and decision makers for this purpose (Moumni, A., et al 2019; Moumni, A., et al 2020). In addition to remote sensing data qualities, classification algorithms play an important role in improving performance accuracies of crop maps. Many previous studies have been focusing on comparing various, well-known classification algorithms in the remote sensing community in order to provide useful documents describing the methods and procedures for image classification . Different articles compared different sets of classification algorithms, Yu, Le, et al., (2014) investigated the relationship between the classification accuracy, publication date, extent of the study area, and accuracies for different sensors and classification algorithms. Li, Congcong, et al., (2014) compared the performances of 15 image classification algorithms, with the same Landsat Thematic Mapper (TM) data set and the same classification scheme over Guangzhou City, China. In terms of algorithms performances, most case studies give different outcomes, despite extensive work on classification methods, questions comparing different techniques remain unanswered (Khatami, R., et al 2016), for example, sometimes Neural Networks (NN) performs slightly better than Support Vector Machine (SVM), sometimes it's the other way, which depends on the size of data, how it is handled and more importantly the parameters configuration of each algorithm, suffering from assignment issues, they significantly

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can sometimes give unsatisfactory results. In this context, certain studies have been focusing on the evaluation of the performance of a given classification algorithm by investigating its parameters. Zhou, L., et al (2008) assessed the impacts of several internal parameters of the multi-layer-perceptron (MLP) neural networks, they reported that a number of internal parameters significantly affect classification accuracy, and proposed a guideline that can facilitate the use of neural networks for land cover classification. Huang et al (2002) compared the outcome of different sets of parameters of the Polynomial and Radial Basis Function Kernels. Keuchel et al. (2003) compared the classification accuracy of SVMs, maximum likelihood and iterated conditional modes (ICM), and suggested that attention should be payed to SVM parameters. One noteworthy mention to Yang, X. (2011), who constructed a set of SVMs with different combinations of Kernel types and parameters, to classify a Landsat Thematic Mapper image, and stated that the improvement of the performance of classification, can in fact be obtained by a careful selection of parameter settings.

Our objective being the assessment of the impact of internal parameters of the theoretically robust classification technique SVM (Kernel types, Pyramid Level, Penalty parameter, Gamma Parameter, the bias and the degree) on the performance of SVM for land-cover classification using remote sensed data. We examined the efficiency of this technique in classifying S2 derived NDVI time-series from 21 dates of 2018. The images were acquired over the Haouz plain, in central of Morocco, and classified into six land-cover classes. The implementation of the algorithms has been software-based, and the results were validated and quantified using ground truth information.

The present work started with an introduction clarifying the importance and the motivations behind the creation of detailed and accurate land cover maps. Then, we illustrated the main materials and methods used in this study. After that, the obtained results were presented and discussed in the third section. Finally, we ended this paper with the main conclusions and perspectives.

2 MATERIAL AND METHODS

2.1 Site Location

The Haouz plain is located in the eastern part of the Marrakech-Safi region in central Morocco. It extends in the west-to-east direction between the High Atlas Mountains in the south and Jebilat hills in the north. It is characterized by a semi-arid climate, where the annual average of the rainfall is about 250mm. It is a predominantly rural area where the agricultural sector plays an important role. The mainly consistent crop types in the area are: Cereals, Citrus and olive trees.

2.2 Sentinel-2 Data

S2 is a series of earth-observation satellites carrying multi-spectral imagery (MSI) optical sensors. The free of charge, atmospherically and geometrically corrected 10-, 20- to 60- meter images are acquired every 5 days. 21 cloud free images, ranged over the seasons from January to December of 2018 were selected to derive the Normalized Difference Vegetation Index (NDVI) time-series. The NDVI was chosen for being an efficient and popular index for monitoring the vegetation. It was first introduced by Tucker (1979). The ground truth samples were collected during the spring of the same year. All the samples were divided into two groups using a proportionate random sampling approach: calibration data and validation data.

2.3 ENVI Software and SVM Parameters

Software-based, automated classification algorithms are widely used in the field of remote sensing. ENVI is a powerful image analysis software, commonly used in the remote sensing society. It includes a suite of image analysis tools, among which a variety of supervised and unsupervised classification algorithms, and particularly the SVM classifier. The choice of a parametrization is always presented before starting the classification. Unfortunately, the parameters are often left by not-familiar users in "default mode". As to our work, evaluating the effect of the parametrization on the outcoming classified images, and presenting a guideline that can help parameterize the SVMs, was part of our interest. Although users do not need to fully understand the theory behind SVM, brief basics are introduced. Support Vector Machine is derived from the statistical learning theory, first introduced by Vapnik in 1979, often gives satisfying results from large and noisy data. It separates the classes with a decision surface called the optimal hyperplane that maximizes the margin between the classes. The original optimal hyperplane algorithm was a linear classifier, nevertheless, SVM can be adapted to become a nonlinear classifier through the use of nonlinear functions called Kernels (Cortes and Vapnik, 1995).

Considering a set of training samples (Xi, Yi), i = 1,……, n where Xi ϵ Rn and y ϵ {1,-1}n, SVM optimizes the problem by searching for a large margin and a small error penalty, from a mathematical point of view (Cortes and Vapnik, 1995), it requires the solution of:

$$Min_{w,b,\varepsilon} \frac{1}{2} w^T w + P \sum_{i=1}^{n} \varepsilon_i$$

Such that:

$$Y_i(w^T \Phi(X_i) + b) \geq 1 - \varepsilon_i \ and \ \varepsilon_i \geq 0$$

Where Φ is a function that project Xi into a higher dimension, and P is the Penalty parameter (P>0). Although new Kernels are being proposed by researchers, the basic Kernels considered in this study include the ones implemented in ENVI: linear, polynomial, radial basis function, and sigmoid:

- Linear: K (Xi , Xj) = XiT Xj.
- Polynomial: K (Xi , Xj) = (γ × XiT Xj + r) d , γ > 0.
- Radial basis function (RBF):
  K (Xi , Xj) = exp (-γ ×||Xi – Xj ||²), γ > 0.
- Sigmoid: K (Xi , Xj) = tanh (γ × XiT Xj + r).

Where K (Xi , Xj) = Φ (Xi)T Φ (Xj), γ is the Gamma parameter, d the Degree and r the Bias.

ENVI's implementation of SVM includes the listed above parameters, which are apparently dependent of the Kernel Type. More details about the default and ranges values are presented in the table below.

Table 1. Kernel functions, Default values and variation ranges of SVM in ENVI.

Kernel Type	Parameters	Default value	Range
Linear	-Penalty parameter (P)	100	Greater than or equal to 0.01
	-Pyramid level (PL)	0	[0.6]
Polynomial	-Degree of Kernel polynomial (d)	2	[1.6]
	- Bias in Kernel function (r)	1	Undefined
	-Gamma in Kernel function (γ)	0.333 for 3 bands	1/ number of bands in the input image
	-Penalty parameter (P)	100	Greater than or equal to 0.01
	-Pyramid level (PL)	0	[0.6]
Radial Basis function or RBF (default Kernel type)	-Gamma in Kernel function (γ)	0.333 for 3 bands	1/ number of bands in the input image
	-Penalty parameter (P)	100	Greater than or equal to 0.01
	-Pyramid level (PL)	0	[0,6]
Sigmoid	- Bias in Kernel function (r)	1	Undefined
	-Gamma in Kernel function (γ)	0.333 for 3 bands	1/ number of bands in the input image
	-Penalty parameter (P)	100	Greater than or equal to 0.01
	-Pyramid level (PL)	0	[0.6]

2.4 Methodology

The methodological approach for this study consists mainly on applying different parameter combination scenarios, with the same input NDVI time series and the same training/validation samples. The accuracy assessment was evaluated using the generated confusion matrix. The resulting OA, Kappa and running time of each model were noted and analyzed for determining the effect of the different sets on the classification outcome. The number of combinations can reach thousands if not millions, therefore the approach consisted on a similar technique used by Zhou, L., et al (2008). They altered the value of one NN's parameter while holding the others unchanged, a way to separately evaluate each parameter's effect on the resulting classification's accuracy and Kappa, or the work of Yang, X. (2011), where he used the same methodology but for SVM classifier. The difference in our approach, is that we regularize one parameter until an optimum is reached, then it's value will be fixed for the rest, a way of ensuring the best performance of the Kernels, the same process is repeated to the next one until all the parameters values are investigated (Figure 1). The default set of parameters of each Kernel function are chosen as starting scenarios.

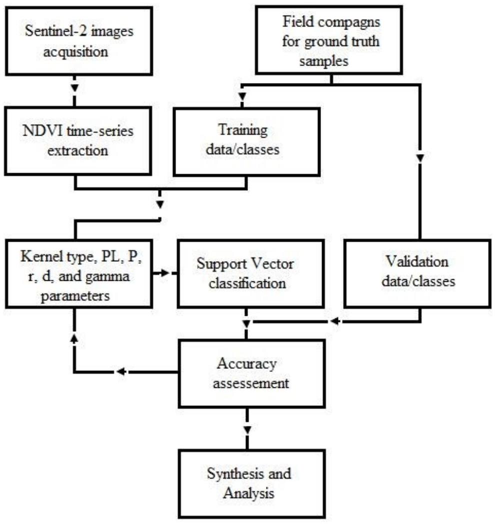

Figure 1: The methodological approach of the procedure followed in this study.

3 RESULTS AND DISCUSSION

The ultimate goal of this study was to assess how internal parameters of support vector machines, can affect land-cover classification, when used to classify NDVI time-series. The final number of models investigated is 85, and which depended on the resulting accuracies. We followed the up and down evolutions of the accuracies until it has been clear where the optimum resides. Radial basis function, with a PL=0, a P=100, and Gamma=0.048, being the default set of parameters for the SVM algorithm in ENVI software, gave an OA of 92.76% and Kappa of 0.91(Table.4). While parameterizing the models, one after another, we observed two important facts, the first is: for all the four Kernel functions, the starting configuration (Default parameters) increases by varying the Penalty parameter for the linear and RBF Kernel functions, the Degree and Bias for the polynomial, and Gamma for the Sigmoid function. The second fact is: generally, except for the polynomial Kernel, increasing the Pyramid Level, only decreases the OA, and surprisingly result in more processing time (Tables.2-5). Polynomial Kernel function, PL=2, P=100, Gamma=0.048, r=3 and d=6, resulted in the best accuracy and kappa in a relatively good amount of processing time, and which are of the order of 94.50% and 0.93 respectively (Table.3).

For better visualization and analysis of the results, figures 2, 3, 4 and 4 represent the variation of the OA as the parameters are investigated. Flat areas reflect the fact that the parameter in question doesn't affect the classification results at all. Meanwhile areas with high slopes confirm that the parameter does affect the outcoming results. A closer look to the results, starting with the linear Kernel, we can summarize by saying that, while it seems unaffected by the Pyramid Level's varying value, the OA increases when the Penalty parameter decreases, and more specifically when its value approaches the number of input classes. It attains a maximum value of 92.43% and a Kappa of 0.91 using this type of Kernel. The polynomial Kernel is slightly sensitive to the degree parameter, small fluctuations are observed, and the OA increased as the degrees get greater, which is consisting to the findings of Huang et al. (2002).

The Bias raised from 1 to 20 with non-regular steps, and performed the best with a value of 3. Gamma seemed to not affect the OA for values between 0.048 and 0.3 and the performance was rather stable. Meanwhile lowering the value of penalty negatively affected it. A penalty of 2 helped the polynomial Kernel to reach the best accuracy and Kappa obtained for all the constructed models, which equals 94.50 % and 0.93 respectively. The RBF function, being the default Kernel, relatively to the others, resulted in moderate OA, it's affected the most by the Penalty parameter and performed at its best with a value of 60, namely, 92.99% OA and 0.91 Kappa. While Gamma does appear to generally not affect the performance, raising the Pyramid Level decreases it. And last, the Sigmoid function, similarly to the RBF, performed best with a Penalty of 60, and was quite sensitive when varying Gamma, still didn't improve. The best OA and Kappa found using this Kernel is 92.99%.

Table 2: Overall accuracies, Kappa and processing time for the linear Kernel type's different combinations

Kernel function	Classification	PL	PP	Processing time	OA (%)	Kappa
Linear	Default	0	100	07min43s	90.77	0.88
	C1	1	100	13min05s	90.74	0.88
	C2	2	100	13min15s	90.71	0.88
	C3	3	100	30min13s	90.77	0.88
	C4	4	100	17min32s	90.77	0.88
	C5	5	100	15min44s	90.77	0.88
	C6	0	80	11min25s	90.77	0.88
	C7	0	60	11min58s	90.84	0.88
	C8	0	40	08min14s	91.04	0.88
	C9	0	20	07min45s	91.34	0.89
	C10	0	10	**12min.27**	**92.20**	**0.90**
	C11	0	8	**10min03s**	**92.23**	**0.90**
	C12	0	7	**15min50s**	**92.43**	**0.90**
	C13	0	6	**05min16s**	**92.43**	**0.90**
	C14	0	5	**15min35s**	**92.20**	**0.90**
	C15	0	3	**16min19s**	**91.24**	**0.89**
	C16	0	0	23min55s	88.72	0.85

Table 3: Overall accuracies, Kappa and processing time for the Polynomial Kernel type's different combinations.

Kernel function	classification	PL	PP	GKF	BKF	DKF	Processing time	OA (%)	Kappa
Polynomial	Default	0	100	0.048	1	2	11min22s	92.26	0.90
	C1	0	100	0.048	1	1	06min27s	92.16	0.90
	C2	0	100	0.048	1	3	08min06s	91.60	0.89
	C3	0	100	0.048	1	4	08min47s	91.69	0.89
	C4	0	100	0.048	1	5	08min33s	92.46	0.90
	C5	0	100	0.048	1	6	07min13s	92.46	0.90
	C6	0	100	0.048	2	6	05min14s	91.90	0.90
	C7	0	100	0.048	3	6	**05min13s**	**93.85**	**0.92**
	C8	0	100	0.048	5	6	**04min16s**	**93.51**	**0.92**
	C9	0	100	0.048	10	6	**04min01s**	**93.42**	**0.91**
	C10	0	100	0.048	20	6	13min09s	91.70	0.89
	C11	0	100	0.06	3	6	**05min19s**	**93.85**	**0.92**
	C12	0	100	0.07	3	6	**05min38s**	**93.85**	**0.92**
	C13	0	100	0.1	3	6	**09min45s**	**93.85**	**0.92**
	C14	0	100	0.2	3	6	**13min43s**	**93.85**	**0.92**
	C15	0	100	0.3	3	6	**14min59s**	**93.85**	**0.92**
	C16	0	80	0.048	3	6	**05min10s**	**93.52**	**0.92**
	C17	0	40	0.048	3	6	05min04s	92.34	0.90
	C18	0	20	0.048	3	6	05min14s	91.70	0.89
	C19	0	6	0.06	3	6	06min14s	91.83	0.89
	C20	0	5	0.048	3	6	05min58s	91.83	0.89
	C21	0	3	0.048	3	6	12min17s	91.73	0.89
	C22	0	6	0.048	3	6	17min37s	90.51	0.89
	C23	1	100	0.048	3	6	**18min31s**	**94.02**	**0.92**
	C24	2	100	0.048	3	6	**19min42s**	**94.50**	**0.93**
	C25	3	100	0.048	3	6	**23min04s**	**93.92**	**0.92**
	C26	4	100	0.048	3	6	**25min26s**	**93.92**	**0.92**
	C27	5	100	0.048	3	6	**25min56s**	**93.92**	**0.92**

Even though the OA and Kappa have increased slightly when comparing the 85 models, given a large area, the weight of this augmentation's importance can be great. For example, for a regular 100×100 Km^2 S2 image, for a spatial resolution of 10m, a 1.51% of improvement represents about 1.51 million corrected pixels, and an area of fifteen thousand one hundred hectares. We mapped the best resulting classifications for each of the four Kernel functions, obtained with the optimal set of parameters.

Table 4: Overall accuracies, Kappa and processing time for the RBF Kernel type's different combinations.

Kernel function	Classification	PL	PP	GKF	Processing time	OA (%)	Kappa
Radial Basis Function (RBF)	Default	0	100	0.048	08min05s	92.76	0.91
	C1	0	80	0.048	06min23s	92.90	0.91
	C2	0	65	0.048	08min08s	92.82	0.91
	C3	0	60	0.048	**12min29s**	**92.99**	**0.91**
	C4	0	55	0.048	08min34s	92.96	0.91
	C5	0	50	0.048	12min05s	92.82	0.91
	C6	0	40	0.048	11min37s	92.16	0.90
	C7	0	20	0.048	10min08s	91.80	0.89
	C8	0	10	0.048	11min51s	91.20	0.88
	C9	0	60	0.06	**10min40s**	**92.99**	**0.91**
	C10	0	60	0.08	**17min43s**	**92.99**	**0.91**
	C11	0	60	0.1	**10min51s**	**92.99**	**0.91**
	C12	0	60	0.2	09min14s	92.12	0.89
	C13	0	60	0.3	**13min50s**	**92.99**	**0.91**
	C14	0	60	0.4	**26min25s**	**92.99**	**0.91**
	C15	0	60	0.01	**11min14s**	**92.99**	**0.91**
	C16	0	60	0.001	**16min06s**	**92.99**	**0.91**
	C17	0	60	0	**18min39s**	**92.99**	**0.91**
	C18	1	60	0.048	20min13s	92.63	0.90
	C19	2	60	0.048	21min37s	92.39	0.90
	C20	3	60	0.048	22min13s	92.39	0.90
	C21	4	60	0.048	25min44s	92.39	0.90
	C22	5	60	0.048	11min96s	92.39	0.90

Table 5: Overall accuracies, Kappa and processing time for the Sigmoid Kernel type's different combinations.

Kernel function	**Classification**	**PL**	**PP**	**GKF**	**BKF**	**Processing time**	**OA (%)**	**Kappa**
Sigmoid	Default	0	100	0.048	1	17min02s	91.34	0.89
	C1	0	80	0.048	1	21min19s	91.20	0.89
	C2	**0**	**60**	0.048	**1**	**08min40s**	**92.99**	**0.91**
	C3	0	40	0.048	1	19min42s	92.16	0.90
	C4	0	20	0.048	1	13min50s	89.29	0.86
	C5	0	10	0.048	1	16min16s	88.82	0.85
	C6	0	5	0.048	1	18min47s	88.62	0.85
	C7	0	60	0.048	2	17min33s	89.09	0.86
	C8	0	60	0.048	4	28min08s	88.03	0.85
	C9	0	60	0.048	0.5	07min22s	91.34	0.89
	C10	0	60	0	1	11min27s	90.64	0.88
	C11	0	60	0.02	1	12min03s	90.64	0.88
	C12	0	60	0.08	1	11min24s	90.64	0.88
	C13	0	60	0.1	1	11min20s	90.64	0.88
	C14	0	60	0.2	1	11min15s	90.64	0.88
	C15	0	60	0.5	1	20min36s	90.64	0.88
	C16	00	60	1	1	21min38s	90.64	0.88
	C17	0	60	2	1	22min02s	90.64	0.88
	C18	**0**	**60**	**4**	**1**	**11min49s**	**92.99**	**0.91**
	C19	0	60	6	1	14min50s	90.94	0.88
	C20	**0**	**60**	**8**	**1**	**14min07s**	**92.99**	**0.91**
	C21	0	60	16	1	22min06s	90.64	0.88
	C22	1	60	0.048	1	12min43s	91.14	0.89
	C23	2	60	0.048	1	13min24s	91.14	0.89
	C24	3	60	0.048	1	13min33s	91.14	0.89
	C25	4	60	0.048	1	14min07s	91.14	0.89
	C26	5	60	0.048	1	13min05s	91.50	0.89

Table 6 summarizes the percentage of resemblance of the four maps and shows the most confused classes. The Linear and RBF Kernels were found to resemble each other the most, and hey both performed like the Sigmoid Kernel more than the Polynomial one. The nearest one to this latter, in terms of performance is the RBF Kernel. A further examination, shows that the classes that were confused the most are fallow and bare soil, which is natural, due to the fact that their spectral signatures overlap, and not to mention that vegetation is absent during the dry months.

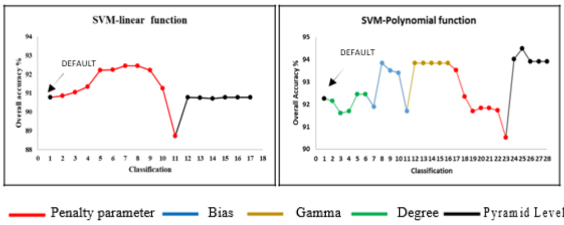

Figure 2 and 3: To the left, combination of different parameters using the Linear Kernel. To the right, combination of different parameters using the polynomial Kernel.

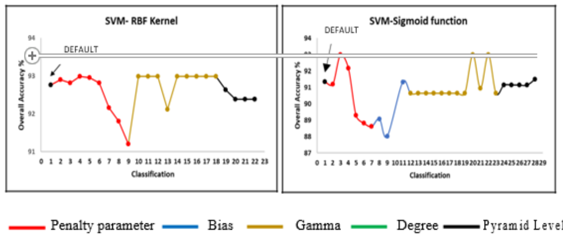

Figure 4 and 5: Combination of different parameters using the RBF Kernel. To the right, Combination of different parameters using the Sigmoid Kernel.

Table 6: Comparison of the four Kernels best combinations.

	Sigmoid		**RBF**		**Polynomial**	
	Resemb lanc%	Most confused classes	Resemb lance%	Most confused classes	Resemb lance %	Most confused classes
Linear	93.84	Olive and citrus	98.56	Olive and cereals	89.65	Fallow and bare soil
Polyno mial	87.39	Fallow and bare soil	89.84	Fallow and bare soil		
RBF	93.28	Olive and cereals				

Additional experiments were done, using the ground truth data of another area in the western part of Haouz plain for the year of 2019. Seven thematic classes were selected, including winter and summer crops, for classification. The obtained results, with standard parameters, gave an OA of 82.19 % and kappa of 0.78. While, using the optimal parameters obtained in this study, the classification accuracy decreased and reached an OA of 72.06% and kappa of 0.66. The main goal of these experiments is to proof that such parameterization should be done for each specific area depending on its land cover types.

4 CONCLUSIONS

This paper highlights the influence of SVM Kernel types and internal parameters over the accuracy of the land-cover classification of remote sensing data. 21 NDVI time-series derived from S2 images was used. 85 models were constructed from a combination of four types of Kernels, between one to four Kernel parameters (depending on Kernel's type: The Penalty parameter Gamma, the Bias and the Degree), and one software-dependent parameter, the Pyramid Level. Each model's OA and Kappa coefficient were noted and served as means of the performance evaluation. The results showed that this techniques effectiveness, does substantially depend on the Kernel's choice and the internal parameters combination. The polynomial kernel outperformed the others, and attained, for PL=2, P=100, r=3, d=6, and Gamma = 0.48, the best OA and Kappa values: 94.50% and 0.93 respectively, while the linear kernel performed the least with an OA that can go down to 88.72% and Kappa of 0.85. Overall, the models were quite sensitive to the Penalty parameter and except for the polynomial type, does not appear to improve when changing the Pyramid Level, if not degrading the performance. We hope that the work provided in the current paper, would help as a guidance to applying SVM classifier for the purpose of land cover classification of satellite data, and encourage users to explore more the different set of parameters. Further work would be carried in exploring other powerful classifiers such as the Neural Networks or the Random Forest.

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